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84

Helinä Laakkonen

Essays on the Asymmetric News Effects on Exchange Rate Volatility

JYVÄSKYLÄN YLIOPISTO

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To my family

ABSTRACT

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One of the fundamental questions in financial economics is how new information is incorporated to asset prices. Four empirical essays preceded by an introductory chapter aim to contribute to the empirical literature on the impact of macroeconomic news on exchange rate volatility. The data set contains 5-minute quotes of the EUR/USD exchange rate from 1999 to 2004 and a comprehensive data set of macroeconomic announcements published in the Bloomberg World Economic Calendar.

Filtering intraday seasonality in volatility is crucial in using high frequency data in econometric analysis. The first essay studies the effects of filtering on statistical inference concerning the impact of news on exchange rate volatility. The properties of different methods are studied by using both real data set and simulated returns. The simulation results suggest that all the methods tend to produce downward-biased estimates of news coefficients, some more than others. The study supports the Flexible Fourier Form method as the best for seasonality filtering.

The second essay studies the asymmetries in the impact of different macroeconomic news categories. The results show that US news increases volatility more than news from the euro area, UK and Japan. While there is no difference in the impact of positive and negative news, volatility increases significantly more when both positive and negative news are announced at the same time compared to when there is only either positive or negative news.

The third essay examines the impact of positive and negative macroeconomic news announcements in different phases of the business cycle. The results suggest that the news effects depend on the state of the economy: negative news increases volatility more in good times than in bad times, while there is no difference between the volatility effects of positive news in bad and good times.

The fourth essay studies whether the accuracy of the news announcements matters in the impact of news on exchange rate volatility. The precision of news is measured in three different ways. When the precision is defined by the size of the first revision of the previous month's figure, precise news increases volatility significantly more than imprecise news. Also, news on indicators that are in general more precise increases volatility more than news on typically imprecise indicators. Finally, real time data is used to measure the 'true' precision of news and the results suggest that the size of the first revision of the previous month's figure is a reasonable signal of 'true' precision.

Keywords: volatility, exchange rates, news, asymmetry, seasonality

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Helsinki, August 2009
Helinä Laakkonen

CONTENTS

CHAPTER 1

INTRODUCTION

1.1 Background

One of the fundamental questions in financial economics is how new information is incorporated to asset prices. This issue is highly relevant also in the foreign exchange markets, which are the most active markets in the world (Bank for International Settlements, 2007). Of all the possible news arriving in the markets, the releases of news concerning the macroeconomic fundamentals like gross domestic product and unemployment rate are of special interest in the context of exchange rates, since the state of the economy is likely to be one factor in the determination of the value of currency. During the last two decades, the empirical literature examining the impact of macroeconomic news on exchange rate dynamics has discovered that macroeconomic news causes a jump in a level of exchange rates and significantly increases volatility of returns.

This dissertation is a collection of four essays that aim to contribute to the empirical literature of the impact of macroeconomic news on exchange rate volatility. The first essay is methodological and it compares the intraday filtering methods used in the literature and the consequences of filtering on the results obtained with the filtered data. The other three essays all study the impact of news on volatility, concentrating on the asymmetries between different news categories. In particular, the second essay studies the difference between the impact of positive and negative news, the third essay examines the business cycle state dependencies in the news effects and the fourth essay studies the relevance of the news precision on the investors' reactions to news.

The plan of the Introduction is as follows. Section 1.1 gives an overview to the relevant literature studying the news effects on exchange rate dynamics. In particular, subsection 1.1.1 provides a general overview of the structure and development of the foreign exchange market, subsection 1.1.2 discusses about the failure of the traditional exchange rate models to explain the currency market dynamics in the short-run, subsection 1.1.3 gives a compendium of the theoretical market microstructure literature related to arrival of new information in the markets, and subsection 1.1.4 summarizes the empirical studies, which are the most relevant in terms of the four essays in the thesis. Section 1.2 then summarizes the main findings and contributions of the four essays. The four essays then follow in Chapters 2, 3, 4 and 5.

1.1.1 Foreign Exchange Markets

The 2007 Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity Report of the Bank for International Settlements, which describes the latest developments in the foreign exchange markets showed that the average daily turnover in the foreign exchange markets has reached to an outstanding 3.2 trillion United States (US) dollars. The currency markets are not only the broadest and most active markets in the world, but they also keep growing and developing all the time.

Table 1.1 highlights some of the main findings of the Bank for International Settlements 2007 report. Besides the unprecedented growth in daily turnover, the foreign exchange market has developed in other means over the years. While there are no dramatic developments in the share of the turnover by instrument, the share of the turnover by counterpart has changed significantly over the years. The most important change has been that the transactions between dealers and financial institutions (e.g. hedge funds and mutual funds) has more than doubled in ten years period. Their share from the overall turnover has changed from 20% to 40%, and also contributed more than half of the increase in the overall turnover. While the share of the trades between dealers and non-financial customers has been rather stable over the years, the share of the transactions between dealers (i.e. interbank markets) has been decreasing quite steadily. The composition of turnover among currencies has not shown any dramatic changes, but the distribution seems to be getting more dispersed. While the shares of the largest currencies are decreasing over the years, the smaller currencies (e.g. emerging market currencies) have increased their share (Bank for International Settlements, 2007).

At the same time with rapidly growing and developing markets, the need to understand foreign exchange market dynamics increases. Understanding the dynamics of foreign exchange markets is as important to private investors, financial institutions as to whole economy. For example, while accurate return volatility forecasts are crucial in the risk management, understanding the market reactions to central bank interventions are essential for the policy makers.

1.1.2 Exchange Rate Determination

In the traditional macroeconomic models, exchange rate has been solved by using different kinds of macroeconomic relations, such as money demand and purchasing power parity. However, the empirical literature on exchange rate determination has shown, that these macro models are only successful in explaining excha-

TABLE 1.1 Structure of the global foreign exchange markets

Table presents the structure of the global foreign exchange markets described in the 2007 Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity Report of the Bank for International Settlements. The figures are daily averages in April, in billions of US dollars and per cent.

	1998		**2001**		**2004**		**2007**	
	Amount	**% share**	**Amount**	**% share**	**Amount**	**% share**	**Amount**	**% share**
Total	1490	-	1200	-	1900	-	3210	
By instrument*								
Spot transactions	568	39.7	387	33.0	631	35.2	1005	32.6
Outright forwards	128	9.0	131	11.2	209	11.6	362	11.7
Swaps	734	51.3	656	55.9	954	53.2	1714	55.6
By counterpart*								
with reporting dealers	908	63.5	688	58.7	956	53.3	1319	42.8
with other financial institutions	279	19.5	329	28.0	585	32.6	1235	40.1
with non-financial customers	242	16.9	156	13.3	252	14.1	527	17.1
* Components do not sum to totals because the estimated gaps in reporting are excluded.								
By currency distribution**								
US dollar	-	-	-	90.3	-	88.7	-	86.3
Euro	-	-	-	37.6	-	36.9	-	37.0
Yen	-	-	-	22.7	-	20.2	-	16.5
Pound sterling	-	-	-	13.2	-	16.9	-	15.0
Emerging market currencies	-	-	-	16.9	-	15.4	-	19.8

** Because two currencies are involved in each transaction, the sum of the percentage shares of the currencies totals 200%. Table presents only the four largest currencies and the share of the emerging market currencies.

nge rate dynamics in the long run or in some exceptional circumstances (e.g. hyperinflation), but explaining short-run (a week or a few months) and very short-run (intraday) dynamics with these models has been very challenging. Several empirical studies have found that in the short run there are substantial movements in exchange rates, which cannot be explained by macroeconomic fundamentals (Meese and Rogoff, 1983; Frankel and Rose, 1995; Taylor, 1995).

The increased criticism for the traditional exchange rate models caused a beginning of new strand of literature on foreign exchange market microstructure, which tries to shed light on the mechanisms generating these deviations from the fundamentals. The market microstructure literature deviates substantially from the traditional exchange rate modelling in both assumptions and research set up. For example, while the market microstructure literature does not assume the market agents to have homogenous strategies or expectations, and that only public information is relevant in the determination of exchange rate, these assumptions are essential in the traditional exchange rate models. Conventional macroeconomic models consider the foreign exchange market structure unimportant, while that is exactly what the market microstructure literature concentrates on explaining: studying the micro side of the market dynamics and answering to questions like ’who are the market participants’, ’what are their expectations and strategies’ and ’how these issues affect the price determination of currency’. Over the last two decades, the vast literature on theoretical and empirical foreign exchange market microstructure has proposed explanations to a wide range of issues related to foreign exchange market dynamics, one of which is the transmission of new information on exchange rates (Sarno and Taylor, 2001).

1.1.3 The Impact of New Information on Exchange Rates

The most distinguishing feature in foreign exchange market microstructure models from traditional macroeconomic models is that the equilibrium spot exchange rate does not come out of a ’black box’, but instead is an outcome of prices quoted by dealers. Another significant difference between these approaches is that in the market microstructure models, the information about the state of the economy affects exchange rates only through dealers’ quotes. In particular, news announcements about the macroeconomic fundamentals that describe the current or future state of the economy have an effect on the value of currency when, and if, dealers revise their quotes in response to new information about the fundamentals (Evans, 2008).

Also, unlike the conventional macroeconomic models that are based on the efficient market hypothesis and rational expectations, the market microstructure models do not assume that only public information matters in the determination of exchange rate. In contrast, news concerning fundamentals affect dealers’ quotes both directly and indirectly. The direct news effects are caused by news announcements about economic fundamentals that are simultaneously available for all dealers, and can also be called ’public information’. Public information is immediately incorporated into prices that dealers quote. Another channel of news effects on dealers’ quotes is indirect, and can be also called as ’private information’. The customers of dealers have dispersed information about the state of the economy, which is based on micro-level information, e.g. the sales and orders of the products of their own company, and is correlated with the macro fundamentals. An individual dealer receives this dispersed information from his customers orders to buy and sell (order flow). The information received through order flow affects dealers quotes and hence the spot exchange rate (Evans, 2008; Sarno and Taylor, 2001).

Apart from the theoretical models that study the transmission mechanisms of new information on exchange rates, there are several market microstructure theories suggesting that market agents' reactions to new information might be asymmetric in different ways. These asymmetries arise e.g. from imperfect information or psychological issues, and they cause underreactions and/or overreactions to news.

The theories relying on imperfect information are e.g. the ones of Damodaran (1985) and Veronesi (1999, 2000). In the model of Damodaran (1985), news is assumed to be reported accurately, but investors make errors in evaluating the meaning of news. The error is assumed to arise e.g. from the need for responding to the new information as quickly as possible, and it causes excess return volatility. Veronesi (2000), on the other hand, suggests that the released information may contain errors. Investors are aware of the fact that some news are more accurate than others and want to hedge against the risk of inaccuracy of news. Depending on the level of the investors' risk aversion, the imprecision of news may cause lower or higher volatility. Veronesi (1999) presents a model where the investors' uncertainty concerns about the future state of the economy. Risk-averse investors require additional discount for bearing the additional risk caused by the uncertainty about the state of the economy, which leads them to overreact to bad news in good times and underreact to good news in bad times.

There are many theoretical frameworks that do not rely on rational expectations, but instead assume that some psychological issues affect investors' reactions to news. One of them is the theory of 'investor conservatism' by Barberis et al. (1998), which suggest that investors react asymmetrically to news due to their 'conservativeness' i.e. reluctance about changing their beliefs in the face of new evidence. In their model investors value an asset by referring to two 'pricing regimes'. The first is the trend regime and the second is the mean reverting regime. If positive (or negative) news is released one after another, the probability of being in the trend regime increases. Conversely, if there is negative news after positive news (or vice versa), the probability of being in the mean reverting regime increases. The investors are reluctant to change to the correct regime in the face of new evidence (news), which causes them to underreact to news in the short run and overreact to them in the long run. Another behavioral model is proposed by Daniel et al. (1998), which is based on investors' overconfidence about their own abilities in various context, and variations in confidence arising from biased self-attribution. Shortly, the overconfident investors overestimate the precision of their private information, but not of public information. The consequence of the model is that the asset prices overreact to private information and underreact to public information. A third example of a behavioral model is the one of Manzan and Westerhoff (2005), which suggest that agents underreact to news in calm periods whereas they overreact to them in more volatile periods.

This asymmetry is caused by the psychological tendency to think that if the historical volatility is high (low), current news must be important (unimportant).

The theoretical microstructure literature is still very dispersed. However, the theories can rather be seen as complements than ruling out each other. All in all, the theories provide good insights on the details of the financial market dynamics. Also, the underlying theories of market microstructure literature provide many testable implications for the empirical literature.

1.1.4 Empirical Literature

This subsection summarizes the findings of the empirical literature studying the impact of news on exchange rate dynamics. Subsection 1.1.4.1 describes the typical data used in the studies and the common methodological issues related to data, subsection 1.1.4.2 discusses about the different definitions of news used in the literature, subsection 1.1.4.3 presents the different ways of news transmitting on exchange rates, and finally subsection 1.1.4.4 summarizes the results of the empirical studies, which are the most relevant in terms of the four essays in this thesis.

1.1.4.1 Data and methodology

In the 1980s and early 1990s the empirical studies on the impact of news were usually based on data observed at daily frequency, while intraday data became available after the introduction of the electronic trading systems in the 1990s. The high-frequency or tick-by-tick data, which contained all the bid and ask quotes announced in the electronic trading system, e.g. Reuters 3000, was a huge improvement and opened up new possibilities for research, because in the active markets the reaction to news is likely to be so quick that the largest jumps on returns occur within the first minutes. Obtaining the high-frequency data was still quite difficult in the early 1990s, because the currency trading institutions were afraid of loosing the privacy of their customers (Goodhart and Payne, 2000). However, in the early 1990s Olsen and Associates released a data set for academic research that contained all the bid and ask quotes for the exchange rates between the US dollar, the Japanese yen and the German mark, and the Reuters news headlines for the time period between October 1992 and September 1993. This data set started a literature, which has been expanded greatly in the recent decades.

While the high-frequency data opened up possibilities, data sets of millions of observations naturally involved also new challenges in terms of data management and statistical analysis. One of the special features of the data is that the quotes are not equally distant discretely sampled observations. Instead, sometimes markets are active and there might be more than one quote per second, and at other times during the lower market activity, there might be long gaps without any quotes (Bollerslev, 2001). The autoregressive conditional duration model of Engle and Russel (1998) was motivated by this problem and has been widely used in modelling high-frequency data. Another 'solution' to the problem has been to decrease the frequency by collecting the quotes e.g. every five minutes.

This way the data has equally distant discretely sampled observations, with more information than in daily data.

One challenge with data sampled at intraday frequencies is the intraday seasonality of volatility. Baillie and Bollerslev (1991) studied the statistical properties of the intraday data of four currency pairs (US dollar against British pound, German mark, Swiss franc and Japanese yen) and found that differences in trading times in the global foreign exchange markets cause the average level of volatility to differ depending on the time of the day. While during the opening hours of the Asian markets volatility is relatively low, during the opening hours of the European and US markets the average level of volatility is significantly higher. These intraday changes that are repeated every day cause periodical U-shape patterns in autocorrelation functions of volatility, and have to be filtered out of intraday data used for statistical inference.

Many methods have been developed to filter the intraday periodicity, but yet there is not a method that could be considered as a standard. The used methods can be divided into three categories. The first category consists of filtering methods that use a linear projection to model the periodicity component: Andersen and Bollerslev (1997) use sinusoids as exogenous variables, while Degennaro and Shrieves (1997) include hourly dummies in the volatility regression to capture the periodicity. The second category comprises methods based on smoothing techniques: Cleveland (1979) adopts a weighted time trend estimation, Engle and Russell (1998) use a cubic splines technique, whereas Veredas et al. (2002) and Ben Omrane and De Bodt (2007) employ kernel estimators for deseasonalizing. In the third category, the methods use the average (absolute/squared) returns per intraday interval to compute the filter: Dacorogna et al. (1993) introduced the ϑ-time transformation, which deseasonalizes volatility by expanding periods with high average market activity and contracting periods with low average market activity, Melvin and Yin (2000) divide each observation by the mean number of quotes for each hour of the business week, while Bauwens et al. (2005) compute the intraday volatility estimate by averaging the squared returns per 5-minute interval over the whole sample period (separately for the different weekdays).

1.1.4.2 News

News is a very broad concept covering everything from a phone call of a customer who wants to make a foreign exchange (FX) transaction to general economic and political news. Therefore, news is very difficult to quantify. In the earliest studies, it was common to use Reuters headlines as news. Typically analysis was based on a dummy variable that takes a value of one if the Reuters headline occurs and zero otherwise (e.g. Goodhart et al., 1993). Alternatively, one could form a measure of 'information flow', indicating how many news headlines were published during a particular time period, e.g. five minutes (Melvin and Yin, 2000; Eddelbüttel and McCurdy, 1998).

In more recent studies it has been common to use the scheduled releases of macroeconomic fundamentals as news. The news of the macroeconomic fundamentals like gross domestic product, unemployment rate and consumer confidence index are naturally only a small part of the news affecting exchange rate dynamics. However, because the state of the economy is likely to be one factor in the determination of the value of currency, and because the macroeconomic releases are publicly available, they are very useful in the empirical analysis on the impact of news on exchange rate dynamics.

By definition, only the part of the released information that surprises the investors, i.e. news, should affect exchange rates. However, the problem is that we usually do not know the market expectations of the event and can not therefore define the size of the surprise, i.e. the difference between the released information and the market expectations. One major advantage of the scheduled macro releases is that because their release day and time are known beforehand in the market, it is possible to try to forecast the figures. The news agencies, e.g. Bloomberg, surveys these forecasts and publish a 'market forecast', which is median of all survey forecasts. Therefore, measuring the unanticipated information is possible in the case of macroeconomic announcements, although it is arguable whether the survey forecast is a perfect proxy for the market forecast.

1.1.4.3 How news is transmitted into prices?

The empirical literature of the news effects on exchange rate dynamics can be divided into two strands: one examines the direct effects of macroeconomic news on exchange rate returns and volatility[1], while the other focuses on the transmission mechanism of new information on prices (e.g. Degennaro and Shrieves, 1997; Evans and Lyons, 2008). As explained in the previous subsection, the market microstructure theories assume that new information is incorporated into prices trough direct and indirect channel. Besides the immediate effects on dealers' quotes after the release, news also affect dealers' quotes through customer order flow.

Evans and Lyons (2008) studied the transmission of new information on DEM/USD (German mark against United States dollar) returns with three explanatory variables in their model: news, order flow caused by news and order flow unaffected by news (caused by the changed liquidity demand of banks, firms or individuals). According to their results, all three variables have significant effects on exchange rate returns. Half of the impact of news is transmitted directly, while the other half through order flow.

Degennaro and Shrieves (1997) studied the effect of news and order flow on JPY/USD (Japanese yen against United States dollar) exchange rate volatility. They considered order flow as 'private information', because it is not available to all market agents, while macroeconomic announcements were considered as public information. Different from Evans and Lyons (2008), Degennaro and Shrieves (1997) did not separate the order flow caused by news announcements from the order flow, which is unaffected by news. According to their results, exchange rate volatility is affected by both public (news) and private (order flow) information.

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1 The literature includes for example Goodhart et al. (1993), Ederington and Lee (1993), Degennaro and Shrieves (1997), Almeida et al. (1998), Andersen and Bollerslev (1998), Eddelbüttel and McCurdy (1998), Melvin and Yin (2000), Andersen et al. (2003, 2007), Chang and Taylor (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006), Faust et al. (2007), Laakkonen (2007) among others.

Even though the order flow studies are an important part of the literature, most of the studies have focused on the direct news effects on exchange rate dynamics. Because the essays of this dissertation also study the direct news effects on exchange rate volatility, the next subsection only summarizes the results of the empirical studies in that strand of the literature.

1.1.4.4 Results

Goodhart et al. (1993) were one of the first that used high-frequency data in modeling the impact of news on exchange rate returns and volatility. They had all the bid and ask quotes of GBP/USD (British pound against United States dollar) exchange rate for a eight week period in 1989 from Reuters FXFX screen. They studied the impact of two US macroeconomic news headlines published in Reuters AAMM pages on GBP/USD returns and volatility, and found that news has a significant positive impact on both.

The studies in the mid 1990s usually used the high-frequency DEM/USD data provided by Olsen and Associates. For example, Eddelbüttel and McCurdy (1998) studied the impact of information flow (how many news headlines is published during a particular time interval in Reuters News Service) on DEM/USD volatility. They used different frequencies from 20-minutes to one hour and found that the frequency of news related to the US, German and the global macro economy has a significant relationship with volatility. In particular, more news is associated with increased volatility.

Chang and Taylor (2003) used the same concept of information flow and the same intraday data as Eddelbüttel and McCurdy (1998), but they separated news into different categories. They found that total headline news counts, US and German macroeconomic news, US Federal Reserve and German Bundesbank monetary policy news all have significant positive impact on DEM/USD volatility, while the German Bundesbank and US macroeconomic news has the largest effects.

Degennaro and Shrieves (1997) used the same Olsen data set but instead of DEM/USD they studied the impact of information arrivals on 10-minutes JPY/USD return volatility. By using key words, they extracted three categories of news from Reuters news headlines. In particular, the news categories included regularly scheduled US and Japan news, unscheduled policy news releases and the unscheduled interest rate reports from the USA and Japan. Their results suggested that regularly scheduled macroeconomic releases increase volatility significantly, unscheduled interest rate news also causes an increase in volatility, while the unscheduled policy announcements are associated with a small but statistically significant reduction in volatility.

The Olsen data set was also used by Andersen and Bollerslev (1998), who analyzed the sensitivity of DEM/USD and JPY/USD volatility with respect to US macroeconomic announcements and seasonal factors. They showed that announcements have a significant positive effect on volatility, which lasts from one to two hours depending on the announcement. Most important US macro announcements, namely employment report, gross domestic product, trade balance figures and durable goods orders are all related to the real economy, while the important German announcements, the Bundesbank meeting and M3 supply figures, are related to monetary policy.

While most of the studies concentrate on the impact of news on volatility, Almeida et al. (1998) studied the effects of US and German macro announcements on the conditional mean of the DEM/USD returns. With a three year data set of intraday returns of different frequencies, they documented systematic, yet short lived news effects: they found significant impacts of macroeconomic news on the exchange rate change in the 15-minutes post-announcement period, although the significance of these effects decreased rapidly as the interval was increased. Almeida et al. (1998) also documented that the German news announcements tend to be incorporated in the exchange rate more slowly and the impact is quantitatively smaller than that of the US news.

A significant study examining the impact of macroeconomic announcements on the exchange rate returns is that by Andersen et al. (2003), who used a much longer and more comprehensive data set of exchange rates than the studies before. With six years of 5-minute data on the US dollar versus German mark, British pound, Japanese yen, Swiss franc, and euro, they found that announcement surprises produce conditional mean jumps, and that market reacts to news in an asymmetric fashion: bad news has greater impact than good news.

While usually the studies have focused on the post-announcement effects, Bauwens, Ben Omrane and Giot (2005) studied the dynamics of exchange rates before the news announcements. They used high-frequency EUR/USD (euro against United States dollar) data, and showed that volatility increases also in the pre-announcement periods, particularly before scheduled events.

The impact of news on different foreign exchange instruments has also been studied, e.g. by Ederington and Lee (1993), who showed that there is a significant positive relationship between the macroeconomic news and the return volatility of foreign exchange futures contracts in the US markets.

More recent literature in the related area of research has typically been focusing either on the impact of macroeconomic news on different assets simultaneously or on some asymmetries in the news effects, e.g. state dependencies. Andersen et al. (2007) characterized the response of US, German and British stock, bond and foreign exchange markets to US macroeconomic news with a high-frequency futures data set. Their results suggest that news produces conditional mean jumps, the bond market reacting most strongly and the equity and foreign exchange market appearing equally responsive. On the other hand, Faust et al. (2007) examined the joint movements of the value of the dollar and the term structure of interest rates denominated in US dollars, British pounds and German mark/euros, over short-time windows around macroeconomic announcements using a 14-year span (1987-2002) of high-frequency data. They found a clear and consistent pattern in the responses to real economy announcements (e.g. nonfarm payroll, gross domestic product, housing starts): stronger than expected news for the US real activity consistently rises the value of the dollar and rises the short-term and long-term interest rates in the US and, to lesser extent, overseas. Faust et al. (2007) also studied state dependencies of news effects, but found only limited evidence of time-variation in responses.

Pearce and Solakoglu (2007) studied the impact of macro news on high frequency DEM/USD and JPY/USD returns and volatility. With a 10 year-long data set, they studied the linearity and symmetry of the responses to news, allowing the effects of the news announcements to vary across the states of the economy. They found that news indicating a stronger US economy causes an appreciation of the US dollar, and that news increases volatility significantly. The effects of news appeared to be symmetric with respect to sign, but they found some evidence that the effects of news would depend on the state of the economy.

All in all, the literature has shown that macroeconomic announcements have an immediate effect on exchange rate dynamics: news causes a jump in the level of exchange rate in minutes after the announcement and a higher volatility from an hour to two hours following the news release.

1.2 Summaries of the Essays

The empirical literature has shown that there is a significant connection between news on macroeconomic fundamentals and exchange rate dynamics. The dynamics of foreign exchange markets have been examined a lot, but there are still many interesting implications of the market microstructure theories to be studied empirically, some of which this thesis wishes to shed light on. The subsection 1.2.1 describes the data used in all of the essays, and the subsections 1.2.2, 1.2.3, 1.2.4 and 1.2.5 then summarize the four essays presenting the main results and contributions to the literature.

1.2.1 Data

The original data set contains 5-minute quotes of the EUR/USD exchange rate from 1 January 1999 to 31 December 2004 and it was obtained from Olsen and Associates. The prices are formed by taking the average between the bid and ask quotes, and the returns are computed as the differences of logarithmic prices.

As the foreign exchange market activity slows down decidedly during weekends and certain holiday non-trading periods, it is standard in the literature to explicitly exclude a number of days from the raw 5-minute return series. Following Andersen and Bollerslev (1998), we exclude the weekends and certain holidays by always excluding the returns from 21:05 GMT the night before to 21:00 GMT that evening. Andersen and Bollerslev (1998) state that this definition of a "day" retains the intraday periodical volatility structure intact. The following holidays are excluded from the data: Christmas, New Year, Good Friday and Easter Monday. Besides holidays, three days are excluded from the data because of lack of observations[2] (10 May 1999, 21 Dec. 2000, 24 Dec. 2000). Daylight savings time is also taken into account as is standard in the literature.

The data set of macro announcements is very comprehensive compared to the earlier literature and that is one of the main contributions of the thesis. In particular, it includes all the scheduled US, UK, Japan and euro area macroeco-

[2] The reason for missing observations is unknown.

nomic news (e.g. gross domestic product, unemployment rate, consumer price index, consumer confidence index) published in the World Economic Calendar (WECO) page of Bloomberg in 1999-2004. The data contains the announcement date and time in one minute accuracy, the announced figure, the first revision of the previous months' figure and the market forecast for the figure. The market forecast is a median of the survey forecasts that Bloomberg collects from the market agents. There were altogether 27410 news announcements. However, because many macroeconomic figures are announced simultaneously, the number of nonzero observations in the news variables is not as high. Also, in different essays we use different subsets of the announcements. The complete list of news announcements is presented in the Appendix.

Besides the Bloomberg announcements data, in the fourth essay we use the Federal Reserve Bank of Philadelphia's (Fed) real time data for five macro indicators: nonfarm payroll, consumer price index, housing starts, industrial production and capacity utilization. Fed's data contains all the monthly or quarterly revisions for the announced figures of these macroeconomic indicators beginning from the first release up to the last estimate released years after the first estimate.

1.2.2 Exchange Rate Volatility, Macro Announcements and Choice of the Intraday Seasonality Filtering Method

Intraday data sets are very informative and provide more accurate results than do daily data sets. Nevertheless, these kinds of data sets have some special features that need to be scrutinized for the sake of reliable results. One crucial issue is the filtering of intraday periodicity of volatility, which is caused by differences in trading times in the global foreign exchange markets.

To study the intraday periodicity of volatility, we use absolute returns as a measure of volatility and expose the average intraday volatility pattern by computing the mean absolute return per every five-minute interval in 24 hours, which is presented in the upper graph of Figure 1.1. The level of volatility during a day depends on the trading times in different markets: the Asian markets open around 23:00 GMT and cause a small increase in the average level of volatility; the European markets open around 7:00 GMT and volatility increases more; and the US markets open around 14:00 GMT after which volatility reaches its highest level. It is noteworthy that there are two spikes in the average volatility pattern: most US macro figures are announced at 13:30 GMT and 15:00 GMT and, as can be seen, they cause significant increases in volatility. When this kind of pattern is repeated every day, it causes a U-shape pattern in the autocorrelation of volatility. The lower graph in Figure 1.1 presents the autocorrelation coefficients of absolute returns for 1500 five-minute lags, i.e. the autocorrelogram for five days. As can be seen, the U-shape pattern is repeated almost identically every day and therefore it has to be filtered out of intraday data used for statistical inference (Baillie and Bollerslev, 1991; Andersen and Bollerslev, 1998; Melvin and Yin, 2000; Cai et al., 2001 and Bauwens et al., 2005).

Usually periodicity is considered as nuisance in time series econometrics, and filtering is something one needs to do before starting the actual work with the data. However, filtering might cause at least three kinds of problems that

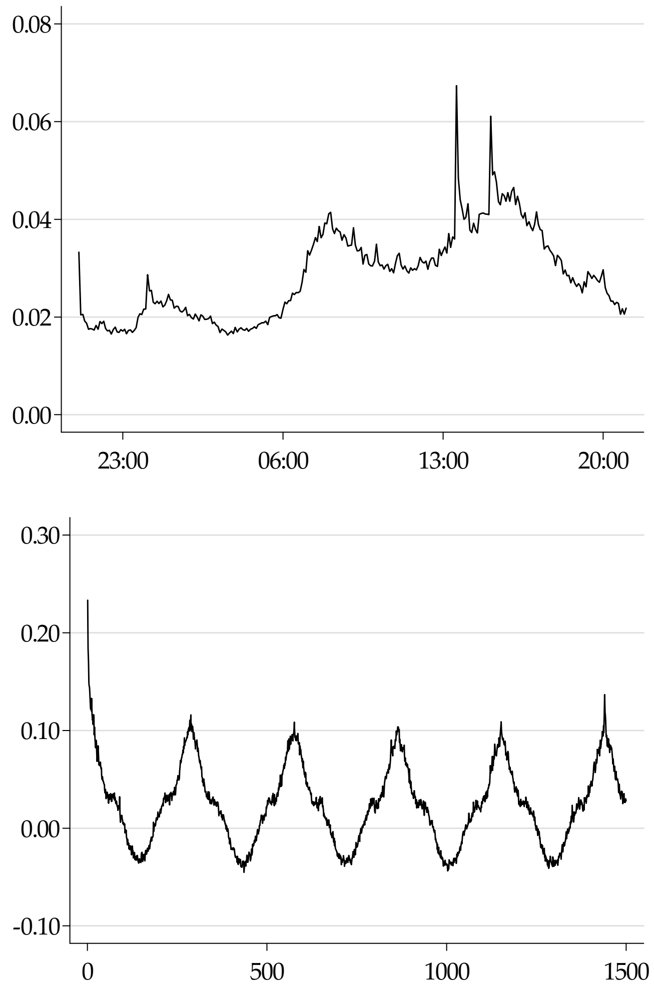

FIGURE 1.1 Intraday periodicity of volatility
The upper figure presents the average intraday EUR/USD volatility pattern, ie. average absolute return per each five minute interval over the whole sample period. Volatility pattern is caused by different trading times in the global foreign exchange markets. The lower figure presents the five day (1500 five minute lags) autocorrelogram of the 5-minute EUR/USD absolute returns.

researchers rarely consider. First, most filtering methods are capable of removing some of the periodicity, but not all of it. The periodicity in volatility that remains after filtering may affect the other results of the study. Second, filtering might generate something new, for example extra jumps, in returns. Third, in filtering out periodicity, something important might be filtered out as well. For example, if one is studying the impact of news on volatility, the filter should not eliminate the news effects.

In the first essay we use 5-minute EUR/USD data to study the problems that filtering might cause: 1) we compare autocorrelation functions of absolute returns filtered with different methods to see if there is periodicity left in volatility after filtering and study the news effects with different filtered returns to see whether the filtering affects the magnitudes of the news coefficients, 2) we compare the key statistical figures of the original and filtered returns to study whether filtering changes the properties of the return process. Furthermore, 3) we use the properties of the EUR/USD data to simulate returns, which comprise the daily volatility component, intraday volatility component, news component and random shocks. We filter the simulated returns, estimate the news effects with the filtered returns and compare the estimated news coefficient values to the simulated ones to see if the estimated news effects are biased.

Compared to the earlier literature that compares the filtering methods (Martens et al., 2001; Ben Omrane and De Bodt, 2007), we concentrate more carefully on the possible consequences that filtering might have. We consider three commonly used methods, each of which belongs to one of three filtering method categories, set out by Ben Omrane and De Bodt (2007). These are the Flexible Fourier Form method (FFF) of Andersen and Bollerslev (1997), which uses sinusoids as exogenous variables to capture the periodicity; the Locally Weighted Scatterplot Smoothing method (LOWESS) of Cleveland (1979), which adopts a weighted time trend estimation for deseasonalizing; and the Intradaily Average Observations Model (IAOM) of Bauwens et al. (2005) in which the intraday volatility estimate is computed by averaging the squared returns per each intraday interval and separately per each weekday over the whole sample period.

The results suggest that all the methods are capable of filtering the periodicity in volatility only if the estimation is done by dividing data into sufficiently short subsets. This indicates that the intraday volatility periodicity is time varying. The filtering method and the selected subset length affect the magnitudes of the estimated news coefficients significantly: when the subset is shortened, the news coefficients increase when the filtering is done by using the FFF method, and decrease, when the LOWESS or IAOM methods are used for filtering.

According to the results of the simulation study, if the returns are not filtered at all, the estimated US and European news coefficients are too large and the Asian news coefficients too small. Also, all the methods tend to produce downward biased estimates for the news coefficients, i.e. to filter out part of the news effects, some worse than others. While the LOWESS is performing the best in terms of getting rid of periodicity in volatility, it also seems to filter out more news effects than do the other two filters. The IAOM performs almost as well as the FFF, but in the case of regularly announced news it produces very downward biased estimates compared to the FFF method. Therefore, the study supports the FFF model as the best for periodicity filtering.

1.2.3 Asymmetric News Effects on Exchange Rate Volatility

In the second essay we study the impact of macroeconomic news on EUR/USD return volatility by focusing on the asymmetries between different news categories. We begin by studying the news effects in general without any asymmetries, and examine the effects of the US, UK (United Kingdom), euro area and Japan news separately. We then proceed to study the differences between the impact of positive and negative news.

The asymmetry with respect to the sign of news has been studied previously, but the results have been mixed: for example, Andersen et al. (2003) find that negative news has larger impact than positive news on exchange rate returns, while Pearce and Solakoglu (2007) do not find asymmetries with respect to sign. We examine two possible reasons, why positive and negative news might cause different reactions in different situations. The first explanation is related to the difficulty of analyzing news. Damodaran (1985) suggests that investors make errors in evaluating the meaning of news, and that is caused by the need for responding to new information as quickly as possible. Therefore, it could be that sometimes investors might have difficulties to evaluate whether the released information is good or bad for the value of the exchange rate, and this task becomes even challenging, when a whole set of macro figures are announced at the same time. One might think that getting more information about the state of the economy at the same time would be useful. However, if some of the news signals better than expected economic conditions and some worse than expected state of the economy, investors could find it difficult to evaluate the overall effect of these kind of 'contradictory' news announcements compared to the situation when there are only either positive or negative, i.e. 'consistent' news in the market. According to the model of Damodaran (1985), the errors in evaluating the meaning of news causes excess volatility on returns.

Another possible explanation could be that investors value the news differently depending on the sign of the previous news. For example, positive news after a series of positive news might gain a different reaction than positive news following negative news. Barberis et al. (1998) suggest that investors are reluctant to change their beliefs about the state of the economy in the face of new evidence. Therefore, they tend to overreact to news in the long run, and underreact to them in the short run. This might imply that the reaction to news that is preceded by a series of news of the same sign would be stronger than the reactions to other news.

The results suggest that macro announcements increase volatility significantly, US news having the strongest effect. UK news seems to increase volatility as much as news from the largest euro area countries, while news from the smallest euro area countries, and from Japan does not seem to affect volatility. We do not find a significant difference between the impact of negative and positive news, but the results suggest that 'contradictory' news increase volatility significantly more than 'consistent' news. The results also suggest that macro news that is preceded by three news of the same sign (e.g. positive employment news when the previous three news announcements on employment have also been positive) increase volatility significantly more than news that is preceded by news of the opposite sign.

1.2.4 Asymmetric News Effects on Exchange Rate Volatility: Good vs. Bad News in Good vs. Bad Times

The third essay contributes to the recent literature that tries to shed light on the relationship between the impact of positive and negative macroeconomic news on exchange rate volatility over the business cycle. This line of research has concentrated mainly on the stock market. McQueen and Roley (1993), Flannery and Protopapadakis (2002), Conrad et al. (2002), Adams et al. (2004), Boyd et al. (2005) and Andersen et al. (2007) all report findings that support the state dependence of announcement effects in the US stock market. In general, news seems to have stronger effect in good times than in bad times. In addition to stock markets, business cycle state dependencies have been studied in the US bond futures market by Veredas (2006) and in the foreign exchange market by Faust et al. (2007) and Pearce and Solakoglu (2007). The findings of Veredas (2006) and Pearce and Solakoglu (2007) are in line with the results from the equity market, but Faust et al. (2007) find only limited evidence in favour of the state dependence of news effects. The state dependencies of asymmetric news effects between positive and negative news have been studied by Conrad et al. (2002) and Veredas (2006). They both find that negative news seems to have a greater effect in good times than in bad times. On the other hand, the impact of positive news seems to be similar in good and bad times.

We study the state dependencies of the macroeconomic news effects on the volatility of the 5-minute EUR/USD exchange rate returns. Our paper contributes to the literature in several aspects. First of all, our data set is much richer than the ones used in the previous literature. Furthermore, besides the US business cycle, we study the asymmetries using a European business cycle indicator. While it is reasonable to concentrate on the US business cycle when studying only the US stock markets, this need not be the case when assets from several countries are considered, although this seems to have been the common procedure in the previous literature (see e.g. Andersen et al., 2007). Moreover, our methodology is more flexible than that in the previous literature. Most of the existing studies define the expansions and contractions beforehand by various criteria: McQueen and Roley (1993) measure the business cycle with industrial production and determine the levels of 'high', 'medium' and 'low' economic activity by estimating a trend and fixing some intervals around it, while Andersen et al. (2007) define contractions as beginning when there are three consecutive monthly declines in nonfarm payroll employment. In contrast, we allow for the state dependence in the news effects by estimating a smooth transition regression model with a business cycle indicator as the transition variable. The main advantage of our approach is that the threshold between the different states is not fixed a priori, but estimated. Therefore, splitting the data beforehand into fixed regimes such as good and bad times is not necessary. Furthermore, the model allows the change from one regime (bad times) to another (good times) to be smooth and the model can be generalized to allow for more than two regimes in a straightforward manner.

We find that news effects are affected by the state of the economy, such that they are stronger in good times than in bad times. Moreover, the impact of bad news seems to be stronger in good times than in bad times, while there is no such asymmetry in the impact of good news. These results are in line with the previous studies from equity and bond markets, and they can be interpreted as supportive for Veronesi's (1999) theory, which suggests that because of asymmetric information concerning the state of the economy, investors overreact to bad news in good times and underreact to good news in bad times.

1.2.5 The Relevance of Accuracy in the Impact of Macroeconomic News on Exchange Rate Volatility

According to theories concentrating on the quality of information (e.g. Veronesi, 2000), investors' reaction to new information does not only depend on the amount of unanticipated information, i.e., the difference between the announced figure and investors' personal expectations of the figure, but also on what they think about the quality of information. Despite this, the extensive literature on the effects of news announcements on financial market dynamics has mostly ignored such quality aspects.

The issue of news accuracy is of particular importance for macroeconomic news because it is widely known that the first released estimate of a macroeconomic indicator, such as the gross domestic product (GDP) often deviates considerably from the 'final' estimate. The figures can be revised for years and the difference between the first and final estimates can be substantial. For example, according to Swanson and van Dijk (2001) it takes at least 12 months for the seasonally adjusted US producer price index and industrial production figures to reach the 'correct' value. Also, there is a large literature confirming that the revisions of macroeconomic figures are somewhat predictable (e.g. Swanson and van Dijk, 2001).

While the literature on the effects of news announcements on financial returns and their volatility is voluminous, there appears to be very little research addressing the consequences of the precision of news announcements. Krueger and Fortson (2003) measure information precision by a linear time trend, which is assumed to capture the increasing precision of news releases over time, and find only limited evidence in favour of the relevance of US employment news accuracy for daily Treasury bond prices. On the other hand, the results of Hautsch and Hess (2007) suggest that more precise news on the US nonfarm payroll has a stronger impact on the intraday prices of Treasury bond futures than less precise news. Hautsch and Hess (2007) state that because the first revision of the previous month's figure (released at the same time as the present month's figure) reveals the measurement error in the previous period, it may help traders to assess the accuracy of the currently released news. Therefore, they measure the precision of an announcement by using the one-step-ahead conditional variance forecast of an ARMA-GARCH model fitted to the time series of revisions of US nonfarm payroll. In particular, the reliability of the announced figure is expected to decrease when the expected revision variance increases.

In the fourth essay, we study the relevance of the precision of news announcements concerning 20 macroeconomic indicators for the effect on the volatility of the EUR/USD exchange rate returns. We consider three ways of defining the precision of news. First, because the revision of the previous month's figure is always announced at the same time as the first estimate of the present month's figure, we follow Hautsch and Hess (2007) and assume that the size of this revision is a signal to investors of the accuracy of the present month's figure. We study whether investors react differently to standardized news surprises, when the standardized absolute revision of the previous month's figure is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. In other words, our first measure of precision is conditional on the previous revision.

The different macroeconomic indicators deviate considerably by the magnitude of revisions. Some indicators are often revised quite considerably (e.g. nonfarm payroll) while others undergo hardly any revision at all (e.g. confidence figures). These differences allow us to study the importance of the overall accuracy of news announcements on volatility. We study this issue by comparing investors' reactions to standardized news on macro indicators, whose mean standardized absolute revision (the first revision of the previous month's figure) is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. Hence, our second measure of precision is unconditional. We also analyze the conditional and unconditional measures jointly to see whether there are differences in investors' reactions to precise and imprecise announcements of indicators that are usually precise or imprecise.

Ex ante, investors do not actually know which announcements are accurate, and they try to resolve this issue by using prior information. Whether they are successful in predicting the accuracy of the announcements can be determined by means of the 'final correct' figures that become available after several revisions. Specifically with such data, we can compute ex post news surprises that should yield similar results as the ex ante measures if investors' signals of news accuracy are efficient. Moreover, by comparing the two precision measures, we can infer whether investors are trying to predict the first release or final figures.

In the previous literature, the paper that comes closest to ours, is Hautsch and Hess (2007). However, while Hautsch and Hess (2007) argue that investors' reaction to news depends on the relative precision of the announced data compared to the precision of the investors' beliefs, we study if the precision of announcements have direct effects on investors' reactions to news. Also, as mentioned above, we study the issue from several different viewpoints, while they only concentrate on the similar ex ante conditional measure of precision as we do. To our knowledge, neither the ex ante unconditional nor the ex post measures have been used earlier in the literature. Finally, while Hautsch and Hess (2007) only use the news on US nonfarm payroll, our data contains 20 US macroeconomic indicators, and the results are therefore more general, albeit the US nonfarm payroll is probably the most important macro indicator. Our paper also differs from the previous literature in that we study the relevance of news accuracy on exchange rate volatility, while the two earlier papers consider US Treasury bond returns.

The results show that when using the revision of the previous month's figure in defining the accuracy of the news releases, the announcements that are more precise, increase volatility significantly more than imprecise ones. Also, the news of the macro indicators that are usually more precise increase volatility significantly more than those of indicators that are usually imprecise. When considering the conditional and unconditional measures of accuracy simultaneously, we find that investors are reacting to both measures of precision. The conditional measure of precision seems to be relevant for investors, because news on the high-precision indicators increase volatility significantly more than news on low-precision indicators only when the announcement is also conditionally precise. On the other hand, among the unconditionally precise or imprecise news, the conditional precision does not cause asymmetric reaction to news, as it does when the indicators are not classified to precise and imprecise by using the unconditional measure. This indicates that the size of the revision of the previous month's figure is not the only signal the investors are using, but that investors react to both, conditional and unconditional measure of precision.

We also find that announcements that ex post turned out to be more precise, increase volatility more than those that turned out to be imprecise. Thus the precision of the previous revision seems to provide an efficient signal of current precision. Moreover, the results suggest that investors try to predict the first-release rather than final figures.

REFERENCES

Adams, G., McQueen, G., Wood, R., (2004) "The Effects of Inflation News on High Frequency Stock Returns" The Journal of Business 77, 547–574

Almeida, A., Goodhart, C., Payne, R., (1998) "The Effects of Macroeconomic News on High Frequency Exchange Rate Behavior" The Journal of Financial and Quantitative Analysis 33, 383-408

Andersen, T., Bollerslev, T., (1997) "Intraday periodicity and volatility persistence in financial markets" Journal of Empirical Finance 4, 115-159

Andersen, T., Bollerslev, T., (1998) "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies" The Journal of Finance 53, 219-265

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2003) "Micro Effects and Macro Announcements: Real-Time Price Discovery in Foreign Exchange" American Economic Review 93, 38-62

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2007) "Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets" Journal of International Economics 73, 251-277

Baillie, R., and Bollerslev, T., (1991) "Intra-day and Inter-market Volatility in Foreign Exchange Market" Review of Economic Studies 58, 565-585

Barberis, N., Schleifer, A., Vishny, R., (1998) "A model of investor sentiment" Journal of Financial Economics 49, 307–343

Bauwens, L., Ben Omrane, W., Giot, P., (2005) "News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market" Journal of International Money and Finance 24, 1108-1125

Ben Omrane, W., De Bodt, E., (2007) "Using self-organizing maps to adjust intraday seasonality" Journal of Banking & Finance 31, 1817-1838

Bank for International Settlements (2007) "Triennial Central Bank Survey: Foreign exchange and derivatives market activity in 2007" Bank for International

Settlements

Bollerslev,T., (2001) “Financial Econometrics: Past developments and future challenges" Journal of Econometrics 100, 41-51

Boyd, J., Hu, J., Jagannathan, R., (2005) “The Stock Market’s Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks“ The Journal of Finance 60, 649-672

Cai, J., Cheung, Y., Lee, R., Melvin, M., (2001) “’Once in a generation’ yen volatility in 1998: fundamentals, intervention and order flow" Journal of International Money and Finance 20, 327–347

Chang, Y., Taylor, S., (2003) “Information arrivals and intraday exchange rate volatility” International Financial Markets, Institutions and Money 13, 85–112

Cleveland, W., (1979) “Robust Locally Weighted Regression and Smoothing Scatterplots" Journal of the American Statistical Association 74, 829-836

Conrad, J., Cornell, B., Landsman, W.R., (2002) “When Is Bad News Really Bad News?“ The Journal of Finance 57, 2507-2532

Dacorogna, M., Müller, U., Nagler, R., Olesen, R., Pictet, O., (1993) “A geographical model for the daily and weekly seasonal volatility in the foreign exchange market" Journal of International Money and Finance 12, 413-438

Daniel, K., Hirshleifer, D., Subrahmanyam, A., (1998) “Investor Psycohology and Security Market Under- and Overreaction" Journal of Finance 52, 1-33

Damodaran, A., (1985) “Economic Events, Information Structure, and the Return-generating Process" The Journal of Financial and Quantitative Analysis 20 No. 4

Degennaro, R., Shrieves, R., (1997) “Public information releases, private information arrival and volatility in the foreign exchange market” Journal of Empirical Finance 4, 295–315

Dominguez, K., Panthaki, F., (2006) “What defines ‘news’ in foreign exchange markets?" Journal of International Money and Finance 25, 168-198

Eddelbüttel D., McCurdy, T., (1998) “The Impact of News on Foreign Exchange Rates: Evidence from High Frequency Data” Manuscript Rotman School of Management, University of Toronto

Ederington, H., Lee, J., H., (1993) “How Markets Process Information: News Releases and Volatility” The Journal of Finance 48, 1161-1191

Engle, R., Russell, J., (1998) “Autoregressive conditional duration: a new approach for irregularly spaced transaction data" Econometrica 66, 1127–1162

Evans, M., (2008) "Foreign Exchange Market Microstructure" in the New Palgrave Dictionary of Economics, Palgrave Macmillan, 2008.

Evans, M., Lyons, R., (2008) “How is macro news transmitted to exchange rates?” Journal of Financial Economics 88, 26-50

Faust, J., Rogers, J., Wang, S.-Y.B., Wright, J., (2007) “The high-frequency response of exchange rates and interest rates to macroeconomic announcements“ Journal of Monetary Economics 54, 1051-1068

Flannery, M., Protopapadakis, A., (2002) “Macroeconomic Factors Do Influence Aggregate Stock Returns“ The Review of Financial Studies 15, 751-782

Frankel, J., and Rose, A., (1995) "Empirical Research on Nominal Exchange Rates in the Handbook of International Economics, Vol. 3, Amsterdam and New

York, North-Holland, Elsevier

Goodhart, C. A. E., Hall, S. G., Henry, S. G. B., Pesaran, B., (1993) "News effects in a high-frequency model of the sterling-dollar exchange rate" Journal of Applied Econometrics 8, 1-13

Goodhart, C. A. E., Payne, R., (2000) "The Foreign Exchange Market, Empirical Studies with High-Frequency Data" MacMillan

Hautsch, N., Hess, D., (2007) "Bayesian Learning in Financial Markets: Testing for the Relevance of Information Precision in Price Discovery" Journal of Financial and Quantitative Analysis 42

Krueger, A., Fortson, K., (2003) "Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality" Journal of the European Economic Association 1, 931-957

Laakkonen, H., (2007) "The Impact of Macroeconomic News on Exchange Rate Volatility" Finnish Economic Papers 20, 23-40

Manzan S., Westerhoff, F., (2005) "Representativeness of news and exchange rate dynamics" Journal of Economic Dynamics and Control 29, 677–689

Martens, M., Chang, Y-C., Taylor, S., (2002) "A comparison of seasonal adjustment methods when forecasting intraday volatility" Journal of Financial Research 25, 283–299

McQueen, G., Roley, VV., (1993) "Stock Prices, News and Business Conditions" The Review of Financial Studies 6, 683-707

Meese, R., Rogoff, K., (1983) "Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?" Journal of International Economics 14, 3–24

Melvin, M., Yin, X, (2000) "Public information arrival, exchange rate volatility and quote frequency" The Economic Journal 110, 644–661

Pearce, D., Solakoglu, N., (2007) "Macroeconomic news and exchange rates" Journal of International Financial Markets, Institutions and Money 17, 307-325

Sarno, L., Taylor, M., (2001) "The microstructure of the foreign-exchange market: a selective survey of the literature" Prinston Studies in International Economics, No 89

Swanson, N., Dijk, D., (2001) "Are statistical reporting agencies getting it right? Data rationality and business cycle asymmetry" Journal of Business & Economic Statistics 24, 24-42

Taylor, M., (1995) "The Economics of Exchange Rates" Journal of Economic Literature 83, 376-391

Veredas, D., (2006) "Macroeconomic surprises and short-term behavior in bond futures" Empirical Economics 30, 843-866

Veredas D., Rodriguez-Poo, J., Espasa, A., (2002) "On the (intradaily) Seasonality and Dynamics of a Financial Point Process: A Semiparametric Approach" CORE DP 2002/23

Veronesi, P., (1999) "Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model" The Review of Financial Studies 12, 975-1007

Veronesi, P., (2000) "How does Information Quality Affect Stock Returns?" Journal of Finance 55, 807-837

APPENDIX

Macroeconomic announcements

Table presents all the macroeconomic indicators in the data. The figures in the parentheses are the number of observations in each macroeconomic indicator.

Country	Macroeconomic indicators
Austria	CPI m (70), CPI y (70), Industrial Production m (16), Industrial Production y (33), New Car Registration y (20), PPI m (30), PPI y (31), Trade Balance (13), Unemployment Rate (61), WPI m (65), WPI y (54)
Belgium	Budget Deficit cumulative (30), Budget Deficit net (30), Business Confidence (60), Consumer Confidence (47), CPI m (72), CPI y (72), Exports (25), GDP q (36), GDP y (35), Imports (25), Industrial Orders m (2), Industrial Orders m sa (2), Industrial Orders y (23), Industrial Production m sa (5), Industrial Production y (35), Manufacturing Industry Index (11), New Car Registration y (38), New Car Registrations (Level) (31), PPI m (42), PPI y (41), Public Deficit (15), Public Deficit net (1), Trade Balance (60), Unemployment Rate (68), Unemployment Rate nsa (1)
ECB	Bloomberg Eurozone Retail PMI (4), Business Climate Indicator (44), ECB Announces Interest Rates (99), ECB Average Lending Rate (8), ECB Euro-Zone Current Account (9), ECB Financial Statement - Bal. (179), ECB Vari. Rate Refinance Auct. (184), ECB Weekly Currency Reserves (140), EU15 CPI m (51), EU15 CPI y (62), EU15 Current Account q (4), EU15 Economic Confidence (17), EU15 GDP Estimate q (2), EU15 GDP Estimate y (2), EU15 GDP q sa (52), EU15 GDP y (52), EU15 Ind. Prod. (trend) (9), EU15 Ind. Production m sa (43), EU15 Ind. Production y wda (62), EU15 Labour Costs y (34), EU15 New Car Reg y (34), EU15 PPI m (58), EU15 PPI y (58), EU15 Retail Trade m (38), EU15 Retail Trade y (38), EU15 Trade Balance (77), EU15 Unemployment Rate (64), Eurostat Eurozone Current Acc (1), Euro-Zone Budget Def/GDP Ratio (5), Euro-Zone Capacity Utilization (3), Euro-Zone Consumer Confidence (49), Euro-Zone CPI Estimate y (36), Euro-Zone CPI m (60), Euro-Zone CPI y (73), Euro-Zone Current Account (73), Euro-Zone Current Account q (26), Euro-Zone Debt to GDP Ratio (5), Euro-Zone Economic Confidence (64), Euro-Zone GDP Estimate q (2), Euro-Zone GDP Estimate y (2), Euro-Zone GDP q sa (50), Euro-Zone GDP y (50), Euro-Zone Govt Expend q (1), Euro-Zone Gross Fix Cap q (1), Euro-Zone Household Cons q (1), Euro-Zone Ind. Prododuction m sa (51), Euro-Zone Ind. Production (trend) (9), Euro-Zone Ind. Production y wda (70), Euro-Zone Industrial Confidence (49), Euro-Zone Labour Costs y (39), Euro-Zone M3 3ma sa (40), Euro-Zone M3 y nsa (27), Euro-Zone M3 y sa (43), Euro-Zone New Car Reg y (40), Euro-Zone OECD Leading

Macroeconomic announcements (cont.)

Country	**Macroeconomic indicators**
ECB (cont.)	Ind. (31), Euro-Zone PPI m (65), Euro-Zone PPI y (65), Euro-Zone Retail Trade Conf. (1), Euro-Zone Retail Trade m (53), Euro-Zone Retail Trade y (53), Euro-Zone Trade Balance (85), Euro-Zone Unemployment Rate (70), Industrial New Orders m sa (12), Industrial New Orders y (12), W. European New Car Reg y (40), ZEW Survey (Econ. Sentiment) (13)
Finland	Consumer Confidence (53), CPI m (72), CPI y (72), Current Account (71), Exports (34), GDP indicator y (72), GDP q sa (23), GDP y (23), HCPI m (11), HCPI y (11), Imports (35), Industrial Prod. y (75), Industrial Production sa m (47), PPI m (72), PPI y (72), Trade Balance (40), Unemployment Rate (72),
France	Bloomberg France Retail PMI (4), Budget (Maastricht) (% of GDP) (1), Budget Deficit (2), Business Climate Indicator (2), Business Confidence Indicator (46), Business Starts (14), Central Govt. Balance (36), Consumer Confidence (65), Consumer Spending m (45), Consumer Spending y (45), CPI m (137), CPI y (136), Current Account (77), Exports q (1), Fixed Cap Formation q (1), France OECD Leading Indicator (5), French Wages q (1), GDP q (51), GDP y (47), HCPI m (100), HCPI y (96), Household Consumption m (24), Household Consumption q (1), Household Consumption y (24), Housing Permits 3M y% Change (40), Housing Starts 3M y% Change (40), Imports q (1), Industrial Production m (68), Industrial Production y (69), Industry Investment Survey (1), INSEE Industrial Trends (22), Manufacturing Production m (69), Manufacturing Production y (69), New Car Registration y (66), Non-Farm Payrolls q (22), PPI m (57), PPI y (55), Production Outlook Indicator (42), Public Expenditure q (1), Trade Balance (39), Unemployment Change (72), Unemployment Rate (71), Wages q (15), Visible Trade Balance (33),
Germany	Bloomberg Germany Retail PMI (4), Budget (Maastricht) (% of GDP) (4), Coincident Index (5), Conference Board Leading Index (10), Construction Investment (5), Construction Orders m sa (69), Construction Orders y sa (69), CPI Baden Wuerttemberg m (72), CPI Baden Wuerttemberg y (72), CPI Bavaria m (72), CPI Bavaria y (72), CPI Brandenburg m (69), CPI Brandenburg y (68), CPI Hesse m (71), CPI Hesse y (71), CPI - North Rhine-West m (72), CPI - North Rhine-West y (72), CPI PG (FSO) m (44), CPI PG (FSO) y (46), CPI Saxony m (70), CPI Saxony y (71), CPI WG (FSO) m (3), CPI WG (FSO) y (3), CPI m (95), CPI y (95), Crude Steel Production y (13), Current Account (72), Domestic Demand (5), Employment Change (18), Equipment Investment (5), Euro-11 M3 Money Supply (YoY) (8), Exports m sa (20), Exports q (5), Factory Orders (BBK) m (71), Factory Orders (BBK) y (71), Factory Orders (MoF/BBK) m (73), Factory Orders (MoF/BBK) y (72), GDP (6)

Macroeconomic announcements (cont.)

Country	**Macroeconomic indicators**
Germany (cont.)	GDP (FSO) y (16), GDP PG (BBK) q (17), GDP PG (BBK) y (16), GDP q sa (15), GDP y nsa (15), GDP y wda (14), Germany OECD Leading Indicator (5), Government Spending (5), HCPI m (106), HCPI y (106), ICON Consumer Confidence (WG) (20), IFO - CURRENT ASSESSMENT (32), IFO - EXPECTATIONS (32), IFO Ind. Survey (Bus. Climate) (72), Imports m sa (20), Imports q (5), Indust. Output (MoF/BBK) m (25), Indust. Output (MoF/BBK) y (24), Industrial Output m (33), Industrial Output y (33), Industrial Production m (79), Industrial Production y (80), IPI m (72), IPI y (72), Leading Index (1), M3 Money Supply (Final) y (1), New Car Registration y (63), PPI m (72), PPI y (72), Private Consumption (5), Retail Sales m sa (72), Retail Sales y (72), Trade Balance (72), Unemployment change (23), Unemployment change sa (44), Unemployment change sa (5), Unemployment Rate EU-Def. (39), Unemployment Rate nsa (35), Unemployment Rate sa (70), VDMA Plant & Machinery Orders (71), Wholesale Sales m r sa (51), Wholesale Sales y r (51), WPI m (72), WPI y (71), Zew Survey (Current Situation) (11), ZEW Survey (Econ. Sentiment) (40), ZEW Survey (Expectations) (1),
Ireland	CPI m (72), CPI y (72), Current Account (19), Exports (3), GDP y (14), HCPI m (12), HCPI y (12), Imports (3), Industrial Production m sa (41), Industrial Production y nsa (41), Live Register Level sa (22), Live Register Monthly Change (22), New Private Car Licences (13), New Vehicle Licences (13), PPI m (68), PPI y (70), Retail Sales m (70), Retail Sales y (71), Trade Balance (39), Unemployment change (47), Unemployment Level (47), Unemployment Rate (71),
Italy	11-City CPI m (14), 11-City CPI y (14), 12-City CPI m (38), 12-City CPI y (38), 13-City CPI m (10), 13-City CPI y (10), Annual GDP (1), Bloomberg Italy Retail PMI (4), Budget Deficit cumulative (55), Budget Deficit net (57), Business Confidence (57), Consumer Confidence nsa (58), Consumer Confidence sa (44), CPI m (123), CPI y (118), Current Account (50), Exports (3), GDP q (41), GDP y (40), Government Spending (3), HCPI m (116), HCPI y (117), Hourly Wages m (69), Hourly Wages y (58), Imports (3), Industrial Orders m sa (47), Industrial Orders y (48), Industrial Orders y nsa (25), Industrial Production m sa (71), Industrial Production y nsa (71), Industrial Production y wda (71), Industrial Sales m sa (42), Industrial Sales y nsa (42), Large Company Employment y (21), Large Industry Employment y (27), New Car Registrations y (70), PPI m (72), PPI y (72), Private Consumption (3), Quarterly Unemployment Adjust (8), Retail Sales m (38), Retail Sales y (72), Retailers' Confid. General (26), Retailers' Confid. Lg. Stores (9), Retailers' Confid. Sm. Stores (9), Serv. Firms Curr. Turnover sa (7), Serv. Firms Current

Macroeconomic announcements (cont.)

Country	**Macroeconomic indicators**
Italy (cont.)	Orders sa (7), Serv. Firms Jobs Outlook sa (7), Serv. Firms Orders Outlook sa (7), Serv. Firms Price Outlook sa (7), Serv. Firms Turn. Outlook sa (7), Services Firm Empl y (29), Services Survey (18), Total investments (3), Trade Balance (22), Trade Balance Eu (72), Trade Balance Non-Eu (71), Unemployment Rate (4), Unemployment Rate sa (13),
Japan	Adjusted Current Account Total (61), Adjusted Merchnds Trade Bal. (62), All Industry Activity Index (24), Annualized Housing Starts (13), Average Lending Rate (57), Bank Lending y (59), Bankruptcies y (58), Broad Liquidity y (26), BSI Large All Industry q (4), BSI Large Manufacturing q (4), Capacity Utilization (34), Capital Spending (14), CGPI m (24), CGPI y (15), Coincident Index (67), Construction Orders y (58), Consumer Confidence (24), Consumer Sentiment Index (21), Convenience Store Sales y (10), Corp Service Price y (58), CPI - Nationwide m (18), CPI - Tokyo m (20), CPI Ex Fresh Food m sa (40), CPI Ex Fresh Food y (40), CPI sa (40), CPI y (40), Crude Oil Imports y (44), Crude Steel Production y (48), Current Account (45), Diffusion Index (13), Diffusion Index – Coincident (1), Eco Watchers Survey: Current (19), Eco Watchers Survey: Outlook (19), Electric Usage y (12), EPI m (9), EPI y (9), Final Industrial Production (1), Foreign Currency Reserves (21), GDP Deflator y (7), GDP Deflator y (4), GDP q (37), GDP y (11), Household Spending y (61), Housing Starts y (58), Industrial Production m (94), Industrial Production y (41), Industrial Production y (21), Int'l Securities Invest (60), IPI m (9), IPI y (8), Job-To-Applicant Ratio (58), Labor Cash Earnings (16), Large Retailers' Sales (58), Leading Economic Index (85), Machine Orders m (59), Machine Orders y (16), Machine Tool Orders y (82), Merchnds Trade Balance Total (59), Mfg. Electricity Usage y (45), Monetary Base y (27), Money Supply M2+CD y (59), Nationwide Dept. Sales y (58), Official Reserve Assets (38), Overall Household Spending (14), Overtime Earnings (16), Preliminary Indust Prod (20), Retail Trade m sa (21), Retail Trade y (21), Small Business Confidence (33), Tankan Lge Manufacturers Index (13), Tankan Non-Manufacturing (12), Tankan Survey Manuf. (11), Tertiary Industry Index m (58), Tokyo Condominium Sales y (58), Tokyo Consumer Confidence (10), Tokyo Consumer Prices (19), Tokyo CPI Ex Fresh Food m sa (40), Tokyo CPI Ex Fresh Food y (39), Tokyo CPI Ex Fresh Food y (1), Tokyo CPI m sa (37), Tokyo CPI y (24), Tokyo Dept. Store Sales y (62), Tokyo Office Vacancy Rate q (16), Trade Balance (28), Unemployment Rate (59), Vehicle Exports y (44), Vehicle Imports y (50), Vehicle Production y (56), Vehicle Sales y (58), Workers' Hhold Spending m (15), Workers' Hhold Spending y (57), WPI (32),

Macroeconomic announcements (cont.)

Country	**Macroeconomic indicators**
Netherlands	Consumer Confidence (63), Consumer Confidence Indicator (2), Consumer Confidence nsa (20), Consumer Confidence sa (28), Consumer Spending y (65), CPI m (71), CPI y (72), GDP q sa (43), GDP y (44), Industrial Prododuction m sa (66), Industrial Prododuction y (67), Industrial sales y (59), PPI m (61), PPI y (62), Producer Confidence (54), Retail Sales y (69), Trade Balance (66), Unemployment Rate (71), Unemployment Rate sa (9),
Portugal	Budget Deficit/Surplus (7), Construction Licences y (22), Consumer Confidence (9), CPI (12-Months Average) (51), CPI m (71), CPI y (71), Current Account (36), GDP q (16), GDP y (19), HCPI m (7), HCPI y (7), Industrial Production m (73), Industrial Production y (70), Industrial Sales m (57), Industrial sales y (57), Labour Costs y (14), Manufacturing Production m (21), Manufacturing Production y (21), New Car Sales y (23), PPI m (70), PPI y (70), Retail Sales m (70), Retail Sales y (69), Total Construction Licences (4), Trade Balance (13), Unemployment Rate q (20),
Spain	Budget Deficit (44), CPI (Core Index) (MoM) (1), CPI (Core Index) m (63), CPI (Core Index) y (64), CPI m (72), CPI y (72), Current Account (64), Factory Orders y (14), GDP (Trend Cycle) q (3), GDP (Trend Cycle) y (3), GDP q (22), GDP y (23), HCPI m (51), HCPI y (62), Hotel Occupancy (24), Hotel Price Index y (24), Household Expenditure q (8), Industrial Output m (19), Industrial Output y (71), Industrial Output y sa (19), Industrial Output y wda (48), Labour Costs y (13), New Car Registration y (92), PPI m (73), PPI y (73), Retail Sales m (73), Retail Sales y (47), Trade Balance (54), Unemployment Change (64), Unemployment Rate (62), Unemployment Rate (Survey) (24),
United Kingdom	Average Earnings (63), Avg Earnings ex bonus (7), BOE ANNOUNCES RATES (70), Budget Deficit (PSNCR) (51), Coincident Indicator Index m (34), Company Insolvencies y (4), Conference Board:Leading Index (7), Conference Brd: Coincident Ind (6), CPI m (8), CPI y (8), Current Account (23), Current Account (2), Exports (4), FT House Price m (9), FT House Prices y (9), GDP q (73), GDP y (72), GfK Consumer Confidence Survey (38), Government Spending (4), Gross Fixed Capital Formation (4), Halifax House Prices m sa (38), Halifax House Prices y (38), HBOS House Price 3Mths/Year (23), HBOS Plc house prices m sa (34), HBOS Plc house prices y (10), HCPI m (4), HCPI y (11), ILO Unemployment Rate (32), Imports (4), Index of Distribution (26), Index of Distribution y (26), Industrial Production m (72), Industrial Production y (71), Leading Indicator Index m (33), M0 Money Supply m (71), M0 Money Supply y (72), M4 Money Supply m (138), M4 Money Supply y (142), M4 Sterling

Macroeconomic announcements (cont.)

Country	**Macroeconomic indicators**
United Kingdom (cont.)	Lending (144), Manu.Unit Wage Cost (69), Manufacturing Production m (61), Manufacturing Production y (72), MORI Economic Optimism Index (5), Nat'wide House prices m sa (70), Nat'wide House prices y (72), Net Consumer Credit (62), Net Lending Sec. on Dwellings (31), New Car Registration y (25), NIESR GDP Estimate (15), ODPM UK House Prices y (13), Official Reserves (71), PPI Input m sa (71), PPI Input y sa (65), PPI Output (ex.FBTP) y sa (71), PPI Output m nsa (72), PPI Output y nsa (72), Private Consumption (4), Public Finances (21), Public Sector Net Borrowing (12), Retail Sales m (72)
United States	ABC Consumer Confidence (49), Advance Retail Sales (71), Atlanta Fed Manufacturing (15), Average Hourly Earnings m (25), Average Hourly Earnings y (25), Average Weekly Hours (35), Bloomberg Retail Sales (24), Budget Statement- Tentative (22), Building Permits (28), Business Inventories (71), Capacity Utilization (70), Change in Manufact. Payrolls (35), Change in Nonfarm Payrolls (71), Change in Payrolls Less Census (4), Chicago Purchasing Manager (71), Construction Spending (70), Consumer Confidence (71), Consumer Credit (44), Continuing Claims (124), CPI Ex Food & Energy m (26), CPI Ex Food & Energy y (26), CPI m (71), CPI nsa (52), CPI y (26), Current Account Balance (24), Domestic Vehicle Sales (25), Durable Goods Orders (71), ECRI - Future Inflation Gauge (36), Empire Manufacturing (26), Employment Cost Index (23), Existing Home Sales (71), Factory Orders (71), FOMC Rate Decision Expected (50), GDP (71), GDP Price Deflator (71), Help Wanted Index (24), Housing Completions (27), Housing Starts (71), Import Price Index m (36), Import Price Index y (26), Imports All Commodity Price (33), Industrial Production (71), Initial Jobless Claims (308), Instinet Redbook Retail Sales (135), ISM Manufacturing (35), ISM Non-Manufacturing (35), ISM Prices Paid (35), Leading Indicators (71), Less Food & Energy (80), Less Transportation (36), LJR Redbook -Total Store Sales (21), MBA Mortgage Applications (51), Monthly Budget Statement (49), NAHB Housing Market Index (21), NAPM (36), NAPM Non-Manufacturing (36), NAPM Prices Paid (18), Net Foreign Security Purchases (3), New Home Sales (72), Nonfarm Productivity (46), PCE Core y (7), PCE Deflator y (9), Personal Consumption (24), Personal Income (71), Personal Spending (35), Philadelphia Fed. (71), PPI Ex Food & Energy m (35), PPI Ex Food & Energy y (26), PPI m (71), PPI y (26), Real Earnings (47), Retail Sales Less Autos (71), Spending (35), Tokyo-Mitsubishi Retail Sales (63), Total Vehicle Sales (8), Trade Balance (35), Trade Balance-Goods & Services (36), U. of Michigan Confidence (133), Unemployment Rate (71), Unit Labor Costs (42), US Average Weekly Hours (34), US Average Weekly Hours- Manu (12), US Avg Hourly Earnings (46), US Change in Manufact. Payroll (36), Wholesale Inventories (71),

CHAPTER 2

EXCHANGE RATE VOLATILITY, MACRO ANNOUNCEMENTS AND THE CHOICE OF INTRADAY SEASONALITY FILTERING METHOD

2.1 Introduction

[1]High frequency data sets have been used extensively since the development of electronic trading systems in the early 1990s. One area of research in which intraday data sets have been widely used concerns the impact of news on exchange rate volatility[2]. Since markets react to new information very quickly, intraday data sets are more informative and provide more accurate results than do daily data sets. Nevertheless, these kinds of data sets have some special features that need to be scrutinized for the sake of reliable results. One crucial issue is the filtering of intraday periodicity of volatility, which is caused by differences in trading times in the global foreign exchange markets. This periodicity causes periodical U-shape patterns in autocorrelation functions of volatility, and therefore it has to be filtered out of intraday data used for statistical inference[3].

Usually periodicity is considered as nuisance in time series econometrics, and filtering is something one needs to do before starting the actual work with the data. However, filtering might cause at least three kinds of problems that researchers rarely consider. First, most filtering methods are capable of removing

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1 A version of this Chapter has appeared in the Bank of Finland Discussion Paper 24/2007 and submitted to Journal of International Money and Finance.

2 Degennaro and Shrieves (1997), Andersen et al. (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006), Laakkonen (2007) among others.

3 Evidence of the intraday volatility pattern has been shown eg by Andersen and Bollerslev (1998), Melvin and Yin (2000), Cai et al. (2001), and Bauwens et al. (2005).

some of the periodicity, but not all of it. The periodicity in volatility that remains after filtering may affect the other results of the study. Second, the filtering might generate something new, for example extra jumps, in returns. Third, in filtering out periodicity, something important might be filtered out as well. For example, if one is studying the impact of news on volatility, the filter should not eliminate the news effects.

To our knowledge, filtering methods have been compared in only two papers so far: Martens et al. (2001) conclude that explicitly modeling the intraday volatility component improves out-of-sample forecasts. However, they compare only the two step Flexible Fourier Form model (FFF) of Andersen and Bollerslev (1997) to the computationaly costly periodical GARCH model, which includes the FFF. Ben Omrane and De Bodt (2007) compare the Intradaily Average Observation method (IAOM) of Bauwens et al. (2005) and a kernel smoothing method to a method that uses self-organizing maps (SOM) to capture periodicity. The authors conclude that while the IAOM and kernel smoothing methods are capable of estimating the deterministic part of periodicity, they both fail to capture the stochastic part. The new method that they propose, SOM, seems to capture also stochastic cycles.

Compared to those two papers, in this paper we concentrate more carefully on the possible consequences that filtering might have. We consider three commonly used methods, each of which belongs to one of three filtering method categories, set out by Ben Omrane and De Bodt (2007). These are the Flexible Fourier Form method (FFF) of Andersen and Bollerslev (1997), which uses sinusoids as exogenous variables to capture the periodicity; the Locally Weighted Scatterplot Smoothing method (LOWESS) of Cleveland (1979), which adopts a weighted time trend estimation for deseasonalizing; and the Intradaily Average Observations Model (IAOM) of Bauwens et al. (2005) in which the intraday volatility estimate is computed by averaging the squared returns per each intraday interval over the entire data sample (separately per each weekday).

We use high-frequency returns to study the possible problems that filtering might cause: 1) we compare autocorrelation functions of different filtered absolute returns to see if there is periodicity left in volatility after filtering and study the news effects with different filtered returns to see whether the filtering affects the magnitudes of the news coefficients, 2) we compare the key statistical figures of the original and filtered returns to study whether filtering changes the properties of the return process.

Our data contain six years of five minute euro against United States dollar (EUR/USD) quotes from 1 January 1999 to 31 December 2004. This data set is longer than those used in most of the earlier literature. As the filtering methods usually perform better when the periodicity is regular (Ben Omrane and De Bodt, 2007), the six year data set complicates the deseasonalizing, because it is very likely that the intraday pattern has developed over the years, especially since the data also cover the early years of the euro. The macroeconomic releases are obtained from the Bloomberg World Economic Calendar (WECO) and contain all the macro announcements from the USA, Germany and Japan.

Furthermore, 3) we use the properties of the EUR/USD data to simulate returns, which comprise the daily volatility component, intraday volatility component, news component and random shocks. We filter the simulated returns, estimate the news effects with the filtered returns and compare the estimated news coefficient values to the simulated ones to see if the estimated news effects are biased.

The results suggest that all the methods are capable of filtering the periodicity in volatility only if the estimation is done by dividing data into sufficiently short subsets. This indicates that the intraday volatility periodicity is time varying. The filtering method and the selected subset length affect the magnitudes of the news coefficients significantly: when the subset is shortened, the news coefficients increase when the filtering is done by using the FFF method, and decrease, when the LOWESS or IAOM methods are used for filtering.

According to the results of the simulation study, if the returns are not filtered at all, the estimated US and European news coefficients are too large and the Asian news coefficients too small. Also, all the methods tend to produce downward biased estimates for the news coefficients, i.e. to filter out part of the news effects, some worse than others. While the LOWESS is performing the best in terms of getting rid of periodicity in volatility, it also seems to filter out more news effects than do the other two filters. The IAOM performs almost as well as the FFF, but in the case of regularly announced news it produces very downward biased estimates compared to the FFF method. Therefore, the study supports the FFF model as the best for periodicity filtering.

The Chapter is divided into six sections. Section 2.2 presents the properties of EUR/USD data and summarizes briefly the filtering methods used in the literature. The problems that filtering might cause are studied in sections 2.3, 2.4 and 2.5. Section 2.6 concludes the study.

2.2 Intraday Periodicity

In this section we present the properties of the EUR/USD data, summarize the filtering methods used in the literature and present the general idea behind in all of the methods.

2.2.1 Data

The original data contain quotes at 5-minute intervals on the EUR/USD exchange rate during 1 January 1999 - 31 December 2004 and is obtained from Olsen and Associates[4]. To study the intraday periodicity of volatility, we use absolute returns as a measure of volatility[5] and expose the average intraday volatility pattern by computing the mean absolute return per every five-minute interval in 24 hours, which is presented in the upper graph of Figure 2.1. The level of volatility during a day depends on the trading times in different markets: the Asian

[4] Weekends and certain holidays were excluded, and daylight saving times in the USA and Europe were taken into account, as is standard in the literature.

[5] Absolute returns have been widely used as a volatility measure in the literature. A literature review of the use of absolute returns is provided by Granger and Sin (1999).

markets open around 23:00 GMT and cause a small increase in volatility; the European markets open around 7:00 GMT and volatility increases more; and the US markets open around 14:00 GMT after which volatility reaches its highest level. It is noteworthy that there are two spikes in the average volatility pattern: most US macro figures are announced at 13:30 GMT and 15:00 GMT and, as can be seen, they seem to cause significant increases in volatility.

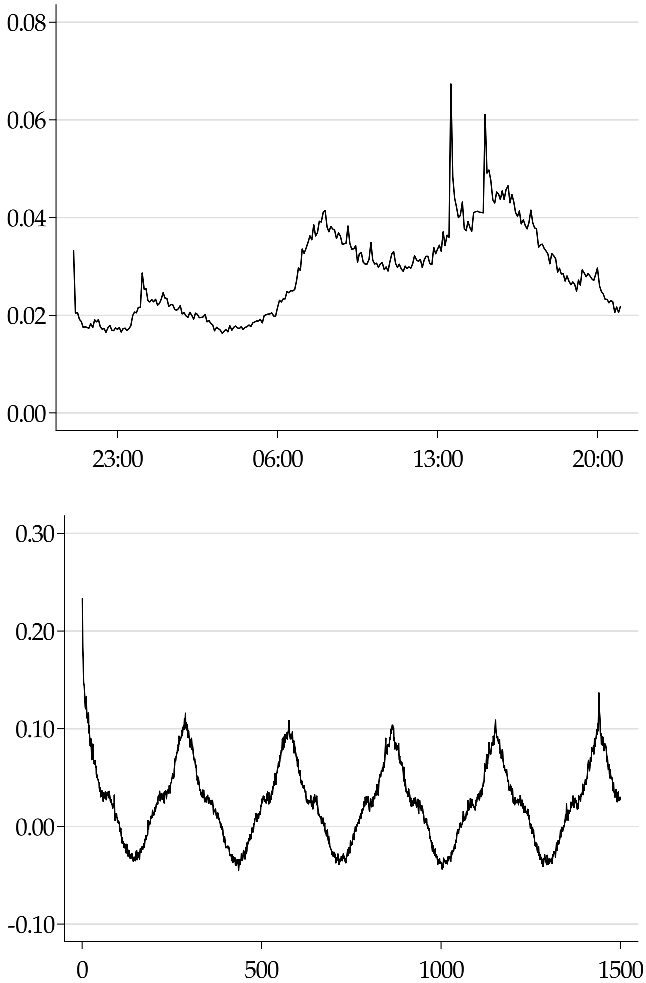

FIGURE 2.1 Intraday periodicity of volatility
The upper figure presents the average intraday EUR/USD volatility pattern, ie. average absolute return per each five minute interval over the whole sample period. Volatility pattern is caused by different trading times in the global foreign exchange markets. The lower figure presents the five day (1500 five minute lags) autocorrelogram of the five minute EUR/USD absolute returns.

When this pattern is repeated every day, it causes a U-shape pattern in the autocorrelation of volatility. The lower graph in Figure 2.1 presents the autocorrelation coefficients of absolute returns for 1500 five-minute lags, i.e. the autocorrelogram for five days. As can be seen, the U-shape pattern is repeated almost identically every day. Therefore, before using these kind of data sets the returns have to be deseasonalized.

2.2.2 Seasonality Filtering

Even though high-frequency data sets have been used for a more than a decade now, research in filtering the periodicity is still very active. Many different methods have been proposed, none of which has become standard in the literature. Ben Omrane and De Bodt (2007) provide a good review and introduce a taxonomy of filtering methods used in the literature.

The first category of filtering methods uses a linear projection to model the periodicity component: Andersen and Bollerslev (1997) use sinusoids as exogenous variables, while Degennaro and Shrieves (1997) include hourly dummies in the volatility regression to capture the periodicity. The second category uses smoothing techniques: Cleveland (1979) adopts a weighted time trend estimation, Engle and Russell (1998) use a cubic splines technique, whereas Veredas et al. (2002) and Ben Omrane and De Bodt (2007) employ kernel estimators for deseasonalizing. The third category uses the average (absolute/squared) returns per intraday interval to compute the filter: Dacorogna et al. (1993) introduced the ϑ-time transformation, which deseasonalizes volatility by expanding periods with high average market activity and contracting periods with low average market activity; Melvin and Yin (2000) divide each observation by the mean number of quotes for each hour of the business week during a subset; while Bauwens et al. (2005) compute the intraday volatility estimate by averaging the squared returns per 5-minute interval over the whole sample period (separately for the different weekdays).

We consider three commonly used methods, each of which belongs to one of the above categories (linear projection, smoothing and average observation). We tried to consider methods that are widely used in the news literature. However, we think the main differences between the filters are between the three categories rather than within any of the categories.

The general idea of filtering in all of the methods is as follows: the model produces an estimate for the intraday volatility, henceforth denoted as $\hat{s}_{t,n}$. This estimate is normalized such that the mean of the normalized intraday volatility estimate (henceforth denoted as $\tilde{s}_{t,n}$) equals one:

$$\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{T/N} \sum_{n=1}^{N} \hat{s}_{t,n}} \tag{2.1}$$

where T is the number of observations in the entire sample, N is the number of observations during one day (288 for 5-minute intervals in the 24 hour market) and T/N then denotes the number of days in the sample[6]. To obtain the filtered returns, the original returns $R_{t,n}$ are divided by the normalized estimate $\tilde{s}_{t,n}$, i.e., $\tilde{R}_{t,n} = \dfrac{R_{t,n}}{\tilde{s}_{t,n}}$. Because the mean of $\tilde{s}_{t,n}$ equals one and $\tilde{s}_{t,n}$ is always positive, the

[6] In the equations, n is an index for 5-minute intraday interval and t for day.

consequences of filtering are that volatility is increased in the low-volatility periods and decreased in the high-volatility periods. Other than that, the returns should remain the same.

2.3 Seasonality After Filtering

In this section we study the ability of different methods to filter the periodicity in intraday volatility. As is common in the literature that compares different filtering methods (Martens et al. (2002), Ben Omrane and De Bodt (2007)), we study graphically whether there is periodicity left in the filtered absolute returns. The filter performs the better, the less the periodicity left in the volatility. In addition, we examine whether the remaining periodicity affects the results of the further study with filtered returns. For this, we look at the impact of news on the volatility of different filtered returns. The results apply only for the used data set, which is very representative of the data sets used in the literature, however.

2.3.1 Flexible Fourier Form Method

Of the linear projection techniques, we consider the Flexible Fourier Form method[7] (FFF) introduced in this context by Andersen and Bollerslev (1997). They state that, because the variability during a day is so systematic, the intraday dynamics of absolute returns can be estimated by using different frequencies of sine and cosine functions. The model takes the following form:

$$R_{t,n} - \bar{R}_{t,n} = \sigma_t \cdot s_{t,n} \cdot Z_{t,n} \tag{2.2}$$

where $R_{t,n}$ denotes the 5-minute EUR/USD returns, $\bar{R}_{t,n}$ is the expected five-minute returns and $Z_{t,n}$ is an i.i.d (with mean zero and unit variance) innovations, σ_t represents daily volatility and $s_{t,n}$ is intraday volatility.

Squaring both sides of (2.2), taking logs, approximating $R_{t,n}$ with the sample mean $\bar{R}$ and eliminating the daily volatility component σ_t from the return process, we end up wit the following expression,

$$2\log\frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t/N^{1/2}} = \log(s_{t,n}^2) + \log\left(Z_{t,n}^2\right) \tag{2.3}$$

where following Andersen and Bollerslev, we replace σ_t by $\hat{\sigma}_t$ predicted by a $GARCH(1,1)$ model for daily volatility and N denotes the number of five-minute intervals in one day (288 in a 24-hour market). Andersen and Bollerslev (1997) suggest a parametric representation of intraday volatility $s_{t,n}$ and estimate the smooth cyclical volatility pattern by using trigonometric functions. The FFF regression model is the following,

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[7] The FFF method is one of the most widely used filtering methods in the news literature. It has been used for example in the studies of Cai et al. (2001), Andersen et al. (2003), Dominquez and Panthaki (2006) and Laakkonen (2007).

$$f_{t,n} = \alpha + \delta_1 n + \delta_2 n^2 + \sum_{l=1}^{L} \lambda_l I_{l;t,n} \\ + \sum_{p=1}^{P} \left(\delta_{c,p} \cos\left(\frac{p2\pi}{N} n\right) + \delta_{s,p} \sin\left(\frac{p2\pi}{N} n\right)\right) + \varepsilon_{t,n}, \tag{2.4}$$

where $f_{t,n} = 2\log\frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. Besides the sinusoids[8], the model contains the intercept α, the quadratic function in the intraday interval n, and the error term of the model $\varepsilon_{t,n}$. The model also contains the indicator variables $I_{l;t,n}$, which are used to control e.g. weekday effects. The estimate for intraday volatility $\hat{s}_{t,n}$ is then obtained as $\hat{s}_{t,n} = \exp(\hat{f}_{t,n}/2)$, where $\hat{f}_{t,n}$ are the fitted values from model (2.4).

If the intraday periodicity pattern would remain constant over the sample period, the FFF model would be estimated for the entire data set. Unfortunately, this seems not to be the case, as we will see later on. Therefore, besides estimating the FFF only once by using the whole sample period, we estimate the model by using subsets of different length. The FFF model is re-estimated yearly, quarterly and weekly. Figure 2.2 presents the autocorrelation coefficients of the filtered absolute returns compared to the raw absolute returns, when periodicity is filtered out by the FFF model.

As can be seen from the first figure, if the FFF model is estimated by using the whole sample period, the model is clearly not capable of filtering out all the periodicity. There is a lot of periodicity left in volatility also after filtering. The situation is not better when the model is re-estimated every year. However, when the model is estimated separately for each quarter, the filter performs better and if the model is estimated separately for each week, there is no periodicity left in the autocorrelation function of absolute returns[9]. Therefore, since estimating the model in subsets seems to improve filtering, it indicates that periodicity of volatility is not constant in time.

2.3.2 Locally Weighted Scatterplot Smoothing Method

Of the smoothing techniques, we consider the Locally Weighted Scatterplot Smoothing method (LOWESS) introduced by Cleveland (1979). Even though the smoothing techniques are often used in the statistics and in the literature using ultra-high frequency data (especially in the Autoregressive Conditional Duration models), they are not so common in the literature studying news effects. The basic idea in the LOWESS method is to create a new variable $\hat{s}_{t,n}$ which contains the corresponding smoothed value for each point of the series $|R_{t,n}|$. The smoothed values are obtained by running a time trend estimation separately for each point of the data and a small number of observations close to each point. The smoothed value

8 The value $P = 9$ was selected by using the Schwarz information criteria.

9 The model was also re-estimated monthly and for each weekday, but either of these did not outperform the weekly re-estimation of the model.

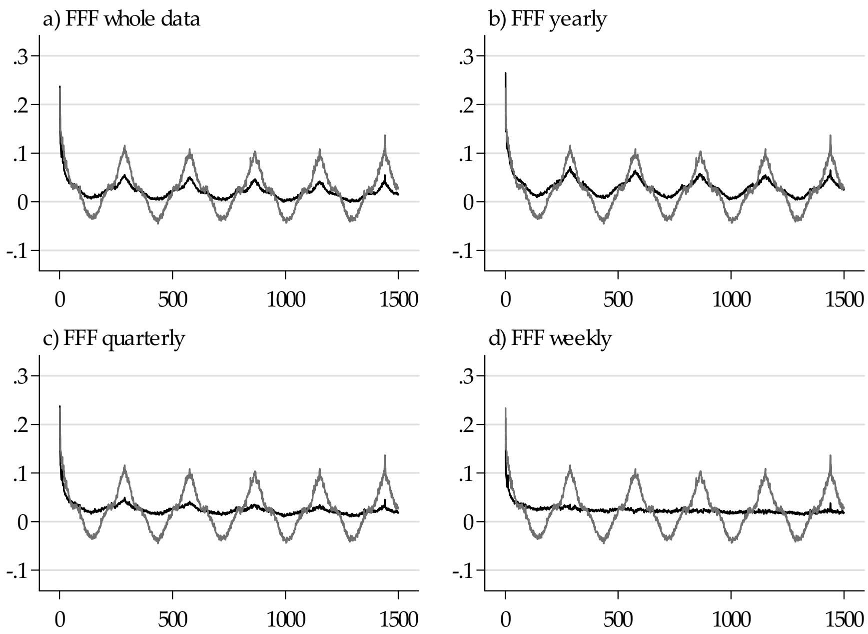

FIGURE 2.2 Autocorrelograms of raw and filtered absolute returns
The figures graph the five day autocorrelogram of the raw and filtered 5-minute absolute EUR/USD returns, when the intraday periodicity of volatility was filtered by using the Flexible Fourier Form method. The FFF model was estimated by using the whole data (upper left corner) and re-estimating the model yearly (upper right corner), quarterly (lower left corner) and weekly (lower right corner).

(which is the estimate for intraday volatility $\hat{s}_{t,n}$) is then the predicted value for the particular point only, which means that a separate regression is performed for every point in the data. Moreover, the observations are weighted so that observations close to the predicted point get larger weights than those further away.

Figure 2.3 presents the autocorrelation coefficients of the filtered absolute returns compared to the raw absolute returns, where the periodicity is filtered out by the LOWESS method. The length of the subset used in the estimation affects the smoothness of the estimated curve: the shorter the estimation subset, the more precisely the smoothed curve follows the original data. We present the results with three different values of parameter δ $(0.0003,\ 0.0002,\ 0.0001)$, which controls the length of the estimation subset. The smaller the value of δ, the shorter the estimation subset[10]. As can be seen, when the parameter value decreases there is less periodicity left after filtering. When the smoothness parameter gets the value 0.0001, there is no autocorrelation left in the filtered absolute returns at all.

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10 For these parameter values the length of the subset is approximately six, four and two hours, respectively.

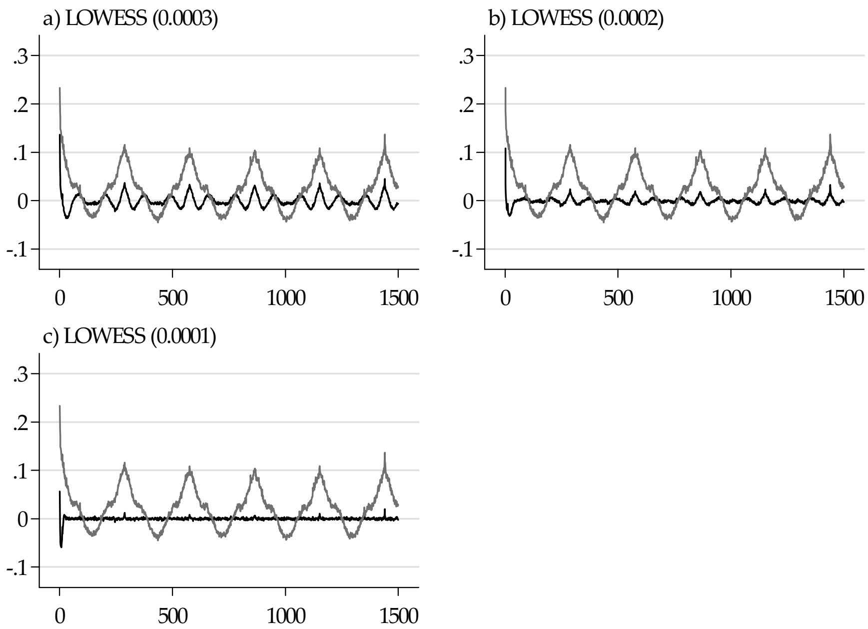

FIGURE 2.3 Autocorrelograms of raw and filtered absolute returns
The figures graph the five day autocorrelogram of the raw and filtered 5-minute absolute EUR/USD returns, when the intraday periodicity of volatility was filtered by using the Locally Weighted Scatterplot Smoothing method. Three different values (a) 0.0003, b) 0.0002 and c) 0.0001) of parameter δ, which controls the length of the estimation subset, was considered. The smaller the value of δ, the shorter the estimation subset.

2.3.3 The Intraday Average Observations Model

The method that we consider of the average observations category is called the Intraday Average Observations Model (IAOM), introduced by Bauwens, Ben Omrane and Giot (2005). This recently proposed method has been used in the macro news literature by Bauwens et al. (2005).

The method that we use differs slightly from the one originally proposed by the authors. First, they did not exclude any holidays from their data and second, their definition of weekend differs from ours[11]. The intraday volatility estimate $\hat{s}_{nk}$ is computed by averaging the squared returns per each intraday interval (separately for each weekday) and then taking the square root:

[11] They exclude the intervals from Fridays at 22.05 through Saturday and Sunday and the first interval on Monday, while we use the definition of Andersen and Bollerslev (1998) and exclude the observations from Friday 21:05 until Sunday 21:00. We also tested for including holidays, and it did not have remarkable effect on the results. However, if the holidays and weekends are both included in the data, the missing observations cause a significant positive autocorrelation for the first lags in the filtered returns.

$$\hat{s}_{n,k} = \left(\frac{1}{M} \sum_{m=1}^{M} R^2_{m,k,n} \right)^{1/2} \tag{2.5}$$

where $k = 1, ..., 5$ denotes a weekday[12] , $n = 1, ..., N$ denotes the intraday interval (288 for five-minute 24-hour market) and M denotes the number of weeks in the data set.

Also in the case of Intraday Average Observations Model, the filtering could be done separately in different subsets. Besides filtering the whole sample period at once, we filtered the returns separately for each year and each quarter. Figure 2.4 presents the autocorrelation coefficients of the filtered absolute returns compared to the raw absolute returns, where periodicity is filtered out by using the IAOM method. Shortening the subset affects the results as in the case of the other two methods: the shorter the subset the better the filter performs. However, the differences are not as large as in the case of the FFF and LOWESS methods.

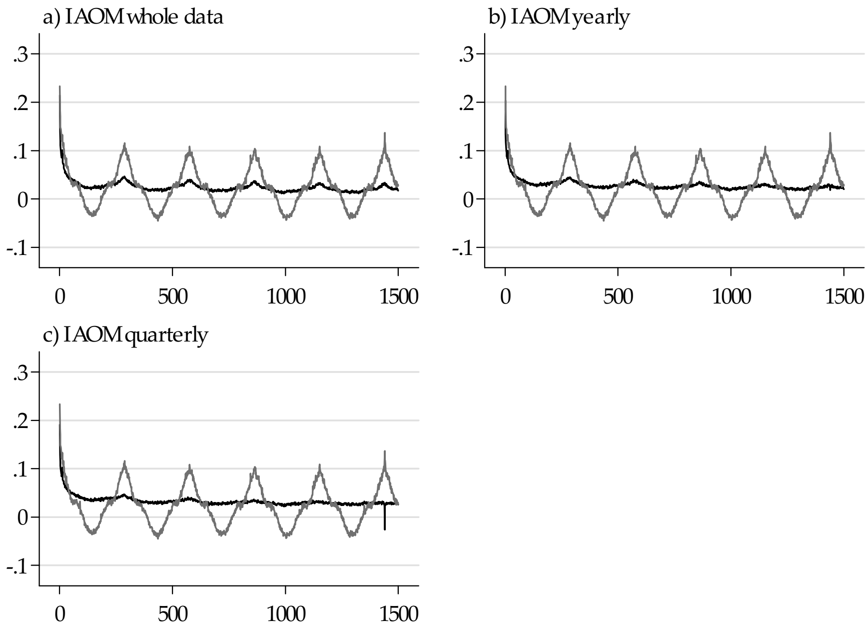

FIGURE 2.4 Autocorrelation coefficients of raw and filtered absolute returns
The figures graph the five day autocorrelogram of the raw and filtered 5-minute absolute EUR/USD returns, when the intraday periodicity of volatility was filtered by using Intraday Average Observations method. The IAOM model was estimated by using a) the whole sample period and re-estimating the model b) yearly and c) quarterly.

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12 For simplicity, Friday and Sunday observations are combined together and treated as one complete day $k = 5$. This should not have any implications to the results, since Friday and Sunday do not share any intervals. Friday observations always end at 21:00, while Sunday observations always begin at 21:05.

2.3.4 The Impact of News on Volatility

The intraday periodicity of volatility is caused by differences in trading times in the global foreign exchange markets (mainly US, European and Asian markets). Therefore, we consider macroeconomic announcements from these three markets. In particular, the data contain all the scheduled macroeconomic news announcements (e.g. gross domestic product figures, confidence indices) for Japan, Germany and the USA published in the World Economic Calendar (WECO) of Bloomberg. The total number of news was 10954, but because many of the macro figures are announced simultaneously, the number of news observations is actually lower. In particular, the number of news observations was 2285, 1804 and 1752 for the US, German and Japan news, respectively.

Because some of the macro figures are always announced at the same time, they might cause some periodicity in the intraday volatility. Most influential of these kind of regular news announcements are probably the US macroeconomic figures announced at 13:30 GMT and 15:00 GMT. We wanted to study these news separately from the other US news and therefore divided the US announcements into two categories: 'USA regular news' that includes the news that are announced at 13:30 GMT and 15:00 GMT and 'USA news' that includes the rest of the US announcements.

In the original model of Andersen and Bollerslev (1997) the news variables are included to the FFF model (2.4). This is also what we do when the FFF model is estimated by using the whole sample period. On the other hand, when filtering is done in subsets, we need two steps for testing the news effects. The first step is to filter the returns, and the second step is to study the impact of news on volatility of the filtered returns. Besides the subset FFF model, the two-step procedure is also used in LOWESS and IAOM methods, because the news variables cannot be included to the LOWESS and IAOM models in the first step as in the FFF model.

To test the news effects in the second step, we use the model

$$2 \log \frac{|\tilde{R}_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = c + \sum_{k=1}^{4} \phi_k N_{k;t,n} + \varepsilon_{t,n} \tag{2.6}$$

where $\tilde{R}_{t,n}$ denotes the filtered returns and $N_{k;t.n}$ are the news variables ($k =$ Japan, Germany, USA, USA regular). c is the constant term and $\varepsilon_{t,n}$ is the error term of the model.

News announcements have been reported to have long-lasting effects on volatility. For instance, according to Andersen and Bollerslev (1998), the impact lasts from one to two hours. To allow for such prolonged effects, we have to modify model (2.6) to some extent. Specifically, following Andersen and Bollerslev (1998), the impact of an announcement is assumed to diminish gradually and go to zero after two hours. We first estimate the average news impact pattern by computing the average absolute returns at each five-minute interval following the news announcements minus the average absolute return over the entire sample period. We then estimate the decay structure of the volatility response pattern of news by fitting a third order polynomial to the average news impact pattern and obtain the following third order polynomial,

$$\lambda_m = 0.054\left(1-(m/25)^3\right) - 0.009\left(1-(m/25)^2\right)m + 0.0007\,(1-(m/25))\,m^2 \tag{2.7}$$

where $m = 1, 2, ...25$ denotes the five-minute interval after the news announcement. The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours[13], as depicted in Figure 2.5.

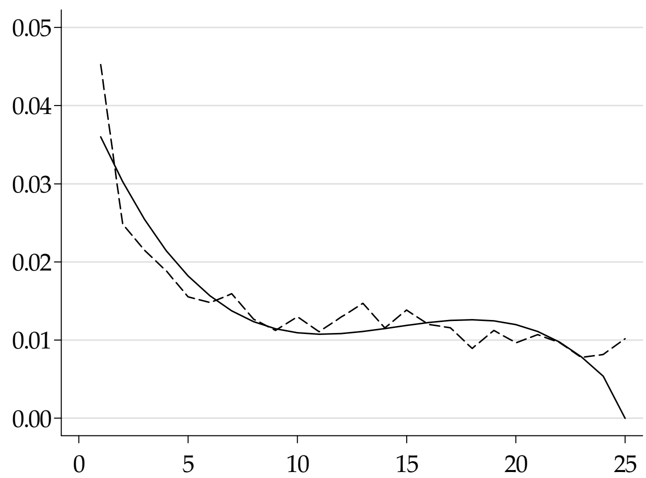


FIGURE 2.5 Estimated intraday volatility pattern
The figure presents the mean absolute returns during two hours (24 intraday intervals) following news announcements (dashed line) and the estimated news impact decay structure (solid line). Decay structure was estimated using the third order polynomial.

In the empirical models, the explanatory variables are hence not the news variables as such, but whenever there is an announcement, in the 25 subsequent 5-minute intervals the news variable $N_{k;t,n}$ equals λ_1, $\lambda_2, ..., \lambda_{25}$ and zero otherwise[14]. The impact of news on volatility $M_{k;m}$ can then be computed for every 25 intervals m separately with the equation

13 Longer dependencies of news could certainly have also been studied for example by using lag dummies. However, the benefit of this polynomial method is, as Bollerslev et al. (2000) state, that it fixes the problem of having only a few announcement observations and it is less sensitive to the inherent noise in the return process. One further advantage of this approach is that compared to lag dummies, we now only need one news variable for each news category. To study the impact of news for a period of two hours after the announcement, we would have needed 24 (two hours is 24 five-minute intervals) news variables for all the news categories. The choice of polynomial order and the length of the news impact were studied more carefully in Laakkonen (2007).

14 Most studies that examine the impact of news on financial market returns, use the actual surprise element (the announced figure less the forecast) as a news variable rather than a dummy variable that does not take into account the size of the news. However, Andersen et al. (2003, 2007) argue that it is the mere presence of an announcement, not so much the size of the corresponding surprise, that tends to boost volatility.

$$M_{k;m} = \exp\left(\frac{\phi_k \cdot \lambda_m}{2}\right) \quad (2.8)$$

Table 2.1 presents the estimated coefficient values ϕ_k for the news variables, as well as the impact of news $M_{k;1}$, computed for the first interval, i.e. five minutes after the announcement. If $M_{k;1}$ is grater than 100%, the news increases volatility, and if less than 100%, the volatility decreases right after the news announcements. The first row presents the results obtained with the returns which were not filtered at all. The following lines present the results obtained with the returns filtered with different methods. What is clear is that filtering has a significant effect on the results. The results obtained with the non-filtered data are very different compared to the results obtained with any of the filtered data.

As can be seen, the regular US news seems to have much greater effects than any other news groups. While the news from Germany and the USA increase volatility significantly, it seems that the news from Japan does not have an effect on the volatility of the EUR/USD exchange rate. Also, the filtering method seems to affect the magnitude of the estimated news variable coefficients. The estimated impact of macroeconomic news from Japan on volatility differs from decrease of 3% to increase of 10% depending on the used method and subset. The differences are very large also in other groups of news: the increase caused by the regular US news is estimated to be 52% at the lowest, and 140% at the highest. What is also worth noticing, is that there are quite clear patterns how the estimated news impacts depend on the used subset: in the case of the FFF models, the shorter the subset, the larger the news coefficients (except in the case of Japan). In contrast, for the LOWESS and IAOM models the news coefficients seem to decrease in size when the subset is shorter. However, the differences are not that large in the case of the IAOM than in the case of the LOWESS and FFF methods.

Figure 2.6 graphs the estimated intraday volatility patterns $\hat{s}_{t,n}$ of different FFF and LOWESS methods, compared to the average volatility during a day. These figures might help us to understand the patterns seen in the estimated coefficient values of the news variables. Because filtering is done by dividing the returns by $\hat{s}_{t,n}$ normalized such that its mean equals one, if $\hat{s}_{t,n}$ is above its average, dividing the original returns by it will decrease volatility, and if $\hat{s}_{t,n}$ is less than its average, filtering will increase volatility. From the Figure 2.6 we can see that during the opening hours of the European and US markets (from 7:00 GMT to 19:00 GMT), the estimated intraday volatility is in general above its average. Hence, the higher the value of $\hat{s}_{t,n}$, the more filtering reduces volatility. Now, in the case of the FFF method, we can see that when the model is re-estimated more frequently, the lower is the estimated intraday volatility during the European and US business hours. Therefore, the more frequently the model is re-estimated, the less filtering decreases volatility and hence cuts down the news effects. That is probably the reason why the estimates of the news variable coefficients increase when the model is re-estimated more frequently. The situation is completely opposite in the LOWESS method. Therefore, it is understandable that when the subset is shortened, the estimated news effects are decreased.

TABLE 2.1 Estimation results

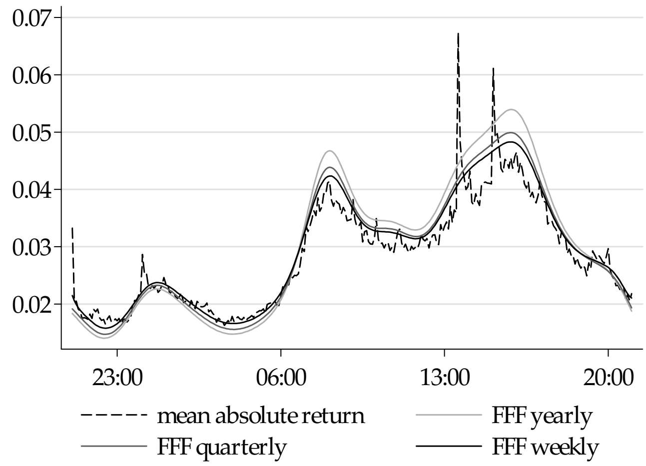
Table presents the parameter estimates of model (2.6) for the returns filtered with different methods (see details in sections 2.3.1–2.3.3. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively.

	Japan		**Germany**		**USA**		**USA regular**	
	ϕ_k	$M_{k;1}$	ϕ_k	$M_{k;1}$	ϕ_k	$M_{k;1}$	ϕ_k	$M_{k;1}$
No filtering	-16.15**	75%	46.99**	233%	39.90**	205%	89.81**	504%
	(1.70)		(1.52)		(3.13)		(1.50)	
FFF								
one step	2.17	104%	6.44**	112%	20.23**	144%	33.54**	183%
	(1.77)		(1.54)		(2.87)		(1.83)	
yearly	5.50**	110%	7.68**	115%	15.93**	133%	23.41**	152%
	(1.55)		(1.29)		(2.62)		(1.32)	
quarterly	2.18	104%	12.35**	125%	18.55**	140%	30.18**	172%
	(1.55)		(1.33)		(2.71)		(1.35)	
weekly	0.09	100%	16.21**	134%	19.42**	142%	34.83**	187%
	(1.52)		(1.30)		(2.64)		(1.30)	
LOWESS								
$\delta(0.0003)$	1.01	102%	27.74**	165%	24.45**	155%	48.63**	240%
	(1.42)		(1.13)		(2.27)		(1.07)	
$\delta(0.0002)$	-0.13	100%	23.69**	153%	21.00**	146%	40.20**	206%
	(1.33)		(1.04)		(2.10)		(0.98)	
$\delta(0.0001)$	-1.43	97%	18.94**	141%	16.10**	134%	31.69**	177%
	(1.21)		(0.93)		(1.87)		(0.87)	
IAOM								
whole data	-1.50	97%	21.46**	147%	21.75**	148%	33.54**	183%
	(1.64)		(1.43)		(2.73)		(1.34)	
yearly	-0.30	99%	21.06**	146%	21.49**	147%	31.88**	178%
	(1.57)		(1.37)		(2.66)		(1.32)	
quarterly	-0.41	99%	20.53**	145%	20.54**	145%	30.91**	174%
	(1.55)		(1.35)		(2.66)		(1.31)	

2.3.5 Properties of the Filtered Returns

In this section we study the statistical key figures of the original and filtered returns to see whether the filtered returns resemble the original returns.

The key statistical figures for the different filtered returns are presented in Table 2.2. As expected, filtering does not affect the mean or standard deviation of the returns. On the other hand, filtering seems to have an effect on the third and fourth moments. While both LOWESS and IAOM method seem to significantly decrease both skewness and kurtosis, the FFF method has no such clear result. In some cases skewness and kurtosis are decreased and in some cases increased,



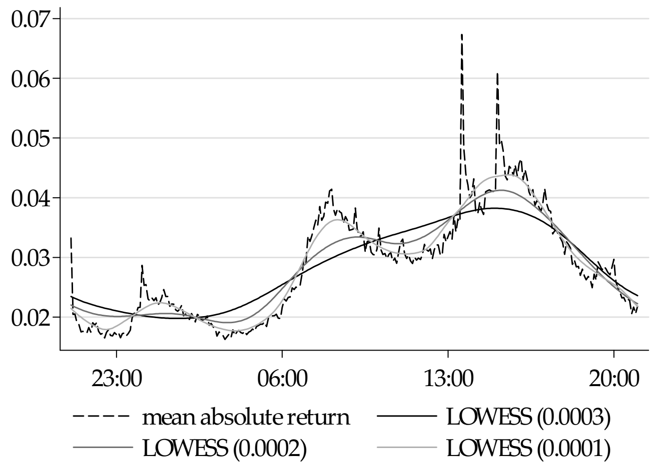


FIGURE 2.6 Estimated intraday volatility patterns
The upper figure graphs the estimated intraday volatility patterns of the FFF models compared to mean absolute five minute returns per intraday intervals. The lower figure presents the same for the LOWESS models.

when the returns are filtered with the FFF method. What is clear is that the kurtosis and skewness are larger in the returns filtered by FFF models than those filtered by LOWESS and IAOM methods.

The same can be also seen in Figure 2.7, which graphs the original returns and returns filtered with the three different methods. It seems that while the LOWESS and IAOM methods seem to shrink the large jumps in the returns, the FFF model saves the jumps but also creates some new ones. Compared to the returns filtered with the LOWESS and IAOM methods, the returns filtered with the FFF model most closely resemble the original returns in terms of key statistical figures.

TABLE 2.2 Key statistical figures

Table presents the key statistical figures for the original and filtered five-minute EUR/USD returns. The returns were filtered by using Flexible Fourier Form model (FFF), Locally Weighted Scatterplot Smoothing method (LOWESS) and Intraday Average Observations Method (IAOM).

	Mean	**St. Dev.**	**Skewness**	**Kurtosis**	**Min**	**Max**
EUR/USD	5.0E-05	0.0432	0.781	65.94	-1.35	2.79
FFF						
whole sample	9.3E-05	0.0445	-0.230	76.00	-2.14	2.41
yearly	1.2E-04	0.0464	-2.138	239.44	-2.13	2.49
quarterly	8.6E-05	0.0439	-0.618	99.95	-2.51	2.38
weekly	6.6E-05	0.0434	-0.154	40.92	-1.69	1.68
LOWESS						
$\delta(0.0003)$	8.0E-05	0.0387	0.011	8.94	-0.95	0.74
$\delta(0.0002)$	8.4E-05	0.0381	0.024	6.68	-0.67	0.56
$\delta(0.0001)$	9.1E-05	0.0373	0.007	5.01	-0.48	0.41
IAOM						
whole sample	6.5E-05	0.0407	0.000	10.01	-0.64	0.73
yearly	8.1E-05	0.0400	0.002	6.06	-0.32	0.37
quarterly	8.3E-05	0.0385	0.000	3.89	-0.18	0.18

2.4 Simulation Study

In this section we study more carefully whether the choice of filtering method has an effect on statistical inference concerning the impact of news on exchange rate volatility. We construct returns by using the properties of the real data, simulate 2000 realizations with 288000 observations (1000 days), deseasonalize the simulated returns by the same three different filtering methods, and test the impact of news variables on the volatility of filtered returns.

2.4.1 Returns

The returns were constructed from the daily volatility component $\frac{\sigma_{t,n}}{\sqrt{288}}$, intraday volatility component $s_{t,n}$, the news component $\eta_{t,n}$ and the error term $\varepsilon_{t,n}$:

$$R^S_{t,n} = \frac{\sigma_{t,n}}{\sqrt{288}} s_{t,n} \eta_{t,n} \varepsilon_{t,n} \tag{2.9}$$

The daily volatility component $\sigma_{t,n}$ was simulated using a GARCH(1,1) model. The estimated coefficient values from daily EUR/USD data were used as trend-setters for the simulated model.

To prevent any possibilities to favour any filtering methods in the simu-

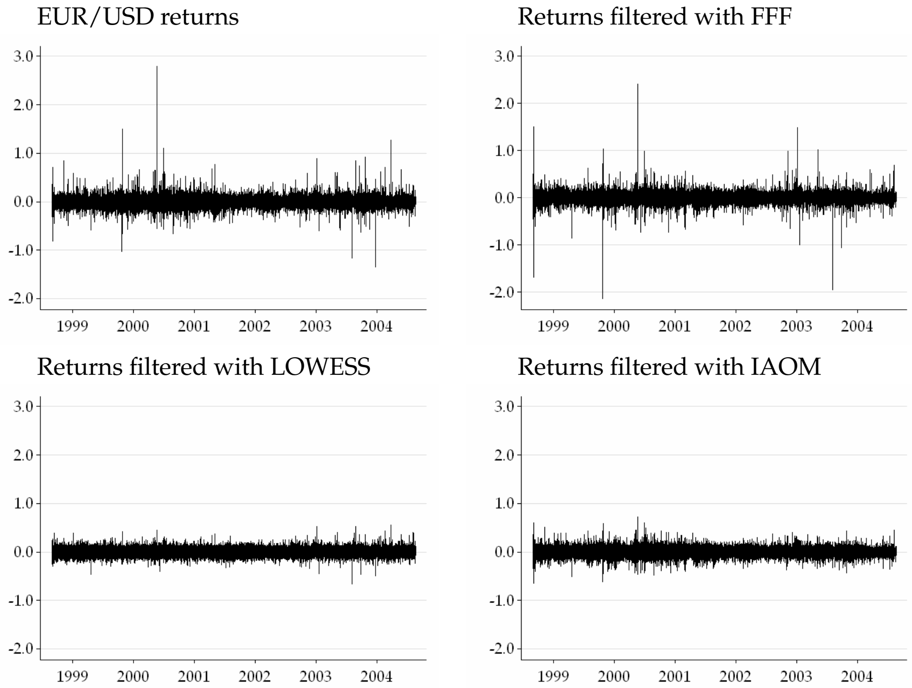


FIGURE 2.7 EUR/USD returns and filtered returns
The figure in the upper left corner present the 5-minute returns on the EUR/USD exchange rate during 1 Jan 1999 – 31 Dec 2004. The graph in the upper right corner presents the returns filtered with the Flexible Fourier Form method. The graphs in the lower panel present the returns filtered with the Locally Scatterplot Smoothing Method and Intradaily Average Observation method, respectively.

lation study, we did not want to use any of the studied models[15] to create the intraday periodicity component $s_{t,n}$. Therefore, we used a modified version of the dummy variable model proposed by Degennaro and Shrieves (1997). We estimated the following model using the EUR/USD data set:

$$2 \ln \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = \alpha + \sum_{h=1}^{47} \beta_h D_{h;t,n} + \varepsilon_{t,n} \tag{2.10}$$

where the $D_{h;t,n}$ are 47 half-hour dummy variables[16]. To capture the possible time variation in intraday volatility, the model was estimated separately for each month in the data set. The fitted values of the model were then saved and used as intraday volatility component $s_{t,n}$.

The news component $\eta_{t,n}$ was constructed as follows: we first created a preliminary news variable $(N_{t,n})$, which takes the value of one in 2% of the observations and zero otherwise, by using equally distributed [1,0] random variables. We

15 Flexible Fourier Form model is the only one of the three methods that could have been considered of using.

16 There are 48 half-hour intervals in the 24-hour market. Since the model includes the constant, we need 47 dummy variables.

then created three dummy variables $(I_{k;t,n})$ which indicate whether a particular market (US, European or Asian) is open or not. For example for the US markets this variable $(I_{usa;t,n})$ gets the value one if the US markets are open and zero otherwise. We also created a dummy variable $I_{usar;t,n}$ which takes the value of one at 13.30 GMT and 15.00 GMT and zero otherwise. This was done to create the 'regular US news' variable.

The market-specific news variables were then created as $N_{k;t,n} = N_{t,n} \cdot I_{k;t,n}$, for k = Asia, Europe, USA, USA regular. We then had four news variables that take the value of one if news is announced and zero otherwise. However, because we want the news impact on volatility to last longer than five minutes, we used the news impact decay structure estimated from the EUR/USD data (see details in subsection 2.3.4). We used the estimated coefficient values from the EUR/USD data as trend-setters and set the news coefficients values such that five minutes after the news announcements, the Asian news increase volatility by 5%, the European news by 20%, the US news 40%, and the regular US news by 80%. The news impact patterns $\lambda_{k;m}$ (where $k = asia, europe, usa, usar$ and $m = 1, ..., 25$ five minute intraday intervals) are presented in Figure 2.8:

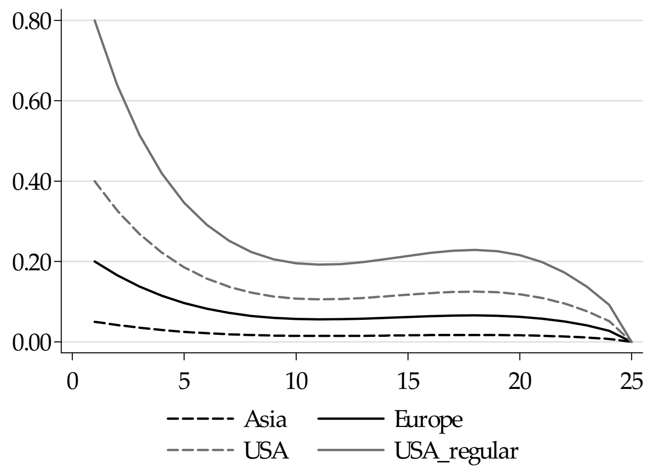


FIGURE 2.8 News impact decay structures
The figure presents the simulated news impact decay structures of different news. Decay structure was simulated using the third order polynomial.

As described in subsection 2.3.4, the news variables are hence not dummy variables as such, but whenever there is an announcement, in the 25 subsequent 5-minute intervals the news variables $(N_{asia;t,n}, N_{europe;t,n}, N_{usa;t,n}, N_{usar;t,n})$ equals $\lambda_{k;1}$, $\lambda_{k;2}$, ... ,$\lambda_{k;25}$ and zero otherwise. Finally, the news component $\eta_{t,n}$ in (2.9) was constructed as

$$\eta_{t,n} = 1 + N_{asia;t,n} + N_{europe;t,n} + N_{usa;t,n} + N_{usar;t,n} \tag{2.11}$$

To obtain returns that resemble the actual returns, we need to generate the shocks from a more leptokurtic distribution than the normal distribution. Therefore, we create the random shocks $\varepsilon_{t,n}$ as a mixture of two normally distributed random variables $\varepsilon_{1;,t,n}$ and $\varepsilon_{2;t,n}$ such that $\varepsilon_{t,n} = \varepsilon_{1;t,n} \sim N(0, 0.5)$ with probability 0.75 and $\varepsilon_{t,n} = \varepsilon_{2;t,n} \sim N(0, 2.0)$ with probability 0.25.

Therefore, while the daily volatility component (which depends on $\varepsilon_{t,n}$) and the random shocks change in every round, the intraday volatility component and the news component remain the same.

2.4.2 Properties of the Simulated Returns

To see whether the simulated returns have the same kinds of properties as the actual returns, we computed the average volatility pattern and the autocorrelation function of the return volatility for one realization (Figure 2.9). As can be seen, the simulated series display an intraday periodicity similar to that of the actual data set used before.

The simulated returns are filtered by the three methods: FFF, LOWESS and IAOM. The subset lengths in all of the methods are selected to be such that there is no periodicity left in volatility after filtering. For the IAOM method, no distinction between the weekdays was made. Since we did not create differences between weekdays in the intraday pattern, the distinction was not necessary.

To demonstrate how well the simulated returns resemble the EUR/USD returns, we computed the descriptive statistics for the simulated returns and the filtered simulated returns for one realization (Table 2.3). The key figures of the simulated returns are quite close to the ones of the EUR/USD returns. Mean and standard deviation of the simulated returns are very close to the ones of EUR/USD returns, but skewness and kurtosis of the simulated returns are smaller than those of the EUR/USD returns. When using the EUR/USD returns, filtering does not affect the mean and standard deviation, but rather the third and fourth moments. Similar findings can be made when the simulated returns are used.

TABLE 2.3 Key statistical figures for the simulated returns

Table presents the key statistical figures for the simulated returns and the simulated returns filtered with different methods. FFF refers to Flexible Fourier Form method, LOWESS to Locally weighted scatterplot smoothing method and IAOM to Intradaily Average Observations Model.

	Mean	Stand. Dev.	Skewness	Kurtosis
Simulated returns	-0.00006	0.056	0.016	21.34
FFF	-0.00011	0.053	0.040	17.10
LOWESS	-0.00012	0.045	0.003	7.03
IAOM	-0.00009	0.053	0.017	15.29

2.4.3 Simulation Results

After deseasonalizing the simulated returns, we studied the impact of news on volatility of filtered returns in the same manner as with the EUR/USD returns (equation 2.6). Table 2.4 presents the results of the simulation study. Besides us-

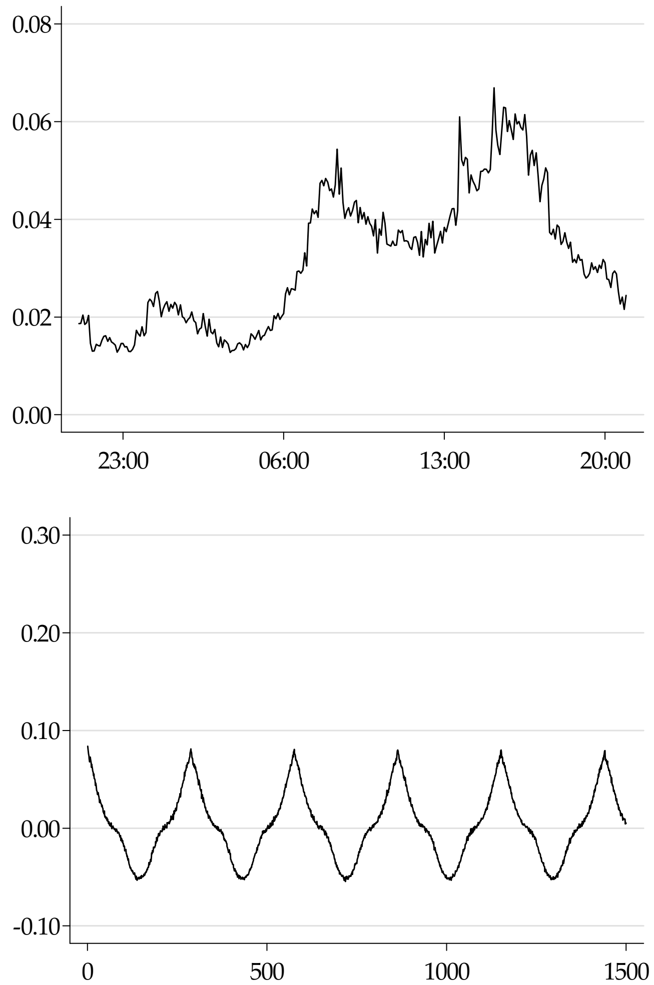


FIGURE 2.9 Intraday periodicity of volatility (simulated returns)
The upper figure presents the average intraday volatility pattern i.e. the mean absolute return per every 5-minute interval of the simulated absolute returns. The lower figure presents the five day (1500 5-minute lags) autocorrelogram of the simulated absolute returns.

ing the returns filtered with the three different methods, we estimated the news impact on volatility by using returns that were not filtered at all. As can be seen, filtering out the periodicity is indeed crucial: if we do not filter the returns, the US and European news coefficients are biased upward and Asian news coefficients downward. We also estimated the news impact on volatility by using the returns which did not have intraday periodicity in volatility, i.e. excluding intraday periodicity component from the return process. As expected, the intraday volatility component is the one causing the problems, since without it the bias is very close to zero.

It seems that almost all of the filtering methods tend to produce downward bi-

TABLE 2.4 Simulation results

2000 simulated realizations of the return process were filtered by FFF, LOWESS and IAOM methods. After filtering the news impact on volatility of different filtered returns was studied. Table presents the key statistics of the estimated news coefficients. The first panel presents the results of the Asian news, the second panel the European news, the third panel the US news and the last panel the regular US news. The first two rows in each panel present the results when the returns were not filtered at all and when the intraday volatility component was excluded in the data generating process when the returns were simulated. The next rows in each panel present the results when the returns were filtered with the FFF, LOWESS and IAOM methods, respectively. The mean bias, standard deviation of bias and minimum and maximum of the estimated news variable coefficient values are presented in the four last columns.

Asia, 5%	**Mean Bias**	**St. Dev.**	**Minimum**	**Maximum**
Returns - no filtering	-0.38	0.012	0.62	0.71
Returns - no intraday periodicity	0.00	0.019	0.98	1.11
FFF	0.04	0.016	1.03	1.15
LOWESS	-0.01	0.012	1.00	1.07
IAOM	0.01	0.022	0.99	1.14
Europe, 20%	**Mean Bias**	**St. Dev.**	**Minimum**	**Maximum**
Returns - no filtering	0.96	0.038	2.05	2.28
Returns - no intraday periodicity	-0.01	0.021	1.13	1.26
FFF	-0.02	0.018	1.11	1.23
LOWESS	-0.12	0.013	1.03	1.12
IAOM	0.06	0.026	1.16	1.33
USA, 40%	**Mean Bias**	**St. Dev.**	**Minimum**	**Maximum**
Returns - no filtering	-0.05	0.024	1.28	1.43
Returns - no intraday periodicity	-0.02	0.024	1.30	1.46
FFF	-0.09	0.019	1.24	1.38
LOWESS	-0.30	0.012	1.06	1.16
IAOM	-0.12	0.024	1.21	1.36
USA regular, 80%	**Mean Bias**	**St. Dev.**	**Minimum**	**Maximum**
Returns - no filtering	2.95	0.092	4.48	5.06
Returns - no intraday periodicity	-0.04	0.034	1.66	1.88
FFF	-0.37	0.021	1.37	1.50
LOWESS	-0.55	0.017	1.20	1.31
IAOM	-0.51	0.031	1.18	1.89

ased estimates for US and European news, and upward biased estimates for Asian news. However, the magnitude of the bias depends on the filter. While the LOWESS is best in terms of filtering the periodicity in volatility, it also seems to produce a larger negative bias than the other two filters. This means that, while filtering the intraday periodicity, it also filters part of the news effects. While the IAOM seems to perform almost as well as the FFF in most cases, it performs much worse than the FFF model when the macro figures are announced regularly. The FFF model produces the smallest bias on average, and therefore we conclude that it performs the best in filtering the periodicity.

2.5 Conclusions

In this essay we studied the capability of different methods to filter out the intraday periodicity of volatility and whether or not the choice of the filtering method affects the results concerning the impact of news on volatility. The results suggest that there are differences between the filters. The FFF model performs poorly if the model is estimated for the whole data set at once, but there is no periodicity left if the model is re-estimated every week. The success of the LOWESS method depends heavily on the chosen value of the smoothness parameter δ. When δ is set to be small enough, the filter is capable of getting rid of all the periodicity in the autocorrelation. The performance of the IAOM method also depends on the length of the estimation subset. The shorter the subset, the better the filter performs. On the other hand, the estimation subset length does not have as large impact on the IAOM method than on the FFF and LOWESS methods.

The choice of the filtering method affects the magnitude of the news coefficients. According to the simulation study, all the methods tend to produce downward biased estimates, which means that while filtering out the intraday periodicity, they also filter out part of the news effects. However, the size of the bias depends on the filter. The magnitude of the news impact and the announcement time regularity also affect the results: the larger news items are filtered more than the smaller ones and the news items that are announced regularly are filtered the most. While the LOWESS is capable of filtering out all the periodicity in volatility, it also seems to filter out more news effects than the other two filters. IAOM performs much worse than FFF in the case of news items that are always announced at the same time. The study supports the FFF model as the best filtering method.

REFERENCES

Andersen, T., Bollerslev, T., (1997) "Heterogenous Information Arrivals and Return Volatility Dynamics: Unrecovering the Long-Run in High Frequency Returns" The Journal of Finance 52, 975-1005

Andersen, T., Bollerslev, T., (1998) "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies" The Journal of Finance 53, 219-265

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2003) "Micro Effects and Macro Announcements: Real-Time Price Discovery in Foreign Exchange" American Economic Review 93, 38-62

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2007) “Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets“ Journal of International Economics 73, 251-277

Bauwens, L., Ben Omrane, W., Giot, P., (2005) "News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market" Journal of International Money and Finance 24, 1108-1125

Ben Omrane, W., De Bodt, E., (2007) "Using self-organizing maps to adjust intraday seasonality" Journal of Banking & Finance 31, 1817-1838

Bollerslev, T., Cai, J., Song, F., (2000) “Intraday Periodicity, Long-Memory Volatility, and Macroeconomic Announcement Effects in the U.S. Treasury Bond Market” Journal of Empirical Finance 7, 37-55

Cai, J., Cheung, Y., Lee, R., Melvin, M., (2001) "Once in a generation yen volatility in 1998: fundamentals, intervention and order flow" Journal of International Money and Finance 20, 327–347

Cleveland, W., (1979) "Robust Locally Weighted Regression and Smoothing Scatterplots" Journal of the American Statistical Association 74, 829-836

Dacorogna, M., Müller, U., Nagler, R., Olsen, R., Pictet, O., (1993) "A geographical model for the daily and weekly seasonal volatility in the foreign exchange market" Journal of International Money and Finance 12, 413–438.

Degennaro, R., Shrieves, R., (1997) “Public information releases, private information arrival and volatility in the foreign exchange market” Journal of Empirical Finance 4, 295–315

Dominguez, K., Panthaki, F., (2006) "What defines ‘news’ in foreign exchange markets?" Journal of International Money and Finance 25, 168-198

Engle, R., Russell, J., (1998) "Autoregressive conditional duration: a new approach for irregularly spaced transaction data" Econometrica 66, 1127–1162

Granger, C., Sin, C-Y., (1999) "Modelling the absolute returns of different stock indices: exploring the forecast ability of an alternative measure of risk" University of California, San Diego, Department of economics

Laakkonen, H., (2007) "The Impact of macroeconomic news on exchange rate volatility" Finnish Economic Papers 20, 23-40

Martens, M., Chang, Y-C., Taylor, S., (2002) "A comparison of seasonal adjustment methods when forecasting intraday volatility" Journal of Financial Research 25, 283–299

Melvin, M., Yin, X, (2000) "Public information arrival, exchange rate volatility and quote frequency" The Economic Journal 110, 644–661

Veredas D., Rodriguez-Poo, J., Espasa, A., (2002) "On the (intradaily) Seasonality and Dynamics of a Financial Point Process: A Semiparametric Approach" CORE DP 2002/23

CHAPTER 3

ASYMMETRIC NEWS EFFECTS ON EXCHANGE RATE VOLATILITY

3.1 Introduction

[1]One of the fundamental questions in financial economics is how new information is incorporated to asset prices. Numerous theoretical studies have suggested that for the various different reasons, e.g. because of the incomplete information (Damodaran, 1985; Veronesi, 1999 and 2000) and psychological issues (Barberis et al., 1998; Daniel et al. 1998; Manzan and Westerhoff, 2005), news not only causes a jump in the prices, but also a significant increase in volatility. An important part of new information in the markets comprises the scheduled releases of macroeconomic figures. The extensive empirical literature[2] has shown that announcements of macro figures cause a jump in the asset prices and significantly increase volatility right after the announcement.

More recent literature in the related area of research has been focusing on examining the asymmetries between different categories of news. For example, there is an extensive literature studying the asymmetric news effects with respect to sign of news. Many studies have found that negative macroeconomic news increase volatility more than positive announcements (e.g. Bauwens et al., 2005; Andersen et al., 2007). However, there are also studies that do not find asymme-

1 A version of this Chapter has appeared in the University of Jyväskylä working paper 353/2008.

2 The literature includes for example Goodhart et al. (1993), Ederington and Lee (1993), Degennaro and Shrieves (1997), Almeida et al. (1998), Andersen and Bollerslev (1998), Eddelbüttel and McCurdy (1998), Melvin and Yin (2000), Andersen et al. (2003, 2007), Chang and Taylor (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006), Faust et al. (2007), Laakkonen (2007a), among others.

tries with respect to sign (e.g. Pearce and Solakoglu, 2007).

We analyze two possible explanations, why positive and negative news might cause different reactions in different situations. The first explanation is related to the difficulty of analyzing news. Damodaran (1985) suggests, that investors make errors in evaluating the meaning of news, and that is caused by the need for responding to new information as quickly as possible. Therefore, it could be that sometimes investors might have difficulties to evaluate whether the released information is good or bad for the value of the exchange rate, and this task becomes even challenging, when a whole set of macro figures are announced at the same time. One might think that getting more information about the state of the economy at the same time would be useful. However, if some news signals better than expected economic conditions and some worse than expected state of the economy, investors could find it difficult to evaluate the overall effect of news. According to the model of Damodaran (1985), the errors in evaluating the meaning of news causes excess volatility on the returns.

Another possible explanation could be that investors value the news differently depending on the sign of the previous news. In particular, positive news after a series of positive news might gain a different reaction than positive news following negative news. Barberis et al. (1998) suggest that investors are reluctant to change their believes about the future state of the economy in the face of new evidence. Therefore, they tend to overreact to news in the long run, especially if the news are of the same sign in succession.

This essay aims to contribute to the literature examines the asymmetries in the news effects on exchange rate volatility. We begin with the preliminary analysis studying the impact of macroeconomic news on exchange rate volatility in general and the effects of news from different countries separately. We then proceed to study the difference between the impact of positive and negative news, after which we examine two types of asymmetries described above, which, to our knowledge has not been studied before. First, we examine, whether 'contradictory' and 'consistent' news affect volatility differently. If there are more than one macro figure released simultaneously, and some of the announced news are positive and some negative, news is classified as 'contradictory' and if all the announced news are either positive or negative, news is classified as 'consistent'. Second, we study if the investors value the news differently depending on the sign of the previous news. In particular, positive (negative) news after a series of positive (negative) news might gain a different reaction than positive (negative) news following negative (positive) news. According to the theoretical model of Barberis et al. (1998), investors tend to overreact to news in the long run, and underreact to them in the short run. This might imply that the reactions to news, which are preceded by a series of news of the same sign would be stronger than the reactions to other news.

We use a 5-minute frequency EUR/USD (Euro against United States Dollar) exchange rate data set running from 1 January 1999 to 31 December 2004 and a more comprehensive data set of macro announcements than has been used in the earlier literature. In particular, while the other studies have usually considered only few of the most important US macro announcements, our macro news data set covers altogether the announcements of 661 macro indicators from the

USA, all the euro countries, the UK and Japan. The announcements have been collected from Bloomberg WECO (World economic calendar), and they consist of scheduled releases for macroeconomic fundamentals such as gross domestic product (GDP), sales figures, consumer confidence indices etc.

The results suggest that macro announcements increase volatility significantly, US news having the strongest effect. UK news seems to increase volatility as much as news from the largest euro area countries, while news from the smallest euro area countries, and from Japan does not seem to affect volatility. We do not find a significant difference between the impact of negative and positive news, but the results suggest that 'contradictory' news increase volatility significantly more than 'consistent' news. The results also suggest that macro news that are preceded by three news of the same sign (e.g. positive employment news when the previous three news announcements on employment have also been positive) increase volatility significantly more than news which are preceded by news of the different sign.

The plan of the Chapter is as follows. Section 3.2 describes the data and methodology and the results of the empirical study are presented in Section 3.3. Finally, Section 3.4 concludes the study.

3.2 Data and Methodology

This section describes the data and the used methodology. We also classify the news in different categories for examining the asymmetries in the news effects.

3.2.1 Exchange Rate Data

The original data set contains the five-minute quotes[3] of the EUR/USD exchange rate from 1 January 1999 to 31 December 2004, and it was obtained from Olsen and Associates. The prices are formed by taking the average of the bid and ask quotes, and the returns are computed as the differences of logarithmic prices.

As the foreign exchange market activity slows down decidedly during weekends and certain holiday non-trading periods, it is standard in the literature to explicitly exclude a number of days from the raw five-minute return series. Following Andersen and Bollerslev (1998), we exclude the weekends and certain holidays by always excluding the returns from 21:05 GMT the night before to 21:00 GMT that evening. Andersen and Bollerslev (1998) state that this definition of a "day" retains intact the intraday periodical volatility structure. The following holidays are excluded from the data: Christmas, New Year, Good Friday and Easter Monday. Besides these holidays, three days are excluded from the data because of lack of observations (10 May 1999, 21 Dec 2000, 24 Dec 2000). Daylight savings time was also taken into account as is standard in the literature.

The five-minute returns exhibit strong intraday periodicity because of the

[3] According to many studies, five-minute returns strike the best balance between the disadvantages of microstructure noise (when sampling too frequently) and the loss of important information (when sampling too infrequently). For a discussion, see Andersen et al. (2007).

different trading times in the global 24-hour foreign exchange markets. This has to be taken into account in modeling news effects, and one way of doing this is to use a filtered return series. Of the alternative models of filtering the periodicity, we chose the Flexible Fourier Form (FFF) model of Andersen and Bollerslev (1997) that uses different frequencies of sine and cosine functions to capture the periodicity. This choice is motivated by Laakkonen (2007b), who studied the consequences of data filtering on the results obtained by using filtered returns. She concluded that for the purpose of studying the impact of news on volatility, the FFF method performs the best in data filtering among a number of commonly acknowledged filtering methods, because it produces the smallest biases in the estimates for the news coefficients compared to other filtering methods.

The FFF method is based on the following decomposition:

$$R_{t,n} - \bar{R}_{t,n} = \sigma_t \cdot s_{t,n} \cdot Z_{t,n} \tag{3.1}$$

where $R_{t,n}$ denotes the five-minute returns, $\bar{R}_{t,n}$ is the expected five-minute returns and $Z_{t,n}$ is an i.i.d (with mean zero and unit variance) innovations, σ_t represents daily volatility and $s_{t,n}$ is intraday volatility[4].

Squaring both sides of (3.1), taking logs, approximating $\bar{R}_{t,n}$ with the sample mean $\bar{R}$ and eliminating the daily volatility component σ_t from the return process, we end up with the following expression,

$$2 \log \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = \log\left(s_{t,n}^2\right) + \log\left(Z_{t,n}^2\right) \tag{3.2}$$

where following Andersen and Bollerslev (1997), we replace σ_t by $\hat{\sigma}_t$ predicted by a $GARCH(1,1)$ model for the daily volatility. N denotes the number of five-minute intervals in one day (288 in a 24-hour market). Andersen and Bollerslev (1997) suggest a parametric representation of the intraday volatility $s_{t,n}$ and estimate the smooth cyclical volatility pattern by using trigonometric functions. The FFF regression model is the following,

$$\begin{aligned} f_{t,n} = \alpha + \delta_1 n + \delta_2 n^2 + \sum_{l=1}^{L} \lambda_l I_{l;t,n} \\ + \sum_{p=1}^{P} \left(\delta_{c,p} \cos\left(\frac{p2\pi}{N} n\right) + \delta_{s,p} \sin\left(\frac{p2\pi}{N} n\right)\right) + \varepsilon_{t,n}, \end{aligned} \tag{3.3}$$

where $f_{t,n} = 2 \log \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. Besides the sinusoids[5], the model contains the intercept α, the quadratic function in the intraday interval n, and the error term of the model $\varepsilon_{t,n}$. The model also contains the indicator variables $I_{l;t,n}$, which are used to control e.g. for weekday effects. The estimate of intraday volatility $\hat{s}_{t,n}$ is then obtained as $\hat{s}_{t,n} = \exp(\hat{f}_{t,n}/2)$, where $\hat{f}_{t,n}$ are the fitted values from model (3.3). This estimate $\hat{s}_{t,n}$ is normalized so that the mean of the normalized peri-

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4 In the equations t denotes the day and n the five-minute interval.

5 The value $P = 9$ was selected by using the Schwarz information criteria.

odicity estimate $\tilde{s}_{t,n}$ equals one: $\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{T/N} \sum_{n=1}^{N} \hat{s}_{t,n}}$ where T is the number of observations in the entire sample and T/N denotes the number of days in the data. To get the filtered returns, the original returns $R_{t,n}$ are divided by the normalized estimate $\tilde{s}_{t,n}$, i.e., $\tilde{R}_{t,n} = \frac{R_{t,n}}{\tilde{s}_{t,n}}$. See Andersen and Bollerslev (1997, 1998) for further details of the method.

If the intraday periodicity pattern is assumed to remain constant over the sample period, the FFF model is estimated for the entire data set. Unfortunately this is not likely to be the case. Laakkonen (2007b) studied the properties of the intraday returns filtered with different methods. She found that all the examined filtering methods were capable of filtering the intraday seasonality only if the filtering was done in subsets of data. Yet, she concluded that the filters performed better the shorter was the subset, which indicates that the intraday volatility pattern was time varying. If the FFF model is estimated only once by using the entire sample period, there are significant periodical autocorrelation left in the absolute filtered returns. To be able to filter all the periodicity in volatility, the data has to be filtered in subsets. Laakkonen (2007b) states that to be able to filter all the periodicity in volatility in this particular data set, the FFF model has to be re-estimated every week.

The autocorrelation coefficients of absolute filtered and original returns for 1500 five-minute lags, i.e., the autocorrelogram for five days, is depicted in Figure 3.1. It is seen that there is still some autocorrelation left in the filtered absolute returns, although much of the intraday periodicity has been filtered out. In the empirical analysis of Section 3.3, the remaining autocorrelation will have to be taken into account in computing the covariance matrix of the errors of the regression models.

Some descriptive statistics of the original and filtered return series are presented in Table 3.1. Mean and standard deviation of the return series are not effected dramatically by filtering. However, filtering does have an effect on skewness and kurtosis. The distribution of financial return series is usually very leptokurtic compared to the normal distribution, which indicates the overabundance of great returns compared to the normal distribution. The distribution of the EUR/USD returns is also positively skewed, which suggests that there are more great positive than negative returns. The distribution of the filtered returns is almost symmetric: due to filtering, skewness falls from 0.78 to -0.15. Also, the extra kurtosis of the distribution falls from 65.9 to 40.9. Although the distribution of the returns seems to be closer to the normal distribution after filtering, neither the original nor filtered returns are normally distributed.

3.2.2 Macro Announcement Data

The macroeconomic news data set includes all the scheduled macroeconomic news published in the World Economic Calendar (WECO) page of Bloomberg. The announcements are collected for all the euro area countries, the US, the UK and Japan for the years 1999-2004. The data include the announcement date and time in one minute accuracy, the announced figure, henceforth denoted $A_{t,n}$ and

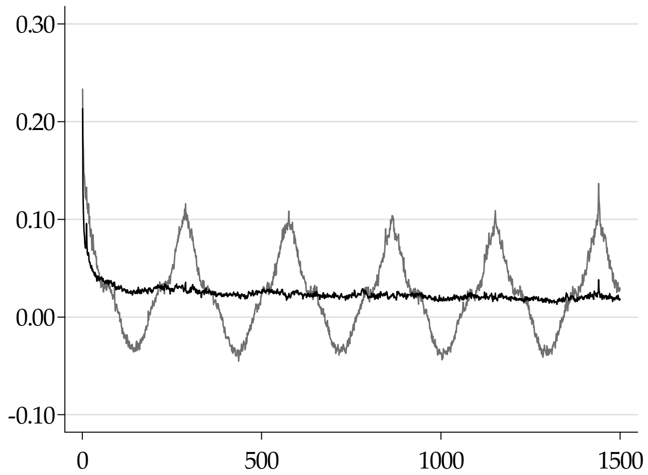

FIGURE 3.1 Autocorrelogram of the original and filtered absolute returns
The figure shows the five day correlogram at lags from 0 to 1500 of the filtered five-minute absolute EUR/USD returns (black line) compared to original absolute returns (grey line). The intraday periodicity was filtered by using the Flexible Fourier Form method.

TABLE 3.1 Key statistical figures
Table presents the key statistical figures for the original and for the filtered returns. The returns were filtered with the Flexible Fourier Form method.

	Returns	**Filtered returns**
Mean	$5.0E-05$	$6.6E-05$
Standard Deviation	0.0432	0.0434
Skewness	0.781	-0.154
Kurtosis	65.94	40.92
Minimum	-1.35	-1.69
Maximum	2.79	1.68

the market forecast of the figure, henceforth denoted $F_{t,n}$. The market forecast is the median of the survey forecasts that Bloomberg collects from the market agents, but unfortunately it is not available for all of the macro figures. For example for the figures from smaller euro countries there is no forecast.

Table 3.2 presents the numbers of observations from different countries and all together. The third column presents the number of news announcements in total and the fourth column presents the number of nonzero observations in different news variables. While the total number of news announcements is as high as 27410, the number of nonzero observations in the 'all news' variable (henceforth denoted $N_{all;t,n}$) is only 12620. The reason for the great discrepancy is the fact that so many macro figures are announced simultaneously. For example, the monthly US unemployment report includes the announcements of average weekly hours, change in manufacturing payrolls, change in nonfarm payrolls, unemployment rate and average hourly earnings. These five simultaneous announcements are all counted in the third column, while they only produce one nonzero news observation for the news variable $N_{all;t,n}$, counted in the fourth column.

TABLE 3.2 Number of macro announcements in different categories

Table presents the number of macroeconomic announcements from different countries. The third column presents the number of news announcements in total and the fourth column presents the number of non-zero news observations in the news variables. The announcements were collected from the Bloomberg World Economic Calendar for the years 1999-2004.

Variable	News category	Number of news	Number of news obs.
$N_{all;t,n}$	All news	27410	12620
$N_{au;t,n}$	Austria	463	285
$N_{be;t,n}$	Belgium	807	513
$N_{ec;t,n}$	ECB	2794	1198
$N_{fi;t,n}$	Finland	855	494
$N_{fr;t,n}$	France	1813	900
$N_{ge;t,n}$	Germany	3671	1804
$N_{ir;t,n}$	Ireland	842	366
$N_{it;t,n}$	Italy	2259	1080
$N_{jn;t,n}$	Japan	3127	1752
$N_{ne;t,n}$	Netherlands	992	601
$N_{po;t,n}$	Portugal	968	478
$N_{sp;t,n}$	Spain	1346	728
$N_{uk;t,n}$	United Kingdom	3317	1128
$N_{us;t,n}$	United States	4156	2285

To study asymmetries, the announcements were divided into different categories. The numbers of nonzero news observations in the different news variables are presented in Table 3.3 for all countries combined and for the euro area, the UK and the US separately. The first two rows show how many of the news has the forecast available (henceforth denoted $N_{f;t,n}$) and how many does not (henceforth denoted $N_{nf;t,n}$). As can be seen in Table 3.3, most of the US and UK news has a forecast available, while this is not the case for the euro area news.

The market forecast is used in classifying the news as positive and negative. A news item is defined positive (henceforth denoted as $N^f_{pos;t,n}$) when the market forecast is smaller than the announced figure, i.e. the announcement is underestimated. Negative news (henceforth denoted as $N^f_{neg;t,n}$), on the other hand, means that agents had overestimated the announced figure, which was less than the forecast. This kind of classification has been standard in the literature (see e.g. Andersen and Bollerslev, 2003). However, it can be argued that positive news classified in this way might not necessarily be good news (for example, an

TABLE 3.3 Number of macro announcements in different categories

Table presents the observations in the different news variables. The third column presents the number of news from all countries combined, while the rest of the columns present the number of news from the euro area, UK and US separately. The announcements were collected from the Bloomberg World Economic Calendar for the years 1999-2004.

Variable	News category	ALL	EURO	UK	USA
$N_{f;t,n}$	Forecast available	6921	3407	753	1925
$N_{nf;t,n}$	Forecast not available	5699	4061	375	360
$N^f_{pos;t,n}$	Positive news, $A_{t,n} - F_{t,n} > 0$	3765	1636	447	1177
$N^f_{neg;t,n}$	Negative news, $A_{t,n} - F_{t,n} < 0$	3637	1642	467	1079
$N^r_{pos;t,n}$	Positive news, $A_{t,n}$ when $R_{t,n+1} > 0$	3391	1654	369	954
$N^r_{neg;t,n}$	Negative news, $A_{t,n}$ when $R_{t,n+1} < 0$	3155	1570	346	897
$N_{one;t,n}$	One announcement	2752	1152	130	1064
$N_{cons;t,n}$	Consistent news	2684	1658	358	420
$N_{cont;t,n}$	Contradictory news	1182	334	246	435
$N_{tr2;t,n}$	Trend news 2	1732	813	187	531
$N_{tr3;t,n}$	Trend news 3	1018	470	135	297
$N_{tr4;t,n}$	Trend news 4	1796	961	263	385
$N_{mr;t,n}$	Mean revert news	4122	1868	516	1223

unexpectedly high increase in the unemployment rate[6]). Therefore, we classified the news to positive and negative also in an alternative way. According to this classification a news announcement is positive (henceforth denoted as $N^r_{pos;t,n}$) if the five-minute return following it is positive (dollar appreciates), and negative (henceforth denoted as $N^r_{neg;t,n}$) if the return is negative (dollar depreciates).

Note, however, that if some of these news announced at the same time were positive and some negative, both news variables $N^f_{pos;t,n}$ and $N^f_{neg;t,n}$ would take a value of one. This is why the sum of the nonzero observations of the $N^f_{pos;t,n}$ and $N^f_{neg;t,n}$ variables is more than the number of the observations in $N_{t,n}$. On the other hand, the numbers of nonzero observations of the sum of $N^r_{pos;t,n}$ and $N^r_{neg;t,n}$ is less than $N_{t,n}$, because the announcement is classified neither positive nor negative if the return following it equals zero.

To study the differences between 'consistent' and 'contradictory' news, we classify the news to three categories. First, if only one macro news was announced, the news was classified as 'one announcement' (henceforth denoted as $N_{one;t,n}$). One the other hand, news is classified as 'contradictory' (henceforth denoted as $N_{cont;t,n}$), if at the same time (same minute) both positive and negative announcements were released and 'consistent' (henceforth denoted as $N_{cons;t,n}$)

6 The estimations were also done with corrected data, where the positive surprise in unemployment was classified as negative news. This did not have a significant effect on the results.

if more than one announcement was released and they all are either positive or negative.

Finally, to study if the investors value the news differently depending on the sign of the previous news, we classify news as 'trend news' or 'mean revert news'. News is classified as 'trend news' (henceforth denoted as $N_{tr2;t,n}$, $N_{tr3;t,n}$, and $N_{tr4;t,n}$), if the sign of the previous month's news was of the same sign as the sign of the currently released news. The numbers two, three and four refer to how many times the sign has been the same in succession. For example, if there was positive news on GDP today, and the previous month's GDP news were also positive, $N_{tr2;t,n}$ would take a value of one. On the other hand, if also news on GDP released two months ago was positive, then instead the variable $N_{tr3;t,n}$ would take a value of one. On the other hand, if the previous month's GDP news was negative, then news was classified as 'mean revert', henceforth denoted as $N_{mr;t,n}$.

3.2.3 The Model

To study the announcement effects on exchange rate volatility, we consider the following model,

$$y_{t,n} = c + \sum_{k=1}^{K} \phi_k N_{k;t,n} + \varepsilon_{t,n} \tag{3.4}$$

where $y_{t,n} = 2 \log \dfrac{|\tilde{R}_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$ is our measure of exchange rate volatility. The dependent variable is of the same form as in the FFF regression (3.3), but now the raw returns, $R_{t,n}$, are replaced by the filtered returns, $\tilde{R}_{t,n}$. This notation is used throughout this section. Apart from the intercept, c, the explanatory variables include the news variables that we denote with a generic symbol $N_{k;t,n}$. Because we are interested in different kinds of asymmetries (e.g. positive vs. negative news, 'consistent' vs. 'contradictory' news, 'trend' vs. 'mean revert' news), we study them with a total of ten models. The only difference between these models is that the set of news variables $\sum_{k=1}^{K} N_{k;t,n}$ differs between the models (see details of the different news categories in Tables 3.2 and 3.3).

News announcements have been reported to have long-lasting effects on volatility. For instance, according to Andersen and Bollerslev (1998), the impact lasts from one to two hours. To allow for such prolonged effects, we have to modify model (3.4) to some extent. Specifically, following Andersen and Bollerslev (1998), the impact of an announcement is assumed to diminish gradually and go to zero after two hours. We first estimate the average news impact pattern by computing the average absolute returns at each five-minute interval following the news announcements minus the average absolute return over the entire sample period. We then estimate the decay structure of the volatility response pattern of news by fitting a third order polynomial to the average news impact pattern. OLS estimation yields the following equation for the average absolute returns following the news announcements,

$$\lambda_m = 0.054\left(1-(m/25)^3\right) - 0.009\left(1-(m/25)^2\right)m + 0.0007\left(1-(m/25)\right)m^2 \tag{3.5}$$

where $m = 1, 2, ...25$ denotes the five-minute interval after the news announcement. The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours[7], as depicted in Figure 3.2.

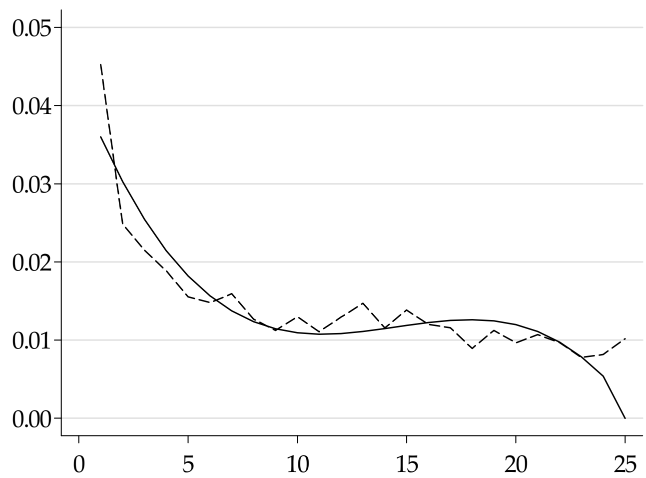

FIGURE 3.2 Decay structure of volatility response pattern after news
The figure presents the mean absolute returns during two hours after news announcements (dashed line) and the estimated news impact decay structure (solid line). Decay structure was estimated using the third order polynomial.

In the empirical models, the explanatory variables are hence not the news variables as such, but whenever there is an announcement, in the 25 subsequent 5-minute intervals the corresponding regressor equals λ_1, λ_2, ..., λ_{25} and zero otherwise[8]. The impact of news on volatility $M_{k;m}$ can then be calculated for every 25 intervals m separately with the equation

7 Longer dependencies of news could certainly have also been studied for example by using lag dummies. However, the benefit of this polynomial method is, as Bollerslev et al. (2000) state, that it fixes the problem of having only a few announcement observations and it is less sensitive to the inherent noise in the return process. One further advantage of this approach is that compared to lag dummies, we now only need one news variable for each news category. To study the impact of news for a period of two hours after the announcement, we would have needed 24 (two hours is 24 five-minute intervals) news variables for all the news categories. The choice of polynomial order and the length of the news impact are studied more carefully in Laakkonen (2007a).

8 Most studies that examine the impact of news on financial market returns, use the actual surprice element (the announced figure less the forecast) as a news variable rather than a dummy variable that does not take into account the size of the news. However, Andersen et al. (2003, 2007) argue that it is the mere presence of an announcement, not so much the size of the corresponding surprise, that tends to boost volatility.

$$M_{k;m} = \exp\left(\frac{\phi_k \cdot \lambda_m}{2}\right) \tag{3.6}$$

3.3 Empirical Analysis

This section presents the results of the empirical analysis on the impact of news on EUR/USD volatility. In the following subsections we study the asymmetric news effects between different news categories.

3.3.1 News by Country

We start by studying the impact of news in general without any asymmetries with the following two models:

$$y_{t,n} = c + \phi_{all} N_{all;t,n} + \varepsilon_{t,n} \tag{3.7}$$

$$\begin{aligned} y_{t,n} = c &+ \phi_{au} N_{au;t,n} + \phi_{be} N_{be;t,n} + \phi_{ec} N_{ec;t,n} + \phi_{fi} N_{fi;t,n} + \phi_{fr} N_{fr;t,n} \\ &+ \phi_{ge} N_{ge;t,n} + \phi_{ir} N_{ir;t,n} + \phi_{it} N_{it;t,n} + \phi_{jn} N_{jn;t,n} + \phi_{ne} N_{ne;t,n} \\ &+ \phi_{po} N_{po;t,n} + \phi_{sp} N_{sp;t,n} + \phi_{uk} N_{uk;t,n} + \phi_{us} N_{us;t,n} + \varepsilon_{t,n} \end{aligned} \tag{3.8}$$

Model (3.7) studies the news effects in general, and model (3.8) examines the effects of macro news from different countries separately. Table 3.4 presents the coefficient values of the news variables ϕ_k as well as the impact of news on volatility ($M_{k;1}$) computed for the first 5-minute interval following the news announcement with equation (3.6). The standard errors in parentheses are computed by using the Newey-West standard errors (288 lags)[9].

The news variable $N_{all;t,n}$ includes all the macroeconomic announcements from all the euro countries, Japan, the UK and the USA. As we can see, in general macroeconomic news increase volatility significantly: volatility increases by approximately 34% after the news announcements. From the results of model (3.8) we can see, that US news increases volatility clearly more than news from the other countries: volatility increases by 72% immediately after the US news announcements, while the next largest effect, caused by news from Germany, is only 24%. The magnitude of the impact of euro area news seem to follow quite closely of the size of the euro countries: news from the ECB and the largest countries, Germany and France, affect volatility the most, while news from the smallest countries like Finland and Austria does not seem to affect volatility significantly. Interestingly, UK news seems to increase volatility as much as the news from the largest euro area countries, while news from Japan does not increase the EUR/USD volatility significantly.

[9] The number of lags is motivated with the 288 5-minute intraday intervals in 24-hour market.

TABLE 3.4 Estimation results: news by country

Table presents the parameter estimates of models (3.7) and (3.8). Model (3.7) studies the impact of macroeconomic news on EUR/USD exchange rate volatility by combining all news to one variable, and model (3.8) studies the impact of news from different countries separately. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively. The last column presents the impact of news on volatility five minutes after the announcement computed with equation (3.6).

News variable k	**Parameter**	(3.7)	(3.8)	$M_{k;1}$
$N_{all;t,n}$	ϕ_{all}	16.33^{**} (0.75)	–	134%
$N_{au;t,n}$	ϕ_{au}	–	4.11 (3.16)	108%
$N_{be;t,n}$	ϕ_{be}	–	7.43^{**} (2.25)	114%
$N_{ec;t,n}$	ϕ_{ec}	–	7.87^{**} (1.64)	115%
$N_{fi;t,n}$	ϕ_{fi}	–	1.51 (2.61)	103%
$N_{fr;t,n}$	ϕ_{fr}	–	8.29^{**} (1.75)	116%
$N_{ge;t,n}$	ϕ_{ge}	–	12.11^{**} (1.33)	124%
$N_{ir;t,n}$	ϕ_{ir}	–	6.32^{*} (2.69)	112%
$N_{it;t,n}$	ϕ_{it}	–	5.46^{*} (2.28)	110%
$N_{jn;t,n}$	ϕ_{jn}	–	1.57 (1.54)	103%
$N_{ne;t,n}$	ϕ_{ne}	–	6.81^{*} (2.15)	113%
$N_{po;t,n}$	ϕ_{po}	–	5.29^{*} (2.28)	110%
$N_{sp;t,n}$	ϕ_{sp}	–	4.24^{*} (1.98)	108%
$N_{uk;t,n}$	ϕ_{uk}	–	10.64^{**} (1.53)	121%
$N_{us;t,n}$	ϕ_{us}	–	30.24^{**} (1.25)	172%

3.3.2 News with Forecast vs. No Forecast

As mentioned earlier, all the announcement do not have the market forecast available. We continue by examining if there are differences between the impact of news which has the forecast available and which has not. For this, we estimate the following two models:

$$y_{t,n} = c + \phi_f N_{f;t,n} + \phi_{nf} N_{nf;t,n} + \varepsilon_{t,n} \tag{3.9}$$

$$\begin{aligned} y_{t,n} = c &+ \phi_{f\_eu} N_{f\_eu;t,n} + \phi_{nf\_eu} N_{nf\_eu;t,n} + \phi_{f\_uk} N_{f\_uk;t,n} \\ &+ \phi_{nf\_uk} N_{nf\_uk;t,n} + \phi_{f\_us} N_{f\_us;t,n} + \phi_{nf\_us} N_{nf\_us;t,n} + \varepsilon_{t,n} \end{aligned} \tag{3.10}$$

Model (3.9) studies the news effects of all the countries combined, whereas model (3.10) examines the effects of macro news from the euro area, UK and US separately. Table 3.5 presents the results of models (3.9) and (3.10). As can be seen, the macro figures for which a forecast exists increase volatility by 40% while the news without a forecast increase volatility by only 13%. It is likely that the forecast is in general collected only for the "most important" macro announcements. Our results support that assumption, since the news with forecast cause a significantly greater impact on volatility than the news without the forecast (p-value = $1.35E-24$). The same phenomenon can be seen in the results of model (3.10), in which news from the euro area, UK and US are studied separately. In all cases the coefficient of news which has a forecast available is larger than the coefficient of news without a forecast.

TABLE 3.5 Estimation results: forecast vs. no forecast

Table presents the parameter estimates of models (3.9) and (3.10) that compare the impact of news which has the market forecast available which do not. Model (3.10) examines the news from the euro area, UK and US separately, while in model (3.9) all news are pooled. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively. The last column presents the impact of news on volatility five minutes after the announcement computed with equation (3.6).

News variable k	**Parameter**	(3.9)	(3.10)	$M_{k;1}$
$N_{f;t,n}$	ϕ_f	18.78** (0.82)	–	140%
$N_{nf;t,n}$	ϕ_{nf}	6.79** (0.89)	–	113%
$N_{f\_eu;t,n}$	ϕ_{f_eu}	–	13.41** (1.03)	127%
$N_{nf\_eu;t,n}$	ϕ_{nf_eu}	–	7.50** (0.95)	115%
$N_{f\_uk;t,n}$	ϕ_{f_uk}	–	11.05** (1.81)	122%
$N_{nf\_uk;t,n}$	ϕ_{nf_uk}	–	9.48** (2.49)	119%
$N_{f\_us;t,n}$	ϕ_{f_us}	–	32.30** (1.29)	179%
$N_{nf\_us;t,n}$	ϕ_{nf_us}	–	11.83** (2.74)	124%
Wald test, p-value				
$\phi_f = \phi_{nf}$	-	$1.35E-24$	–	
$\phi_{f\_eu} = \phi_{nf\_eu}$	-	–	$2.79E-05$	
$\phi_{f\_uk} = \phi_{nf\_uk}$	-	–	0.608	
$\phi_{f\_us} = \phi_{nf\_us}$	-	–	$4.67E-11$	

3.3.3 Positive vs. Negative News

Next, we study the differences between the impact of positive and negative news with the following two models:

$$y_{t,n} = c + \phi_{pos} N_{pos;t,n} + \phi_{neg} N_{neg;t,n} + \varepsilon_{t,n} \tag{3.11}$$

$$\begin{aligned} y_{t,n} = c &+ \phi_{pos\_eu} N_{pos\_eu;t,n} + \phi_{neg\_eu} N_{neg\_eu;t,n} + \phi_{pos\_uk} N_{pos\_uk;t,n} \\ &+ \phi_{neg\_uk} N_{neg\_uk;t,n} + \phi_{pos\_us} N_{pos\_us;t,n} + \phi_{neg\_us} N_{neg\_us;t,n} + \varepsilon_{t,n} \end{aligned} \tag{3.12}$$

Again, we first study the news effects of all the countries combined with model (3.11), and then continue examining the effects of macro news from the euro area, UK and US separately with model (3.12). Note, that in models (3.11) and (3.12) we use a generic symbol for positive and negative news. The classification to positive and negative news is based on two alternative ways: Bloomberg market forecast ($N^{f}_{pos;t,n}$ and $N^{f}_{neg;t,n}$) and the sign of the return following the news ($N^{r}_{pos;t,n}$ and $N^{r}_{neg;t,n}$). We estimate models (3.11) and (3.12) by using both of these classification methods, and Table 3.6 presents the results.

The estimated values of the coefficients for negative news seem to be larger than those for positive news, however, the Wald tests do not reject the equality of the coefficients in any of the cases. Interestingly, when the sign of the return is used in the classification, negative (dollar depreciates) UK and US news increases volatility more than positive UK and US news, while positive (euro depreciates) euro area news increases volatility more than negative euro area news.

We also studied the impact of the largest and the smallest positive and negative news announcements to see if the magnitude of the surprise matters. Following Vähämaa, Watzka and Äijö (2005) we excluded the low surprise announcements by using the upper and lower quartiles as the sampling boundaries. This did not have an effect on the results.

We are not the first ones examining the asymmetries between the impact of positive and negative news, but the earlier results have been incongruous: for example Andersen et al. (2003) find that negative news have larger impact than positive news, while Pearce and Solakoglu (2007) do not find the asymmetries with respect to sign.

One explanation for these mixed findings could be the time span of the data set. Laakkonen and Lanne (2009) find that negative news increases volatility more than positive news, but only when the economy is in expansion. Andersen and Bollerslev (2003), who find asymmetries between positive and negative news, use data that cover only a period when economy is in boom. The asymmetric state dependencies could be explained with the theory of Veronesi (1999), which suggests that the reaction to positive and negative news would depend on the state of the economy: due to the investors' willingness to hedge against the uncertainty about the state of the economy, they overreact to bad news in good times and underreact to good news in bad times.

On the other hand, there could be also other explanations for the mixed findings, two of which we study in the following two subsections.

3.3.4 Consistent vs. Contradictory News

We continue by studying the asymmetric news effects between the 'consistent' and 'contradictory' news in the following two models:

$$y_{t,n} = c + \phi_{one} N_{one;t,n} + \phi_{cons} N_{cons;t,n} + \phi_{cont} N_{cont;t,n} + \varepsilon_{t,n} \tag{3.13}$$

TABLE 3.6 Estimation results: positive and negative news

Table presents the parameter estimates of models (3.11) and (3.12) that compare the impact of positive and negative news. Model (3.12) examines the news from the euro area, UK and US separately, while in model (3.11) all news are pooled. Two different methods have been used to classify news to positive and negative (market forecast and sign of the return). Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively. The last columns presents the impact of news on volatility five minutes after the announcement computed with equation (3.6).

		Market forecast $(N^f_{pos;t,n}, N^f_{neg;t,n})$			**Sign of the return** $(N^r_{pos;t,n}, N^r_{neg;t,n})$		
News variable k	**Parameter**	(3.11)	(3.12)	$M_{k;1}$	(3.11)	(3.12)	$M_{k;1}$
$N_{pos;t,n}$	ϕ_{pos}	13.87** (1.02)	–	128%	20.25** (0.98)	–	144%
$N_{neg;t,n}$	ϕ_{neg}	14.25** (1.06)	–	129%	21.47** (0.99)	–	147%
$N_{pos\_eu;t,n}$	ϕ_{pos_eu}	–	11.04** (1.36)	122%	–	16.60** (1.26)	135%
$N_{neg\_eu;t,n}$	ϕ_{neg_eu}	–	10.92** (1.39)	122%	–	14.27** (1.26)	129%
$N_{pos\_uk;t,n}$	ϕ_{pos_uk}	–	5.49* (2.74)	110%	–	13.15** (2.37)	127%
$N_{neg\_uk;t,n}$	ϕ_{neg_uk}	–	10.80* (2.73)	121%	–	19.22** (2.48)	141%
$N_{pos\_us;t,n}$	ϕ_{pos_us}	–	21.91** (1.70)	148%	–	32.70** (1.66)	180%
$N_{neg\_us;t,n}$	ϕ_{neg_us}	–	25.56** (1.82)	158%	–	35.54** (1.70)	190%
Wald test, p-value							
	$\phi_{pos} = \phi_{neg}$	0.819	–		0.379	–	
	$\phi_{pos\_eu} = \phi_{neg\_eu}$	–	0.957		–	0.212	
	$\phi_{pos\_uk} = \phi_{neg\_uk}$	–	0.264		–	0.079	
	$\phi_{pos\_us} = \phi_{neg\_us}$	–	0.222		–	0.246	

$$y_{t,n} = c + \phi_{one\_eu} N_{one\_eu;t,n} + \phi_{cons\_eu} N_{cons\_eu;t,n} + \phi_{cont\_eu} N_{cont\_eu;t,n} \\ + \phi_{one\_uk} N_{one\_uk;t,n} + \phi_{cons\_uk} N_{cons\_uk;t,n} + \phi_{cont\_uk} N_{cont\_uk;t,n} \\ + \phi_{one\_us} N_{one\_us;t,n} + \phi_{cons\_us} N_{cons\_us;t,n} + \phi_{cont\_us} N_{cont\_us;t,n} + \varepsilon_{t,n} \tag{3.14}$$

Model (3.13) studies the news effects of all the countries combined, whereas model (3.14) examines the impact of macro news from the euro area, UK and US separately. Table 3.7 presents the results of models (3.13) and (3.14), which show that there are differences between the impact of 'one announcement', 'contradictory' news and 'consistent' news. Contradictory news increase volatility significantly more than consistent news and the times when only one macro news is announced (p-values for $\phi_{one} = \phi_{cont}$ and $\phi_{cons} = \phi_{cont}$ equal 0.012 and $3.28 - E06$, respectively.

Interestingly, the times when there is only one macro announcement seem to increase volatility more than consistent news (p-value = 0.012). Therefore, it indicates that it is the clearness of the signal that matters. If several macro figures are announced at the same time, we could imagine that it would help the agents to get a broader picture of the state of the economy. However, this seems not to be the case if the agents do not get a clear positive or negative signal. If some of the figures are underestimated and some overestimated, the market agents are likely to have more difficulties to evaluate the effect of the news and this causes excess volatility to the exchange rates.

3.3.5 Trend vs. Mean Revert News

Finally, we study the difference between macro news that are of the same sign (positive or negative) successively and the macro news which are positive and negative in turns with the following two models:

$$y_{t,n} = c + \phi_{tr2} N_{tr2;t,n} + \phi_{tr3} N_{tr3;t,n} + \phi_{tr4} N_{tr4;t,n} + \phi_{mr} N_{mr;t,n} + \varepsilon_{t,n} \tag{3.15}$$

$$y_{t,n} = c + \phi_{tr2\_eu} N_{tr2\_eu;t,n} + \phi_{tr3\_eu} N_{tr3\_eu;t,n} + \phi_{tr4\_eu} N_{tr4\_eu;t,n} \\ + \phi_{mr\_eu} N_{mr\_eu;t,n} + \phi_{tr2\_uk} N_{tr2\_uk;t,n} + \phi_{tr3\_uk} N_{tr3\_uk;t,n} \\ + \phi_{tr4\_uk} N_{tr4\_uk;t,n} + \phi_{mr\_uk} N_{mr\_uk;t,n} + \phi_{tr2\_us} N_{tr2\_us;t,n} \\ + \phi_{tr3\_us} N_{tr3\_us;t,n} + \phi_{tr4\_us} N_{tr4\_us;t,n} + \phi_{mr\_us} N_{mr\_us;t,n} + \varepsilon_{t,n} \tag{3.16}$$

Model (3.15) studies the news effects of all the countries combined, whereas model (3.16) examines the effects of macro news from euro area, the UK and the US separately. The results of Models (3.15) and (3.16) are presented in Table 3.8. While the coefficients of the 'trend news' variables seem in general to be a little bit larger than the coefficients of the 'mean revert news' variables, only in the case of the US news the pattern seem clear: the 'trend news' seem to increase volatility more than the 'mean revert' news. However, only the macro news that

TABLE 3.7 Estimation results: consistent and contradictory news

Table presents the parameter estimates of models (3.13) and (3.14) that compare the impact of 'consistent news' and 'conflicting news'. Model (3.14) examines the news from the euro area, UK and US separately, while in model (3.13) all news are pooled. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively. The last column presents the impact of news on volatility five minutes after the announcement computed with equation (3.6).

News variable k	**Parameter**	(3.13)	(3.14)	$M_k(1)$
$N_{one;t,n}$	ϕ_{one}	17.22^{**} (1.13)	–	136%
$N_{cons;t,n}$	ϕ_{cons}	13.25^{**} (1.09)	–	127%
$N_{cont;t,n}$	ϕ_{cont}	22.17^{**} (1.61)	–	149%
$N_{one\_eu;t,n}$	ϕ_{one_eu}	–	13.78^{**} (1.61)	128%
$N_{cons\_eu;t,n}$	ϕ_{cons_eu}	–	11.76^{**} (1.30)	124%
$N_{cont\_eu;t,n}$	ϕ_{cont_eu}	–	11.51^{**} (2.85)	123%
$N_{one\_uk;t,n}$	ϕ_{one_uk}	–	19.52^{**} (3.62)	142%
$N_{cons\_uk;t,n}$	ϕ_{cons_uk}	–	9.04^{**} (2.63)	118%
$N_{cont\_uk;t,n}$	ϕ_{cont_uk}	–	14.47^{**} (3.30)	130%
$N_{one\_us;t,n}$	ϕ_{one_us}	–	23.94^{**} (1.71)	154%
$N_{cons\_us;t,n}$	ϕ_{cons_us}	–	31.88^{**} (2.29)	178%
$N_{cont\_us;t,n}$	ϕ_{cont_us}	–	40.89^{**} (2.34)	209%
Wald test, p-value		$\phi_{one} = \phi_{cons}$	$\phi_{one} = \phi_{cont}$	$\phi_{cons} = \phi_{cont}$
model (3.13)		0.012	0.012	$3.28 - E06$
model (3.14), euro		0.356	0.503	0.938
model (3.14), UK		0.020	0.299	0.200
model (3.14), USA		0.007	0.000	0.006

is preceded by the news of the same sign for four or more months in succession increase volatility significantly more compared to news that is preceded by news of opposite sign. These results might indicate that if positive (negative) news are followed by negative (positive) news, the investors are not sure whether news of opposite sign indicate a turning point of the state of the economy or not. Therefore, they might undervalue the meaning of news. On the other hand, if positive (negative) news come after another, they start to believe the signals of expansion (contraction) and give higher value for news and eventually overreact to them.

3.4 Conclusions

This paper studies the impact of macroeconomic news on EUR/USD exchange rate volatility, focusing on asymmetries between different news categories. According to our results, macroeconomic announcements increase volatility signifi-

TABLE 3.8 Estimation results: trend and mean revert news

Table presents the parameter estimates of models (3.15) and (3.16) that compare the impact of 'mean revert news' and 'trend news'. Model (3.16) examines the news from the euro area, UK and US separately, while in model (3.15) all news are pooled. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively. The last column presents the impact of news on volatility five minutes after the announcement.

News variable k	**Parameter**	(3.15)	(3.16)	$M_{k;1}$
$N_{tr2;t,n}$	ϕ_{tr2}	10.89^{**} (1.36)	–	122%
$N_{tr3;t,n}$	ϕ_{tr3}	13.59^{**} (1.79)	–	128%
$N_{tr4;t,n}$	ϕ_{tr4}	12.99^{**} (1.41)	–	126%
$N_{mr;t,n}$	ϕ_{mr}	11.39^{**} (1.05)	–	123%
$N_{tr2\_eu;t,n}$	ϕ_{tr2_eu}	–	6.03^{**} (1.91)	111%
$N_{tr3\_eu;t,n}$	ϕ_{tr3_eu}	–	10.72^{**} (2.40)	121%
$N_{tr4\_eu;t,n}$	ϕ_{tr4_eu}	–	9.87^{**} (1.78)	119%
$N_{mr\_eu;t,n}$	ϕ_{mr_eu}	–	8.37^{**} (1.43)	116%
$N_{tr2\_uk;t,n}$	ϕ_{tr2_uk}	–	14.54^{**} (3.64)	130%
$N_{tr3\_uk;t,n}$	ϕ_{tr3_uk}	–	13.71^{**} (4.98)	128%
$N_{tr4\_uk;t,n}$	ϕ_{tr4_uk}	–	8.37^{*} (3.55)	116%
$N_{mr\_uk;t,n}$	ϕ_{mr_uk}	–	3.87 (2.98)	107%
$N_{tr2\_us;t,n}$	ϕ_{tr2_us}	–	20.17^{**} (2.30)	144%
$N_{tr3\_us;t,n}$	ϕ_{tr3_us}	–	24.58^{**} (3.20)	156%
$N_{tr4\_us;t,n}$	ϕ_{tr4_us}	–	29.75^{**} (2.90)	171%
$N_{mr\_us;t,n}$	ϕ_{mr_us}	–	21.43^{**} (1.82)	147%
Wald test, p-value		$\phi_{tr2} = \phi_{mr}$	$\phi_{tr3} = \phi_{mr}$	$\phi_{tr4} = \phi_{mr}$
model (3.15)		0.794	0.332	0.419
model (3.16), euro		0.389	0.447	0.564
model (3.16), UK		$3.71E-08$	0.145	0.418
model (3.16), USA		0.713	0.443	0.035

cantly, US news causing a much larger effect than news from the other countries. UK news increases volatility as much as news from the largest euro area countries while news from the smallest euro area countries and Japan does not increase volatility statistically significantly. We also studied the difference between the impact of positive and negative news. The estimated values of the coefficients for negative news are larger than those of positive news, however, the difference is not statistically significant.

Damodaran (1985) suggests, that investors make errors in evaluating the meaning of news, because of the need for responding to the new information as quickly as possible. The task to evaluate the meaning of news becomes even challenging, when a whole set of macro figures are announced at the same time. One might think that getting more information about the state of the economy at the same time would be useful. However, if some of the news gives signals of better than expected economic conditions and some of them give signals of worse than expected state of the economy, investors could find it difficult to evaluate the overall effect of the news. We found that news that gives contradictory information on the state of the economy increases volatility more than news that gives consistent information. By contradictory news we mean times when both positive and negative news arrives in the market. News is consistent, on the other hand, when only either positive or negative news arrives. Therefore, our results support the theory of Damodaran (1985), which states that the errors in evaluating the meaning of news causes excess volatility on the returns.

We also found that macro news which are preceded by three news of the same sign (e.g. positive employment news when the previous three news announcements on employment have also been positive) increase volatility significantly more than news which are preceded by news of the opposite sign. This result might be explained by the theory of 'investor conservatism' proposed by Barberis et al. (1998), which suggests that investors overreact to macro indicators which successively give positive (or negative) signals of the state of the economy.

REFERENCES

Almeida, A., Goodhart, C., Payne, R., (1998) "The Effects of Macroeconomic News on High Frequency Exchange Rate Behavior" The Journal of Financial and Quantitative Analysis 33, 383-408

Andersen, T., Bollerslev, T., (1997) "Intraday periodicity and volatility persistence in financial markets" Journal of Empirical Finance 4, 115-158

Andersen, T., Bollerslev, T., (1998) "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies" The Journal of Finance 53, 219-265

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2003) "Micro Effects and Macro Announcements: Real-Time Price Discovery in Foreign Exchange" American Economic Review 93, 38-62

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2007) "Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets" Journal of International Economics 73, 251-277

Barberis, N., Schleifer, A., Vishny, R., (1998) "A model of investor sentiment" Journal of Financial Economics 49, 307–343

Bauwens, L., Ben Omrane, W., Giot, P., (2005) "News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market" Journal of International Money and Finance 24, 1108-1125

BIS (2007) "Triennial Central Bank Survey: Foreign exchange and derivatives market activity in 2007" Bank for International Settlements

Bollerslev, T., Cai, J., Song, F., (2000) "Intraday Periodicity, Long-Memory Volatility, and Macroeconomic Announcement Effects in the U.S. Treasury Bond Market" Journal of Empirical Finance 7, 37-55

Chang, Y., Taylor, S., (2003) "Information arrivals and intraday exchange rate volatility” International Financial Markets, Institutions and Money 13, 85–112

Damodaran, A., (1985) “Economic Events, Information Structure, and the Return-generating Process” The Journal of Financial and Quantitative Analysis 20 No. 4

Daniel, K., Hirshleifer, D., Subrahmanyam, A., (1998) “Investor Psycohology and Security Market Under- and Overreaction" Journal of Finance 52, 1-33

Degennaro, R., Shrieves, R., (1997) “Public information releases, private information arrival and volatility in the foreign exchange market” Journal of Empirical Finance 4, 295–315

Dominguez, K., Panthaki, F., (2006) “What defines ‘news’ in foreign exchange markets?” Journal of International Money and Finance 25, 168-198

Eddelbüttel D., McCurdy, T., (1998) “The Impact of News on Foreign Exchange Rates: Evidence from High Frequency Data” Manuscript Rotman School of Management, University of Toronto

Ederington, H., Lee, J., H., (1993) “How Markets Process Information: News Releases and Volatility” The Journal of Finance 48, 1161-1191

Faust, J., Rogers, J., Wang, S.-Y.B., Wright, J., (2007) “The high-frequency response of exchange rates and interest rates to macroeconomic announcements“ Journal of Monetary Economics 54, 1051-1068

Goodhart, C. A. E., Hall, S. G., Henry, S. G. B., Pesaran, B., (1993) “News effects in a high-frequency model of the sterling-dollar exchange rate” Journal of Applied Econometrics 8, 1-13

Laakkonen, H., (2007a) “The Impact of Macroeconomic News on Exchange Rate Volatility” Finnish Economic Papers 20, 23-40

Laakkonen, H., (2007b) “Exchange Rate Volatility, Macro Announcements and the Choice of the Intraday Seasonality Filtering Method” Bank of Finland Discussion Papers 23/2007

Laakkonen, H., Lanne, M., (2009) “Asymmetric News Effects on Volatility: Good vs. Bad News in Good vs. Bad Times” Studies in Nonlinear Dynamics & Econometrics, forthcoming

Manzan S., Westerhoff, F., (2005) “Representativeness of news and exchange rate dynamics” Journal of Economic Dynamics and Control 29, 677–689

Melvin, M., Yin, X., (2000) “Public information arrival, exchange rate volatility and quote frequency” The Economic Journal 110, 644-661

Payne, R. (2003) “Informed trade in spot foreign exchange markets: an empirical analysis” Journal of International Economics 61, 307–329

Pearce, D., Solakoglu, N., (2007) “Macroeconomic news and exchange rates” Journal of International Financial Markets, Institutions and Money 17, 307-325

Veronesi, P., (1999) “Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model” The Review of Financial Studies 12, 975-1007

Veronesi, P., (2000) “How does Information Quality Affect Stock Returns?” Journal of Finance 55, 807-837

Vähämaa, S., Watzka, S., Äijö, J., (2005) “What moves option-implied bond market expectations?” Journal of Futures Markets 25, 817-843

CHAPTER 4

ASYMMETRIC NEWS EFFECTS ON VOLATILITY: BAD VS. GOOD NEWS IN BAD VS. GOOD TIMES

4.1 Introduction

[1]The volatility of prices reflects uncertainty in the markets, and the ability to model and forecast volatility is crucial for risk management, security pricing and portfolio management. The extensive literature on the impact of news on exchange rate volatility[2] has indicated news concerning macroeconomic fundamentals as one source of volatility on various markets. Typically, there is an increase in volatility right after the announcement and its impact gradually fades away. While this literature is voluminous, relatively little work has been done on the nonlinearities, such as state-dependence, in the impact of news on volatility. The most notable exception is the asymmetry with respect to sign of the news. There are many studies that have found that negative macroeconomic news increase volatility more than positive announcements (e.g. Bauwens et al., 2005; Andersen et al., 2007). However, there are also studies that do not find asymmetries with respect to sign (e.g. Pearce and Solakoglu, 2007; Balduzzi et al., 2001). One explanation for these mixed findings could be the time span of the data set: the market reaction to positive and negative news might be different e.g. in different

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1 This Chapter is a joint work with Professor Markku Lanne. A version of this Chapter has appeared in the HECER Discussion Paper series No. 207 / 2008 and is forthcoming in Studies in Nonlinear Dynamics & Econometrics.

2 The literature includes for example Degennaro and Shrieves (1997), Almeida et al. (1998), Andersen and Bollerslev (1998), Eddelbüttel and McCurdy (1998), Melvin and Yin (2000), Andersen et al. (2003, 2007), Chang and Taylor (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006), Faust et al. (2007), Laakkonen (2007a), Laakkonen (2008) among others.

states of the economy.

Recently, there has been active research that tries to shed light on the relationship between the impact of macroeconomic news on financial instruments and the state of the business cycle. This line of research has concentrated mainly on the stock market. McQueen and Roley (1993), Flannery and Protopapadakis (2002), Conrad et al. (2002), Adams et al. (2004), Boyd et al. (2005) and Andersen et al. (2007) all report findings that support the state dependence of announcement effects in the US stock market. In general, news seem to have stronger effect in good times than in bad times. In addition to stock markets, business cycle effects have been studied in the US bond futures market by Veredas (2006) and in the foreign exchange market by Faust et al. (2007) and Pearce and Solakoglu (2007). The findings of Veredas (2006) and Pearce and Solakoglu (2007) are in line with the results from the equity market, but Faust et al. (2007) find only limited evidence in favour of the state dependence of news effects. The state dependencies of asymmetric news effects between positive and negative news have studied by Conrad et al. (2002) and Veredas (2006). They both find that bad news seems to have a greater effect in good times than in bad times. On the other hand, the impact of good news seems to be similar in good and bad times.

In this essay, we study the relationship between the impact of positive and negative macroeconomic news on exchange rate volatility over the business cycle. Our study contributes to the literature in several aspects. First of all, our data set is much richer than the ones used in the previous literature. We use a new 5-minute frequency EUR/USD exchange rate data set from 1 January 1999 to 31 December 2004 and a macro news data set that is more comprehensive than those used in earlier studies. In particular, the news data set includes all the macroeconomic announcements from the US and all euro countries published in the Bloomberg WECO (World economic calendar). Furthermore, besides the US business cycle, we study the asymmetries using a European business cycle indicator. While it is reasonable to concentrate on the US business cycle when studying only the US stock markets, this need not be the case when assets from several countries are considered, although this seems to have been the common procedure in the previous literature (see e.g. Andersen et al., 2007).

Our methodology is more flexible than that in the previous literature. Most of the existing studies define the expansions and contractions beforehand by various criteria: McQueen and Roley (1993) measure the business cycle with industrial production and determine the levels of 'high', 'medium' and 'low' economic activity by estimating a trend and fixing some intervals around it, while Andersen et al. (2007) define contractions as beginning when there are three consecutive monthly declines in nonfarm payroll employment. Veredas (2006), on the other hand, uses the Institute for Supply Management Survey (ISM) index as a measure of the business cycle: he divides the state of the economy into four different phases: 1) top or 2) bottom if the value of the index is above 55 or below 50; 3) expanding or 4) contracting if it is between them and increasing or decreasing, respectively. In contrast, we allow for the state dependence in the news effects by estimating a smooth transition regression model with a business cycle indicator as the transition variable. The main advantage of our approach is that the threshold between the different states is not fixed a priori, but estimated. Therefore, splitting the data beforehand into fixed regimes such as good and bad times is not necessary. Moreover, the model allows the change from one regime (bad times) to another (good times) to be smooth. Furthermore, the model can be generalized to allow for more than two regimes in a straightforward manner.

We find that, in general, macro news does increase volatility significantly. The results also suggest that news effects are affected by the state of the economy, such that they are stronger in good times than in bad times. Moreover, the impact of bad news seems to be stronger in good times than in bad times, while there is no such asymmetry in the impact of good news. These results are in line with the previous studies from equity and bond markets, and they can be interpreted as supportive for Veronesi's (1999) theory, which suggests that because of asymmetric information concerning the state of the economy, investors overreact to bad news in good times and underreact to good news in bad times.

The plan of the Chapter is as follows. Section 4.2 reviews the related literature, and Section 4.3 describes the data and methodology. The empirical results are presented in Section 4.4. Finally, Section 4.5 concludes.

4.2 News Effects and Business Cycles

The impact of news on exchange rate dynamics has been studied extensively in recent decades. The earliest studies in the 1980s used daily return data and simple regressions, but in the 1990s the increasing availability of high-frequency data and improved methods (see, e.g., Andersen and Bollerslev, 1997) has facilitated a more detailed study of the news effects.

The news data that have usually been used are Reuter's headlines or scheduled macro announcements, but also the impact of the headlines of financial newspapers have been studied (for example, by Chan et al., 2001). In line with the findings in other financial markets, the results indicate that news causes a jump in the level of the exchange rate and increases the volatility of returns from one hour to two hours after the arrival of information (see e.g. Andersen and Bollerslev, 1998). The most important macroeconomic announcement seems to be the monthly employment report of the US (Andersen et al., 2003).

The relationship between the impact of macroeconomic news on financial markets instruments and the state of the business cycle has been addressed by Veronesi (1999), whose theoretical results suggest that because of asymmetric information about the state of the economy, investors overreact to bad news in good times and underreact to good news in bad times. The model is based on the idea that the economy follows a two-state regime-switching process, where the "low" and "high" states are recession and expansion, respectively. The investor has to solve the problem of determining the probability $\pi(t)$ of the economy being in the high state in period t (if $\pi(t)$ is close to zero, the investor is almost sure that economy is in recession, whereas the uncertainty is at its maximum when $\pi(t) = 0.5$). Veronesi (1999) shows that the equilibrium price of an asset is an increasing and convex function of the probability $\pi(t)$, and, because of that, the reaction to good and bad news depends on the state of the economy. If the economy is in expansion and bad news arrives, the expected future asset value decreases as does $\pi(t)$ (which means that uncertainty increases). Risk-averse investors require additional return for bearing this additional risk and, therefore, require an additional discount on the asset price, which drops by more than it would in a present-value model. On the other hand, if the economy is in recession and good news arrives, the expected future asset value increases. However, since $\pi(t)$ and, hence, uncertainty increase as well, the price does not increase as much as it would increase without the additional uncertainty concerning the future state of the economy[3].

While the asymmetries between negative and positive news effects have been studied quite extensively (see, e.g., Andersen et al., 2003), the empirical literature examining the asymmetries in the news effects over the business cycle is not voluminous, partly because long time series are required to cover the different states of the economy.

Most of the existing papers have concentrated on the stock and bond markets. For example, McQueen and Roley (1993), Flannery and Protopapadakis (2002) and Adams et al. (2004) all studied the effect of macro news on the US stock returns and found that macro information matters more in times of high economic activity than in the other states of the economy. McQueen and Roley (1993) also found that good news results in lower stock prices when the state of the economy is 'high', whereas the corresponding surprise in a weak economy is associated with higher stock prices. The findings of Boyd et al. (2005) are similar. They study the impact of unemployment news on the daily S&P 500 stock index and bond returns and found that an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions. On the other hand, bond prices rise when there is bad unemployment news during expansions, but do not respond significantly during recessions.

Conrad et al. (2002) also studied the asymmetries in the case of stock markets, albeit concentrating on the asymmetric reaction to positive and negative news in the different states of stock market. They examined the impact of earnings announcements on individual stocks, and concluded that investors react more strongly to bad news in good times, while the reaction to good news is the same in bad and good times. Veredas (2006) examined similar asymmetries in the effect of news concerning 15 macroeconomic fundaments on the returns of the ten-year US Treasury bond futures. His findings are very similar to those of Conrad et al. (2002): negative news has a stronger effect in good times than in bad times, while positive news has only little effect in bad times. On the other hand, he found that in good times positive and negative news have similar effect on US bond returns.

The state dependencies of news effects have also been studied in the foreign

[3] Veronesi's theory concentrates on the impact of news on returns, but due to the positive risk-return relationship derived from Merton's (1973) Intertemporal Capital Asset Pricing Model, we should be able to interpret it in terms of news effects on volatility. In particular, in the presence of such a relationship, changes in expected returns are accompanied by corresponding change in conditional volatility. See Lanne and Saikkonen (2006) and the references therein for a discussion on the empirical evidence for the risk-return tradeoff.

exchange market by Pearce and Solakoglu (2007), Faust et al. (2007) and Andersen et al. (2007). Pearce and Solakoglu (2007) used intradaily data of DEM/USD and JPY/USD exchange rates and studied the asymmetries with respect to sign and the state dependencies of news effects on returns and volatility. They found some evidence in favour of the responses to some news events depending on the state of the economy. In particular, they found that some indicators are state dependent, and some are not. However, they did not find any asymmetries between positive and negative news. Faust et al. (2007) studied the joint movements of exchange rates and the term structure of interest rates denominated in dollars, UK pounds, and German marks/euros around the macro news announcements. They tested for parameter constancy by using a structural stability test, but found only little evidence of time-variation in news responses. In particular, the null hypothesis of parameter constancy was the most strongly rejected for the trade balance, producer price index, consumer price index and nonfarm payrolls surprises, but for most asset-announcement pairs, the null was not rejected. Andersen et al. (2007) also studied a broad set of asset classes (stocks, bonds and exchange rates), and, in addition, used assets from different countries. They found state dependent news effects in stock markets, but not in foreign exchange markets or bond markets.

All in all, the previous literature has shown that the impact of news is in general stronger in good than bad times. Also, news of a certain sign (positive or negative) might have positive impact in other times while negative in others. Moreover, negative news seem to have stronger effect in good than bad times, while the reaction to good news is the same in bad and good times. The strongest state dependencies have been found in the stock and bond markets, while the evidence from the foreign exchange markets has so far been rather weak.

In terms of asset class, our study resembles most to that of Pearce and Solakoglu (2007), who also study news effects on exchange rate volatility. However, they only study the asymmetries with respect to sign and state of the economy separately, while we combine them, as do Conrad et al. (2002) and Veredas (2006). Therefore, our study complements the empirical literature on the state dependent news effects by confirming the same results in foreign exchange market that have earlier been found in stock market by Conrad et al. (2002) and bond markets by Veredas (2006). First, we study whether the news effects in general differ in different states of the economy and find that news has a stronger effect in good than in bad times. Second, as Conrad et al. (2002) and Veredas (2006), we also divide news to positive and negative and study if their impact differ in different states of the economy. Our findings are very similar to theirs. We find that the impact of bad news seems to be stronger in good times than in bad times, while the impact of good news is the same in both bad and good times.

Our paper contributes to the literature also in many other ways. Our data set of macro announcement is much richer than those used in the previous literature. While the other studies have usually considered only few of the most important US macro announcements, our macro news data set covers altogether 228 US and euro area macro indicators published in the Bloomberg World Economic Calendar, the total number of news announcements being 10232. Also, the earlier studies have usually studied the macro announcements separately, while we study the joint effects of all news. While it might be interesting to compare the differences in the impact between different indicators, it is difficult to draw any general conclusions when studying the indicators separately. Furthermore, studying the joint news effects solves the problem of having too few observations of the news variables. When studying the impact of news of different indicators separately, the estimated coefficients of the news variables are usually found significant when no asymmetries are studied. However, when the news observations are divided into positive and negative, and on top of that the data period is divided to different business cycle states, there are only very few observations in each news category, and the coefficients of the news variables are estimated inaccurately, which leads to low power of tests.

The impact of the different news indicators have been studied by Veredas (2006), Pearce and Solakoglu (2007) and Faust et al. (2007), among others. Veredas (2006) had nine years of intradaily T-bond data, and therefore, the indicators, which are released monthly, had about 110 observations. He divided news to positive and negative and the sample period to four different states. When the total of 110 news observations were divided into eight categories, there were only very few news observations in each category. Veredas (2006) found that the coefficients in only few of these eight news categories were statistically significant. However, he did not test the equality of the coefficients, and therefore it is quite difficult to draw strong conclusions about the state dependence of the news effects.

One could criticize our choice of using such a large number of indicators, because some of them might not have such a great importance on the asset prices than others. This is why we only consider macro indicators that have a Bloomberg market forecast available. The results of Laakkonen (2008) suggests that the macro announcements that have the Bloomberg survey forecast available, have a significantly greater impact on exchange rate volatility than those with no forecast available. Therefore, we consider news with forecast as more important for the market agents than those without the forecast, and restrict our analysis to those.

In addition to using better data, another significant contribution of our paper is the used methodology, which is more flexible than that in the previous literature. Most of the existing studies define the expansions and contractions beforehand by various criteria: McQueen and Roley (1993) measure the business cycle with industrial production and determine the levels of 'high', 'medium' and 'low' economic activity by estimating a trend and fixing some intervals around it, while Andersen et al. (2007) define contractions as beginning when there are three consecutive monthly declines in nonfarm payroll employment. Veredas (2006), on the other hand, uses the Institute for Supply Management Survey (ISM) index as a measure of the business cycle: he divides the state of the economy into four different phases: 1) top or 2) bottom if the value of the index is above 55 or below 50; 3) expanding or 4) contracting if it is between them and increasing or decreasing, respectively. In contrast, we estimate the state dependence in the news effects by using a smooth transition regression model with a business cycle indicator as the transition variable. The main advantage of our approach is that the threshold between the different states is not fixed a priori, but estimated.

Therefore, splitting the data beforehand into fixed regimes such as good and bad times is not necessary. Moreover, the model allows the change from one regime (bad times) to another (good times) to be smooth. Furthermore, the model can be generalized to allow for more than two regimes in a straightforward manner. We do not think that this methodology would necessarily yield stronger evidence of the state dependencies of news in the foreign exchange markets than in Pearce and Solakoglu (2007), Faust et al. (2007) and Andersen et al. (2007). However, we argue that estimating the good and bad times is, in general, a great improvement to the subjective decisions concerning the threshold made in the previous literature.

To our knowledge, we are the first to consider the asymmetries using a European as well as a US business cycle indicator. While it is reasonable to concentrate on the US business cycle when studying only the US stock markets, this need not be the case when assets from several countries are considered, although this seems to have been the common procedure in the previous literature (see e.g. Andersen et al., 2007).

4.3 Data and Methodology

This section describes the data of exchange rate returns, macroeconomic news and business cycle indicator and the methodology used.

4.3.1 Exchange Rate Data

The original data set contains 5-minute quotes[4] of the EUR/USD (Euro against United States Dollar) exchange rate from 1 January 1999 to 31 December 2004, and it was obtained from Olsen and Associates. The prices are formed by taking the average between the bid and ask quotes, and the returns are computed as the differences of logarithmic prices.

As the foreign exchange market activity slows down decidedly during weekends and certain holiday non-trading periods, it is standard in the literature to explicitly exclude a number of days from the raw 5-minute return series. Following Andersen and Bollerslev (1998), we exclude the weekends and certain holidays by always excluding the returns from 21:05 GMT the night before to 21:00 GMT that evening. Andersen and Bollerslev (1998) state that this definition of a "day" retains intact the intraday periodical volatility structure. The following holidays are excluded from the data: Christmas, New Year, Good Friday and Easter Monday. Besides holidays, three days are excluded from the data because of lack of observations[5] (10 May 1999, 21 Dec 2000, 24 Dec 2000). Daylight savings time was also taken into account as is standard in the literature.

The 5-minute returns exhibit strong intraday periodicity, because of the dif-

4 According to many studies, 5-minute returns strike the best balance between the disadvantages of microstructure noise (when sampling too frequently) and the loss of important information (when sampling too infrequently). For a discussion see Andersen et al. (2007).

5 The reason for missing observations is unknown.

ferent trading times in the global 24-hour foreign exchange markets. This has to be taken into account in modeling news effects by using a filtered return series. Of the alternative models of filtering the periodicity, we chose the Flexible Fourier Form (FFF) model of Andersen and Bollerslev (1997) that uses different frequencies of sine and cosine functions to capture the periodicity[6]. This choice is motivated by Laakkonen (2007b), who studied the consequences of data filtering on the results obtained by using filtered returns. She concluded that for the purpose of studying the impact of news on volatility, the FFF method performs the best among a number of commonly acknowledged filtering methods, because it produces the smallest biases in the estimates for the news coefficients compared to other methods.

The FFF method is based on the following decomposition:

$$R_{t,n} - \bar{R}_{t,n} = \sigma_t \cdot s_{t,n} \cdot Z_{t,n} \tag{4.1}$$

where $R_{t,n}$ denotes the 5-minute EUR/USD returns, $\bar{R}_{t,n}$ is the expected five-minute returns and $Z_{t,n}$ is i.i.d (with mean zero and unit variance) innovation, σ_t is the daily volatility and $s_{t,n}$ is the intraday volatility[7].

Squaring both sides of (4.1), taking logs and approximating $\bar{R}_{t,n}$ with the sample mean $\bar{R}$ and eliminating the daily volatility component σ_t from the return process we end up with the following expression:

$$2\log\frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = \log\left(s_{t,n}^2\right) + \log\left(Z_{t,n}^2\right) \tag{4.2}$$

where $\hat{\sigma}_t$ is the $GARCH(1,1)$ model estimate for daily volatility[8] and N denotes the number of 5-minute intervals in one day (288 in a 24-hour market). Now, Andersen and Bollerslev (1997) suggest a parametric representation of the intraday volatility $s_{t,n}$ and estimate the smooth cyclical volatility pattern by using trigonometric functions. The ensuing FFF regression model is the following:

$$\begin{aligned} f_{t,n} &= \alpha + \delta_1 n + \delta_2 n^2 + \sum_{lk=1}^{L} \lambda_l I_{l;t,n} \\ &\quad + \sum_{p=1}^{P} \left(\delta_{c,p} \cos\left(\frac{p2\pi}{N} n\right) + \delta_{s,p} \sin\left(\frac{p2\pi}{N} n\right) \right) + \varepsilon_{t,n}, \end{aligned} \tag{4.3}$$

where $f_{t,n} = 2\log\frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. Besides the sinusoids[9], the model contains the intercept α,the quadratic function in the intraday interval n,and the error term of the model $\varepsilon_{t,n}$. The model also contains the indicator variables $I_{l;t,n}$, which are

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6 The FFF model was originally introduced by Gallant (1981) and proposed in this context by Andersen and Bollerslev (1997).

7 In the equations t denotes day and n the 5-minute interval.

8 $GJR - GARCH(1,1)$ was also considered but the asymmetries between positive and negative daily shocks was not found.

9 The value $P = 9$ was selected by using the Schwarz information criteria.

used to control e.g. for weekday effects. The estimate of the intraday volatility $\hat{s}_{t,n}$ is then obtained as $\hat{s}_{t,n} = \exp(\hat{f}_{t,n}/2)$, where $\hat{f}_{t,n}$ are the fitted values from model (4.3). This estimate $\hat{s}_{t,n}$ is normalized so that the mean of the normalized periodicity estimate equals one: $\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{T/N} \sum_{n=1}^{N} \hat{s}_{t,n}}$, where T is the number of observations in the entire data set and T/N denotes the number of days in the data. The original returns $R_{t,n}$ are then divided by the normalized estimate $\tilde{s}_{t,n}$ to get the filtered returns $\tilde{R}_{t,n} = \frac{R_{t,n}}{\tilde{s}_{t,n}}$. See Andersen and Bollerslev (1997, 1998) for further details of the method.

If the intraday periodicity pattern is assumed to remain constant over the sample period, the FFF model is estimated for the entire data set. Unfortunately this is not likely to be the case. Laakkonen (2007b) studied the properties of the intraday returns filtered with different methods. She found that all the examined filtering methods were capable of filtering the intraday seasonality only if the filtering was done in subsets of data. Yet, she concluded that the filters performed better the shorter was the subset, which indicates that the intraday volatility pattern was time varying. If the FFF model is estimated only once by using the entire sample period, there are significant periodical autocorrelation left in the absolute filtered returns. To be able to filter all the periodicity in volatility, the data has to be filtered in subsets. Laakkonen (2007b) states that to be able to filter all the periodicity in volatility, for this particular data set the FFF model has to be re-estimated every week.

The autocorrelation coefficients of absolute filtered and original returns for 1500 five-minute lags, i.e., the autocorrelogram for five days, is depicted in Figure 4.1. It is seen that there is still some autocorrelation left in the filtered absolute returns, although much of the intraday periodicity has been filtered out. In the empirical analysis of Section 4.4, the remaining autocorrelation will have to be taken into account in computing the covariance matrix of the errors of the regression models.

Some descriptive statistics of the original and filtered return series are presented in Table 4.1. Mean and standard deviation of the return series are not effected dramatically by filtering. However, filtering does have an effect on skewness and kurtosis. The distribution of financial return series is usually very leptokurtic compared to the normal distribution, which indicates the overabundance of great returns compared to the normal distribution. The distribution of the EUR/USD returns is also positively skewed, which suggests that there are more great positive than negative returns. The distribution of the filtered returns is more symmetric: due to filtering, skewness falls from 0.78 to -0.15. Also, the extra kurtosis of the distribution falls from 65.9 to 40.9. Although the distribution of the returns seems to be closer to the normal distribution after filtering, neither the original nor filtered returns are normally distributed.

4.3.2 Macro Announcement Data

The macroeconomic news data set includes all the scheduled macroeconomic news published in the World Economic Calendar (WECO) page of Bloomberg.

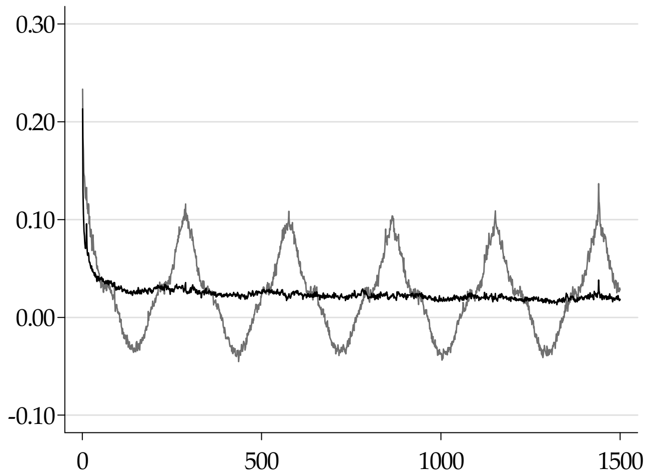

FIGURE 4.1 Autocorrelogram of the original and filtered absolute returns
The figure shows the five day correlogram at lags from 0 to 1500 of the filtered five-minute absolute EUR/USD returns (black line) compared to original absolute returns (grey line). The intraday periodicity was filtered by using the Flexible Fourier Form method.

TABLE 4.1 Key statistical figures
Table presents the key statistical figures for the original and for the filtered returns. The returns were filtered with the Flexible Fourier Form method.

	Returns	**Filtered returns**
Mean	$5.0E-05$	$6.6E-05$
Standard Deviation	0.0432	0.0434
Skewness	0.781	-0.154
Kurtosis	65.94	40.92
Minimum	-1.35	-1.69
Maximum	2.79	1.68

The announcements are collected for all the euro area countries and the USA for the years 1999-2004. The data include the announcement date and time in one minute accuracy, the announced figure, henceforth denoted $A_{t,n,k}$, and the market forecast of the figure, henceforth denoted $F_{t,n;k}$. The market forecast is the median of the survey forecasts that Bloomberg collects from the market agents, but unfortunately it is not available for all of the macro figures. For example for the figures from smaller euro countries there is no forecast. Since the figures having a forecast available are probably the most important ones, we focus on those.

The market forecast is used in classifying the news as positive and negative. A news item is defined positive (henceforth denoted as $Npos^{f}_{t,n}$) when the market forecast is smaller than the announced figure, i.e. the announcement is underestimated. Negative news (henceforth denoted as $Nneg^f_{t,n}$), on the other hand, means that agents had overestimated the announced figure, which was less than the forecast. This kind of classification has been standard in the literature (see e.g. Andersen and Bollerslev, 2003). It can be argued that positive news classified in this way might not necessarily be good news (for example, an unexpectedly high increase in the unemployment rate). Therefore, we classified the news to positive and negative also in an alternative way. According to this classification a news announcement is positive (henceforth denoted as $Npos^r_{t,n}$) if the five-minute return following it is positive (dollar appreciates), and negative (henceforth denoted as $Nneg^r_{t,n}$) if the return is negative (dollar depreciates).

Table 4.2 presents the numbers of nonzero observations in the different news variables. While the total number of macroeconomic news from the euro area and the USA in the WECO is as high as 10232, the number of nonzero observations of the news variable $N_{t,n}$ is 5236. The reason for the great discrepancy is the fact that so many macro figures are announced simultaneously. For example, the monthly US unemployment report includes the announcements of average weekly hours, change in manufacturing payrolls, change in nonfarm payrolls, unemployment rate and average hourly earnings. However, these simultaneous announcements are marked as only one nonzero observation in the news variable $N_{t,n}$. Note, however, that if some of these news announced at the same time were positive and some negative, both news variables $Npos^f_{t,n}$ and $Nneg^f_{t,n}$ would take a value of one. This is why the sum of the nonzero observations of the $Npos^f_{t,n}$ and $Nneg^f_{t,n}$ variables is more than the number of the observations in $N_{t,n}$. On the other hand, the numbers of nonzero observations of the sum of $Npos^r_{t,n}$ and $Nneg^r_{t,n}$ is less than $N_{t,n}$, because the announcement is classified neither positive nor negative if the return following it equals zero.

TABLE 4.2 Number of news announcements in different categories

Table presents the number of announcements in each news category. The first news category contains all the euro area and US macro announcements published in Bloomberg World Economic Calendar during years 1999-2004, for which the Bloomberg forecast is available, and the corresponding variable $N_{t,n}$ takes on value 1 on all periods with news announcements. $Npos^f_{t,n}$ and $Nneg^f_{t,n}$ take on value 1 on periods with positive and negative news, respectively. The classification is based on the difference between the announced figure and market forecast. $Npos^r_{t,n}$ and $Nneg^r_{t,n}$ are the corresponding variables based on the sign of the return following the news announcement.

Variable	**News category**	**Numb. of obs.**
$N_{t,n}$	All macro announcements $A_{t,n;k}$ for which the market forecast $F_{t,n;k}$ is available	5236
$Npos^f_{t,n}$	Positive news: $A_{t,n;k} - F_{t,n;k} > 0$	2771
$Nneg^f_{t,n}$	Negative news: $A_{t,n;k} - F_{t,n;k} < 0$	2683
$Npos^r_{t,n}$	Positive news: $A_{t,n;k}$ when $R_{t,n+1;k} > 0$	2432
$Nneg^r_{t,n}$	Negative news: $A_{t,n;k}$ when $R_{t,n+1;k} < 0$	2556

News announcements have been reported to have long-lasting effects on volatility. For instance, according to Andersen and Bollerslev (1998), the impact lasts from one to two hours. To allow for such prolonged effects, we have to modify the news variables to some extent. Specifically, following Andersen and Bollerslev (1998), the impact of an announcement is assumed to diminish gradually and go to zero after two hours. We first estimate the average news impact pattern by computing the average absolute returns at each five-minute interval following the news announcements minus the average absolute return over the entire sample period. We then estimate the decay structure of the volatility response pattern of news by fitting a third order polynomial to the average news impact pattern. OLS estimation yields the following equation for the average absolute returns following the news announcements,

$$\lambda_m = 0.054\left(1-(m/25)^3\right) - 0.009\left(1-(m/25)^2\right)m + 0.0007\left(1-(m/25)\right)m^2 \tag{4.4}$$

where $m = 1, 2, ...25$ denotes the five-minute interval after the news announcement. The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours[10], as depicted in Figure 4.2. In the empirical models, the explanatory variables are hence not the news variables as such, but whenever there is an announcement, in the 25 subsequent 5-minute intervals the corresponding regressor equals $\lambda_1, \lambda_2, ..., \lambda_{25}$ and zero otherwise[11].

4.3.3 Business Cycle Indicator

The NBER dates of recessions and expansions are a standard measure of the state of the economy. However, because this measure only identifies recession and expansion periods rather than the level of the business conditions, it is not adequate for our purposes. In our analysis we need a continuous measure of the business cycle. Many different macroeconomic indicators have been used as a business cycle indicator in the previous literature: e.g. industrial production (McQueen and Roley, 1993) and unemployment rate (Andersen et al., 2007). Veredas (2006), on the other hand, used the Institute for Supply Management (ISM) PMI index[12]

10 Longer dependencies of news could certainly have also been studied for example by using lag dummies. However, the benefit of this polynomial method is, as Bollerslev et al. (2000) state, that it fixes the problem of having only a few announcement observations and it is less sensitive to the inherent noise in the return process. One further advantage of this approach is that compared to lag dummies, we now only need one news variable for each news category. To study the impact of news for a period of two hours after the announcement, we would have needed 24 (two hours is 24 five-minute intervals) news variables for all the news categories. The choice of polynomial order and the length of the news impact are studied more carefully in Laakkonen (2007a).

11 Most studies that examine the impact of news on financial market returns, use the actual surprice element (the announced figure less the forecast) as a news variable rather than a dummy variable that does not take into account the size of the news. However, Andersen et al. (2003, 2007) argue that it is the mere presence of an announcement, not so much the size of the corresponding surprise, that tends to boost volatility.

12 Prior to January, 2002, the acronym (PMI) stood for Purchasing Managers' Index. ISM now uses only the acronym, PMI, due to ISM's name change from the National Association of Purchasing Management (NAPM) in early 2002. We refer to this index as ISM index.

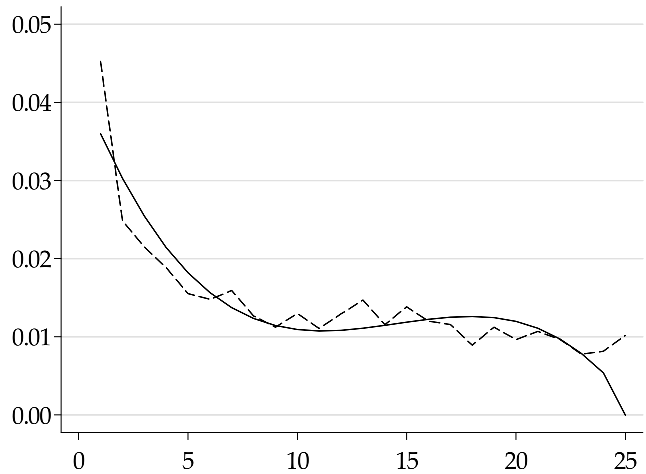

FIGURE 4.2 Decay structure of volatility response pattern after news
The figure presents the mean absolute returns after news announcements (dashed line) and the estimated news impact decay structure (solid line). Decay structure was estimated using the third order polynomial λ_m

as a measure of the business cycle.

The ISM index is constructed from of a survey among more than 300 purchasing and supply executives from across the country. Members of the ISM Business Survey Committee respond to a monthly questionnaire about changes in new orders, production, employment, the timeliness of supplier deliveries and inventories in their companies comparing the current month to the previous one. By averaging the respondents' answers, the value 50 of the index represents an equal balance between manufacturers reporting growths and declines in their business, while index over or under 50 represents growth or contraction within the manufacturing sector of the economy compared with the prior month, respectively.

According to Veredas (2006) the ISM index is better than other measures like gross domestic product (GDP), unemployment rate or industrial production, because being based on expectations, it is the most forward-looking measure available of the market. Moreover, reliable GDP figures are available only on a quarterly basis, with considerable delay, and they are subject to revisions afterwards. Therefore we use the ISM index as a business cycle indicator for the US market.

On the other hand, we use the IFO (Information und Forschung) Business Sentiment Germany index to measure the business sentiment in the European markets. The survey is very similar to that of the ISM index; it is conducted monthly, querying German firms on the current German business climate as well as their expectations for the next six months. Germany is the largest economy in the Euro-zone and it is responsible for approximately a quarter of the total Euro-Zone GDP. Therefore, the German business sentiment index is a significant indicator for the whole Euro-zone business cycle.

Figure 4.3 graphs the time series of the two indices. The correlation between the them is positive (0.3835), but not extremely high. While the ISM index reaches the maximum values at the end of the sample period, the IFO index predicts expansions in the early years of the data. So, it seems that the business cycles of the USA and Europe might coincide, but there are some differences as well.

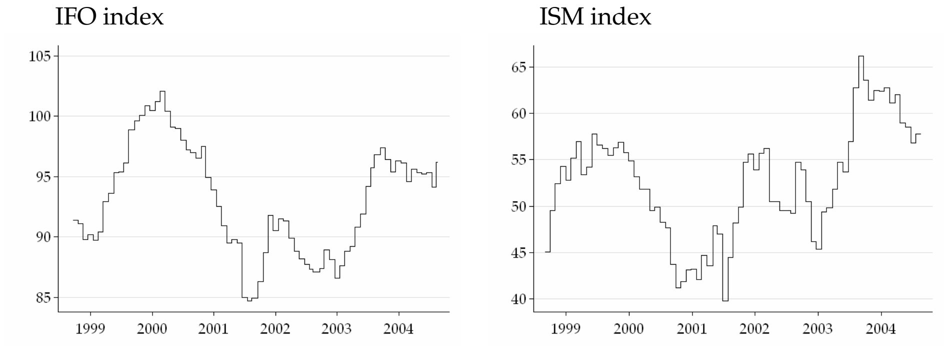

FIGURE 4.3 Business sentiment indices for Europe and the USA
The figure on the left presents the IFO (Information und Forschung) Business Sentiment Germany index and the figure on the right presents the Institute for Supply Management (ISM) PMI index for the years 1999-2004.

4.3.4 Smooth Transition Regression Model

To study the asymmetric news effects, we use the following two-regime Smooth Transition Regression (STR) model[13]:

$$y_{t,n} = \boldsymbol{\phi}' \boldsymbol{x}_{t,n} + \boldsymbol{\theta}' \boldsymbol{x}_{t,n} G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \tag{4.5}$$

where $y_{t,n} = 2 \log \dfrac{|\tilde{R}_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$ is our measure of exchange rate volatility. The dependent variable is of the same form as in the FFF regression (4.3), but now the raw returns, $R_{t,n}$, are replaced by the filtered returns, $\tilde{R}_{t,n}$. Now, on the right-hand side we have a vector of explanatory variables, $\mathbf{x}'_{t,n}$, which includes a constant and the news variables. $\boldsymbol{\phi}$ and $\boldsymbol{\theta}$ are parameter vectors and $\varepsilon_{t,n}$ is a mean zero normally distributed error term. Our primary choice for the transition function is the general logistic function of the form,

$$G(\gamma, c, h_{t,n-1}) = \left(1 + \exp\left\{-\gamma \prod_{k=1}^{K} (h_{t,n-1} - c_k)\right\}\right)^{-1}, \gamma > 0, \tag{4.6}$$

where $h_{t,n-1}$ denotes the continuous transition variable[14], and γ and c are the slope and threshold parameters, respectively. Due to the functional form of the

13 This section is strongly based on Section 4.2 in Granger and Teräsvirta (1993). The model can be generalized to more than two regimes in a straightforward manner, but this simple model turned out to be satisfactory for our purposes.

14 The value of the transition function depends on the lagged transition variable. Note, however, that in our case the data frequency is five minutes, while the business cycle indicator

transition function, the model is in this case called the logistic STR $(LSTR)$ model. The transition function takes on values between zero and one. The slope parameter γ controls the slope of the function: when γ is small, the transition from one regime to another is very smooth. On the other hand, as γ tends to infinity, the model becomes the switching regression model. The threshold parameter c determines the location of the transition between two regimes.

Different values of K lead to very different transition functions. The most common choices for K are $K = 1$ $(LSTR1)$ and $K = 2$ $(LSTR2)$. If $K = 1$, the parameters change monotonically as a function of $h_{t,n}$ from $\boldsymbol{\phi}$ (lower regime, $G = 0$) to $\boldsymbol{\phi} + \boldsymbol{\theta}$ (upper regime, $G = 1$). On the other hand, if $K = 2$, the parameter values change symmetrically around the mid-point $(c_1 + c_2)/2$ where the logistic function equals zero. An alternative to the $LSTR2$ model is the so called exponential STR $(ESTR)$ model, when $c_1 = c_2$. The transition function of $ESTR$ model is of the form: $G(\gamma, c, h_{t,n-1}) = 1 - \exp\left\{-\gamma(h_{t,n-1} - c)^2\right\}$,where $\gamma > 0$ and it is symmetric around c. Since there is one parameter less to estimate, the $ESTR$ model is preferable to the $LSTR2$ model, when $c_1 \simeq c_2$ and γ is not too large.

In the empirical analysis, we will consider the following two models:

$$y_{t,n} = \phi_0 + \phi_1 N_{t,n} + [\theta_0 + \theta_1 N_{t,n}] G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \tag{4.7}$$

and

$$\begin{aligned} y_{t,n} = {} & \phi_0 + \phi_1 Npos_{t,n} + \phi_2 Nneg_{t,n} \\ & + [\theta_0 + \theta_1 Npos_{t,n} + \theta_2 Nneg_{t,n}]\, G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \end{aligned} \tag{4.8}$$

where $N_{t,n}$ denotes a news variable, which includes all news, both positive and negative and $Npos_{t,n}$, $Nneg_{t,n}$ denote positive and negative news variables, respectively. So, model (4.7) allows the impact of news to be different in different states of the economy, while model (4.8), in addition, facilitates the different effect of positive and negative news in each state. Model (4.8) is estimated by using two alternative definitions of positive and negative news. When classification is based on the Bloomberg market forecast, the positive and negative news variables are denoted as $Npos^f_{t,n}$ and $Nneg^f_{t,n}$, whereas the news variables classified by using the sign of the return are denoted as $Npos^r_{t,n}$ and $Nneg^r_{t,n}$. See details of the different classifications in Table 4.2. Also, note that we have used a short-hand notation for the news variables in models (4.7) and (4.8). The explanatory news variables are not the news variables as such in Table 4.2, but wherever there is a news announcement, in the 25 subsequent 5-minute intervals the corresponding regressor equals $\lambda_1, \lambda_2, ..., \lambda_{25}$ and zero otherwise. See details in Section 4.3.2.

4.3.5 Linearity Testing

We start the analysis by testing for linearity against STR-type nonlinearity. Although we propose these types of models as plausible alternatives to linearity, it

(transition variable) only changes once a month. Therefore, the value of the transition variable stays constant for a very long time, and the lagged value is the same as today's value, except at the time when the monthly value of the business cycle indicator (IFO index or ISM index) is announced.

should be kept in mind that these tests have power against many kinds of nonlinear models. The well-known problem that under the null hypothesis, γ and c are not identified is circumvented by approximating the transition function by a third order Taylor approximation, following Saikkonen and Luukkonen (1988). They suggest LM-type tests based on the following auxiliary regression,

$$y_{t,n} = \boldsymbol{\beta}_0' \boldsymbol{x}_{t,n} + \sum_{j}^{3} \boldsymbol{\beta}_j' \boldsymbol{x}_{t,n} h_{t,n-1}^{j} + u_{t,n} \tag{4.9}$$

estimated by ordinary least squares. For our models (4.7) and (4.8), $\boldsymbol{x}_{t,n} = (1, N_{t,n})'$ and $\boldsymbol{x}_{t,n} = (1, Npos_{t,n}, Nneg_{t,n})'$, respectively. The null hypothesis of linearity can be expressed as $H_0 : \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = \boldsymbol{\beta}_3 = 0$, and the LM-type test statistics F is computed as follows,

$$F = \frac{(SSR_0 - SSR_1)/3m}{SSR_1/(T - 4m - 1)}, \tag{4.10}$$

where SSR_0 is sum of the squared residuals from a regression of $y_{t,n}$ on $\boldsymbol{x}_{t,n}$, SSR_1 is sum of squared residuals from auxiliary regression (4.9) and m is the number of explanatory variables in (4.9). Under linearity F follows approximately the $F(3m, T - 4m - 1)$ distribution.

If STR-type nonlinearity is detected, the tests of Saikkonen and Luukkonen (1988) can also be used for selecting the type of the STR model. The test has power against all the STR models discussed above. The following sequence of tests is suggested by Teräsvirta (1994):

1. $F1$: Test the null hypothesis $H_{01} : \boldsymbol{\beta}_1 = 0 | \boldsymbol{\beta}_2 = \boldsymbol{\beta}_3 = 0$.
2. $F2$: Test $H_{02} : \boldsymbol{\beta}_2 = 0 | \boldsymbol{\beta}_3 = 0$.
3. $F3$: Test $H_{03} : \boldsymbol{\beta}_3 = 0$.

If the rejection is the strongest against H_{02} (measured by the p-value), choose the $LSTR2$ or $ESTR$ model. Otherwise choose the $LSTR1$ model. Choosing the model by using this test sequence is based on the test derived specifically for $ESTR$-type of nonlinearity. The test is based on the similar auxiliary regression as (4.9), except that it only includes the first and second powers of the transition function, instead of the first, second and third in (4.9). Therefore, rejection in test $F3$ can in principle be interpreted as a rejection of the $ESTR$ model family. On the other hand, if $F2$ is not rejected, it can be taken as evidence in favour of a $LSTR$ model, because $\boldsymbol{\beta}_2$ cannot equal 0 if the model is an $ESTR$ model (except for a very special case of $\boldsymbol{\theta} = 0$). Moreover, after accepting $F2$, the rejection of $F1$ supports the choice of a $LSTR$ model (see Teräsvirta (1994) for details).

4.4 Empirical Results

In this section, we present the empirical results. First, we test for linearity using the procedure discussed in Section 4.3.5. As the results in Table 4.3 show, the p-values of the F-statistic are all very small, indicating a rejection of linearity in all models using either transition variable. In each case, the p-value of the F1-test is the smallest, suggesting the $LSTR1$ model.

TABLE 4.3 Results of the linearity test against STR-type nonlinearity

Table presents the results of the linearity test against STR type nonlinearity by Saikkonen and Luukkonen (1988). The first column describes the news variables used in the test and the second column presents the considered transition variables (demeaned IFO and ISM indices). The third column presents the p-values of the F test. The next three columns present the p-values of the hypotheses $F1_,$ $F2$ and $F3$ tests (see details in section 4.3.5), and the last column presents the type of the model suggested by the sequented test procedure.

News var.	Trans. var.	F	$F1$	$F2$	$F3$	Model
$N_{t,n}$	IFO	$7.1E-11$	$2.9E-10$	$3.3E-01$	$1.9E-03$	$LSTR1$
	ISM	$1.5E-08$	$5.2E-06$	$1.0E-02$	$1.2E-03$	$LSTR1$
$Npos^f_{t,n}, Nneg^f_{t,n}$	IFO	$8.2E-10$	$1.6E-09$	$2.9E-01$	$3.1E-03$	$LSTR1$
	ISM	$5.0E-08$	$2.0E-05$	$3.9E-02$	$3.1E-04$	$LSTR1$
$Npos^r_{t,n}, Nneg^r_{t,n}$	IFO	$6.5E-09$	$1.5E-08$	$6.9E-01$	$1.0E-03$	$LSTR1$
	ISM	$5.9E-08$	$4.4E-06$	$2.4E-02$	$2.8E-03$	$LSTR1$

4.4.1 Estimation Results

Table 4.4 presents the estimation results of model (4.7). As can be seen, the estimate of the slope parameter γ is very large irrespective of the transition variable. The large values of parameter γ indicate that the switch from the lower to the upper regime is not smooth, but rather very abrupt. Figure 4.4 depicts the graphs of the transition functions against the transition variables, and they are indeed very steep, and the model is actually quite close to a switching regression model.

TABLE 4.4 Estimation results, all news

Table presents the parameter estimates of the Smooth Transition Regression model (4.7). The German IFO index and the ISM index are used as transition variables. The Newey-West standard errors (288 lags) are in the parentheses. * and ** denote rejection at the 5% and 1% significance level, respectively.

	IFO index	ISM index
ϕ_0	-2.21^{**} (0.008)	-2.13^{**} (0.007)
ϕ_1	22.03^{**} (0.514)	22.59^{**} (0.504)
θ_0	0.12^{**} (0.015)	-0.22^{**} (0.017)
θ_1	4.65^{**} (1.034)	3.34^{**} (1.069)
γ	368.7 (70.38)	2949.1 (42.22)
c	3.28 (0.011)	4.35 (0.001)

Note that the transition variables have been demeaned for estimation purposes. Therefore, the values of parameter c do not refer to the actual value of the index, but rather to the demeaned index. Hence, the estimated values of parameter c

correspond to the following values of the original indices: ISM: 56.951 and IFO: 96.385. Figure 4.5 graphs the transition functions against time. In general, it seems that there have been two spells of "good" times, one at the beginning of the sample period (1999-2000) and the other at the end of the sample period (2004). The duration of these expansion periods depends on the transition variable.

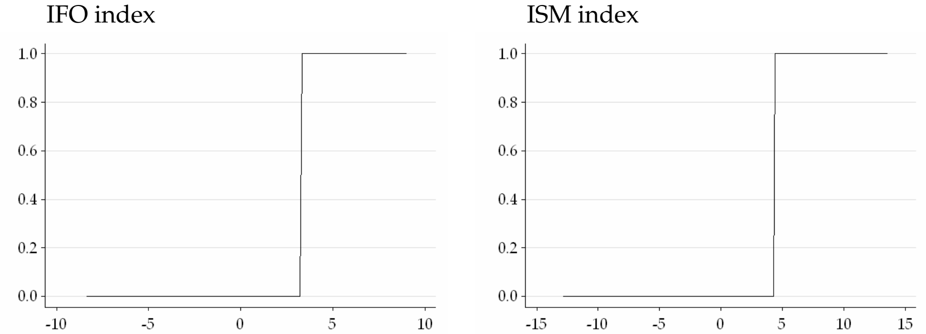

FIGURE 4.4 Transition function vs. transition variable
The figures present the estimated logistic transition functions (4.6) against the used transition variables (IFO index and ISM index). The steeper the function, the faster is the transition from the lower regime to the upper regime.

Are the identified good and bad times then believable? Andersen et al. (2007) defined the expansion period in their data from July 1998 to February 2001, and the contraction period from March 2001 to December 2002[15]. The National Bureau of Economic Research (NBER) has reported one contraction period during our sample period, from March 2001 to November 2001. So, the first spell of "good" times is well in line with the Andersen et al. (2007) estimates, but the estimated business cycle phases are not quite the same as those reported by the NBER. On the other hand, according to Veredas (2006), the historical data show that the value of 54.5 of the ISM index indicates an expansion in the economy. Our estimate (56.951) is a bit higher than that, but yet around the same magnitude. Nevertheless, we are not necessarily making a statement of the phases of the business cycle with our model, but rather examining of how 'good' the times must be for the investors to react differently to news.

Parameter ϕ_1 gives the impact of news in the "lower" regime, or in "bad" times, and $\phi_1 + \theta_1$ gives the impact of news in the "upper" regime, or in "good times". If θ_1 is significantly different from zero, news effects depend on the state of the business cycle. As can be seen, the news effects are positive and significantly different from zero at the 1% significance level. Therefore, we conclude that macroeconomic news increases volatility significantly. We can also see that the news effects are state dependent. Irrespective of the transition variable, the estimate of θ_1 is significantly greater than zero. This implies, that macro news increases volatility more in good times than in bad times. Similar findings of stronger news effects in good than bad times have been reported e.g. Flannery and Protopapadakis (2002) and Adams et al. (2004) on stock market returns.

15 Their data ends in 2002.

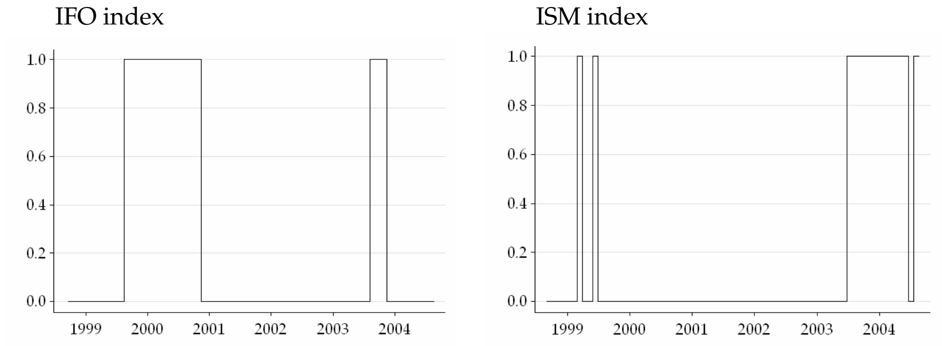

FIGURE 4.5 Transition function vs. time
The figures present the estimated logistic transition functions (4.6) against time. IFO index and ISM index were used as transition variables. The lower regime ($G = 0$) indicates 'bad times' and the upper regime ($G = 1$) indicates 'good times'.

Table 4.5 presents the estimation results of model (4.8), where the news are divided into positive and negative based on the two classification methods. We can first conclude that the estimates of γ and c are comparable to those obtained for model (4.7). Parameters ϕ_1 and ϕ_2 give the impact of positive and negative news in "bad" times and $\phi_1 + \theta_1$ and $\phi_2 + \theta_2$ give the impact of positive and negative news in "good" times, respectively. The effect of negative news seems to be different in the two regimes, while the coefficient θ_1 for the nonlinear part is insignificant for the positive news. This implies that there seems to be no state dependence in positive news, but the impact of negative news is higher in good times than in bad times. This is well in line with the results of the previous studies from stock and bond markets (Conrad et al., 2002; Veredas, 2006). Also, the results support the theory of Veronesi (1999) suggesting that investors overreact to bad news in good times and underact to good news in bad times, due to aversion of uncertainty concerning the state of the economy.

Table 4.6 summarizes the estimates of the coefficients for the positive and negative news variables when the transition function takes on values $G = 0$ and $G = 1$. Clearly, in bad times, the impact of positive and negative news is not significantly different (p-values vary between 0.401 and 0.896). On the other hand, in good times the impact of negative news seems to be greater than that of positive news. However, the difference is statistically significant only when the market forecast is used for classifying news into positive and negative (p-values are 0.017 for IFO index and 0.008 for ISM index). However, the p-values of 0.128 (IFO index) and 0.081 (ISM index) obtained when the classification is based on the sign of the return are also quite small.

4.4.2 Diagnostics

As diagnostic checks we use the LM-type tests of no remaining autocorrelation, no remaining nonlinearity and parameter constancy developed specifically for STR models by Eitrheim and Teräsvirta (1996). The test of no remaining autocorrelation has under the alternative hypothesis a nonlinear model with autocorrela-

TABLE 4.5 Estimation results, positive and negative news

Table presents the parameter estimates of the Smooth Transition Regression model (4.8). News is classified as positive and negative by using the Bloomberg market forecast (left panel) and the sign of the return following the news (right panel). The German IFO index and the ISM index are used as transition variables. The Newey-West standard errors (288 lags) are in the parentheses. * and ** denote rejection at the 5% and 1% significance level, respectively.

	Market forecast $(Npos^f_{t,n}, Nneg^f_{t,n})$		**Sign of the return** $(Npos^r_{t,n}, Nneg^r_{t,n})$	
	IFO index	**ISM index**	**IFO index**	**ISM index**
ϕ_0	-2.20^{**} (0.008)	-2.12^{**} (0.007)	-2.21^{**} (0.008)	-2.14^{**} (0.007)
ϕ_1	16.06^{**} (0.658)	16.57^{**} (0.636)	21.57^{**} (0.635)	22.55^{**} (0.628)
ϕ_2	16.29^{**} (0.679)	16.70 (0.652)	22.34^{**} (0.631)	22.96^{**} (0.611)
θ_0	0.12^{**} (0.015)	-0.22^{**} (0.017)	0.12^{**} (0.015)	-0.21^{**} (0.017)
θ_1	1.87 (1.288)	-0.08 (1.362)	2.26 (1.237)	-0.32 (1.300)
θ_2	5.81^{**} (1.293)	4.99^{**} (1.379)	5.34^{**} (1.266)	2.92^{*} (1.297)
γ	435.8 (82.76)	3870.2 (41.41)	1806.9 (166.2)	2897.3 (42.24)
c	3.286 (0.010)	4.351 (0.001)	3.285 (0.005)	4.351 (0.001)

TABLE 4.6 Estimation results, summary

Table presents the estimated coefficients of the positive and negative news variables computed for the values of $G = 0$ (Bad times) and $G = 1$ (Good times) and the p-values of the Wald-tests for the equality of the impact of positive and negative news. $Npos^f_{t,n}$ and $Nneg^f_{t,n}$ denote the positive and negative news classified by using the Bloomberg market forecast, and $Npos^r_{t,n}$ and $Nneg^r_{t,n}$ denote the positive and negative classified by using the sign of the return following the news.

		IFO index		**ISM index**	
$Npos^f_{t,n}, G = 0$	ϕ_1	16.057		16.566	
$Nneg^f_{t,n}, G = 0$	ϕ_2	16.285	0.833	16.702	0.896
$Npos^r_{t,n}, G = 0$	ϕ_1	21.570		22.554	
$Nneg^r_{t,n}, G = 0$	ϕ_2	22.335	0.401	22.956	0.650
$Npos^f_{t,n}, G = 1$	$\phi_1 + \theta_1$	17.928		16.485	
$Nneg^f_{t,n}, G = 1$	$\phi_2 + \theta_2$	22.096	0.017	21.688	0.008
$Npos^r_{t,n}, G = 1$	$\phi_1 + \theta_1$	23.833		22.237	
$Nneg^r_{t,n}, G = 1$	$\phi_2 + \theta_2$	27.672	0.128	25.874	0.081

tion of order q. The tests for no remaining nonlinearity and parameter constancy closely resemble the linearity test described in subsection 4.3.5. In both tests the dependent variable is the model residual, and in the parameter constancy test, the time index is used as the transition variable.

As for the test of remaining autocorrelation, we considered lags from 1 to 24, and the null hypothesis of no remaining autocorrelation is strongly rejected with all the considered lags at conventional significance levels. This comes as no surprise, considering the autocorrelation structure of the absolute filtered returns in Figure 4.1.

The test of remaining nonlinearity rejects (p-values equal 0.006 and 0.007, when the IFO and ISM indices are used as transition variables, respectively). The alternative model in this test is an additive STR model, where instead of two regimes there are three regimes (low, middle, high). Therefore, we estimated the model with a third regime. The estimated coefficient values do not look reasonable in view of the results of the two-regime model[16]. Moreover, we had computational difficulties with some of the news variables and transition variables. The probable reason for the unreasonable results and the computational difficulties with the covariance matrix could be the fact that even though the test suggests a three-regime model, there are actually only two regimes. In the estimated three-regime model the estimated value for the second threshold parameter was so high that the "high" regime was reached only once during a short period (only by 2.8% of the observations). Therefore, this regime is rather considered an "outlier" regime, and the two-regime model is deemed an adequate description of the data. One potential problem with the test for no remaining nonlinearity is that it also has power against remaining autocorrelation (Teräsvirta, 1994), suggesting that the rejection in the linearity test might be spurious. The fact that the test rejects the hypothesis of no remaining nonlinearity also after the three regime model (e.g. with p-value 0.007 when ISM index is used as a transition variable) only strengthens this suspicion. Moreover, the test of linearity has high power against various nonlinear alternatives. Hence, the rejection could be caused also other than STR-type of nonlinearity.

In addition to remaining autocorrelation and nonlinearity, we tested for parameter constancy. All tests of Eitrheim and Teräsvirta (1996) reject at conventional significance levels, which suggests that some kind of time-varying Smooth Transition (TV-STR) Model with multiple time regimes in addition to regimes governed by the transition variable could be more adequate for the data. However, due to the interactive nature of the three diagnostic tests considered, the rejection could also be caused by the remaining autocorrelation or nonlinearity, but the known strong autocorrelation is the likeliest explanation of all the rejections. The outcome of trying to model time varying STR model supports this view. When estimating the TV-STR model we faced significant problems in convergence, probably caused by the fact that the second time regime turned out to be situated in the end of the data sample, and, therefore, rendering the estimation of the two states of the business cycle in the second time regime impossible. We also estimated the model on data excluding the end of the sample (i.e. the second time regime). The results concerning the news variables did not change at all and the parameter constancy test was still rejecting as strongly as after the original two-regime model.

Another possible problem affecting our results is that there are many stages before the estimation of the news variables, which can cause bias in our standard errors. The first possible source of such bias is caused by the estimated daily volatility. Andersen and Bollerslev (1998) carefully discuss the potential problem caused by the estimation of the sigma in the first stage. They state, that the sigma

[16] These results are not reported, but they are available upon request.

could alternatively be set to constant, which would solve the "generated regressor" problem but not eliminate the daily heteroskedasticity as does the estimated sigma. They demonstrate that the problem is negligible by estimating the model by using both estimated sigma and constant sigma. The results are very similar with both estimated and constant sigma. Therefore, because we are using very similar data set compared to that of Andersen and Bollerslev (1998), we do not think the issue is so crucial in our study either.

The second possible source of the bias is caused by the estimated average response pattern of news. Instead of the estimated polynomial, we could use e.g. lagged dummies to capture longer news impacts. The dummy variable approach would not create a bias as the polynomial approach, but the polynomial approach has other significant benefits over the lagged dummies. For example, the advantage of using the polynomial instead of lagged dummies approach is the number of estimated variables. When using the polynomial, we only need one variable for each studied news group. When the lagged dummy method is used, the 24 dummy variables for each news category are needed. In the nonlinear model with more than 400 000 observations, this produces significant increase in computational burden. Another benefit of the polynomial method is that it fixes the problem of having only a few announcement observations and it is not so sensitive to the inherent noise in the return process. Laakkonen (2007a) studied the impact of news on volatility by using a subset of a data sample that we are using in our study. She studied the impact of news using both the polynomial approach and the lagged dummy variable approach. The results obtained with the dummy variable approach were not different from the results when the estimated impact structure was used. The same news categories were significant with both of the methods. This supports our view that the problem caused by the estimated average response pattern of news is not very critical.

The third possible source of bias occurs in estimating the news effects in two stages: first filtering the data in subsets and then estimating the news effects. Laakkonen (2007b) studied the properties of the intraday returns filtered with different methods. She found that all the examined filtering methods were capable of filtering the intraday seasonality only if the filtering was done in subsets. Yet, she concluded that the filters performed better the shorter was the subset, which indicates that the intraday volatility pattern was time varying. If the FFF model is estimated only once for the whole data sample, with news variables included in the model, we can avoid the problem caused by the uncertainty in the FFF parameter estimates, but then we have to face the problem of having significant periodical autocorrelation left in the absolute filtered returns. The results of Laakkonen (2007b) shows that the size of the estimated news variable coefficients differ significantly, when the FFF model is estimated only once compared to the model re-estimated weekly. Because the differences are larger in the values of the estimated coefficients than in the standard errors, we suggest that in this context the problem of remaining periodicity in autocorrelation is more serious than the problem caused by the parameter uncertainty.

All in all, the diagnostic tests suggest that there is still some unexplained regularity. However, we believe that the two-regime model is more reasonable than the three-regime model, and that the rejections in both the remaining nonlinearity and parameter constancy tests are caused by the strong residual autocorrelation. Since we are not interested in using the model for forecasting, but instead testing the hypotheses of asymmetries in the news effects, we follow Andersen and Bollerslev (1998) and take the remaining autocorrelation into account only by using Newey-West robust standard errors. Also, the several stages before estimating the news effects might cause the standard errors to be biased downwards. However, as motivated above, we think the problem is negligible and does not affect our conclusions.

4.5 Conclusions

In this paper, we study the relationship between the asymmetric news effects on exchange rate volatility and the state of the economy. We study the impact of the US and European macroeconomic announcements on the volatility of high-frequency EUR/USD returns. We use the Smooth Transition Regression model to capture the state dependencies and consider business cycle indices from both the USA and Europe as transition variables. By using a broader data set of macro announcements and more flexible methodology than earlier studies, we uncover evidence on state dependence of the positive and negative news effects in the foreign exchange markets.

According to our results, macro news increases volatility more in good times than in bad times. However, negative news has stronger effects in good times than in bad times, but positive news effects do not seem to depend on the state of the economy at all. Our results are well in line with the previous results from the equity and bond markets, and they also support the theory of Veronesi (1999).

Our results might be found interesting e.g. by the central banks, since the central bank interventions have found to increase volatility of exchange rates rather than having the desired effect on exchange rates (see, e.g., Dominguez, 1998). Perhaps similar asymmetries apply in the central bank interventions that we found for the news concerning macro economic indicators.

REFERENCES

Adams, G., McQueen, G., Wood, R., (2004) "The Impact of Inflation News on High Frequency Stock Returns" The Journal of Business 77, 547–574

Almeida, A., Goodhart C., Payne, R., (1998) "The Effects of Macroeconomic News on High Frequency Exchange Rate Behaviour" Journal of Financial and Quantitative Analysis 33, 383-408

Andersen, T., Bollerslev, T., (1997) "Intraday periodicity and volatility persistence in financial markets" Journal of Empirical Finance 4, 115-158

Andersen, T., Bollerslev, T., (1998) "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies" The Journal of Finance 53, 219-265

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2003) “Micro Effects and Macro Announcements: Real-Time Price Discovery in Foreign Exchange“ American Economic Review 93, 38-62

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2007) “Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets“ Journal of International Economics 73, 251-277

Balduzzi, P., Elton, E., and Green T., (2001) "Economic News and Bond Prices: Evidence from the U.S. Treasury Market" The Journal of Financial and Quantitative Analysis 36, 523-543

Bauwens, L., Ben Omrane, W., Giot, P., (2005) “News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market“ Journal of International Money and Finance 24, 1108-1125

Boyd, J., Hu, J., Jagannathan, R., (2005) “The Stock Market’s Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks“ The Journal of Finance 60, 649-672

Chan, Y., Chui, A., Kwok, C., (2001) “The impact of salient political and economic news on the trading activity“ Pacific-Basin Finance Journal 9, 195–217

Chang, Y., Taylor, S., (2003) “Information arrivals and intraday exchange rate volatility" International Financial Markets, Institutions and Money 13, 85–112

Conrad, J., Cornell, B., Landsman, W.R., (2002) “When Is Bad News Really Bad News?“ The Journal of Finance 57, 2507-2532

Degennaro, R., Shrieves, R., (1997) “Public information releases, private information arrival and volatility in the foreign exchange market“ Journal of Empirical Finance 4, 295-315

Dominguez, K., (1998) "Central Bank Intervention and Exchange Rate Volatility" Journal of International Money and Finance 17, 161-190

Dominguez, K., Panthaki, F., (2006) “What defines ‘news’ in foreign exchange markets?“ Journal of International Money and Finance 25, 168-198

Eddelbüttel, D., McCurdy, T., (1998) “The Effects of News on Foreign Exchange Rates: Evidence from High Frequency Data.” Manuscript Rotman School of Management, University of Toronto.

Eitrheim, O., Teräsvirta, T., (1996), “Testing the adequacy of smooth transition autoregressive models“ Journal of Econometrics 74, 59-75

Faust, J., Rogers, J., Wang, S.-Y.B., Wright, J., (2007) “The high-frequency response of exchange rates and interest rates to macroeconomic announcements“ Journal of Monetary Economics 54, 1051-1068

Flannery, M., Protopapadakis, A., (2002) “Macroeconomic Factors Do Influence Aggregate Stock Returns“ The Review of Financial Studies 15, 751-782

Gallant, R., (1984) "The Fourier Flexible form" American Journal of Agricultural Economics 66, 204-208

Granger, C.W.J., Teräsvirta, T., (1993) “Modelling Nonlinear Economic Relationships, Advanced Texts in Econometrics“ Oxford University Press

Laakkonen, H., (2007a) “The Impact of macroeconomic news on exchange rate volatility“ Finnish Economic Papers 20, 23-40

Laakkonen, H., (2007b) “Exchange Rate Volatility, Macro Announcements and Choice of the Intraday Seasonality Filtering Method“ Bank of Finland Discussion Paper 23/2007

Laakkonen, H., (2008) "Asymmetric News Effects on Exchange Rate Volatility" University of Jyväskylä working paper 353/2008

Lamoureux, C.G., Lastrapes, W.D., (1990) “Persistence in variance, structural change and the GARCH model“ Journal of Business and Economic Statistics 8, 225-234

Lanne, M., Saikkonen, P., (2006) “Why is it so difficult to uncover the risk-return tradeoff in stock returns?“ Economic Letters 92, 118-125

Saikkonen, P., Luukkonen, P., (1988) “Lagrange Multiplier Tests from Testing Non-Linearities in Time Series Models" Scandinavian Journal of Statistics 15, 55-68

McQueen, G., Roley, VV., (1993) “Stock Prices, News and Business Conditions“ The Review of Financial Studies 6, 683-707

Melvin, M., Yin, X., (2000) “Public information arrival, exchange rate volatility and quote frequency“ The Economic Journal 110, 644-661

Merton, R.C., (1973) “An intertemporal capital asset pricing model“ Econometrica 41, 867-887

Pearce, D., Solakoglu, N., (2007) “Macroeconomic news and exchange rates“ Journal of International Financial Markets, Institutions and Money 17, 307-325

Teräsvirta, T., (1994) “Specification, estimation, and evaluation of smooth transition autoregressive models“ Journal of the American Statistical Association 89, 208-218

Veredas, D., (2006) “Macroeconomic surprises and short-term behavior in bond futures“ Empirical Economics 30, 843-866

Veronesi, P., (1999) “Stock market overreaction to bad news in good time: A rational expectations equilibrium model“ Review of Financial Studies 12, 975-1007

CHAPTER 5

THE RELEVANCE OF ACCURACY FOR THE IMPACT OF MACROECONOMIC NEWS ON EXCHANGE RATE VOLATILITY

5.1 Introduction

[1]According to theories concentrating on the quality of information (e.g. Veronesi, 2000), investors' reaction to new information does not only depend on the amount of unanticipated information, i.e., the difference between the announced figure and investors' personal expectations of the figure, but also on what they think about the quality of information. Despite this, the extensive literature on the effects of news announcements on financial markets has mostly ignored such quality aspects. To the best of our knowledge, only two previous empirical studies (Krueger and Fortson (2003) and Hautsch and Hess (2007)), discussed in more detail below, have specifically addressed this issue.

The scheduled releases of macroeconomic indicators comprise an important part of new information in the markets. The extensive empirical literature (Degennaro and Shrieves, 1997; Andersen et al., 2003, 2007; Bauwens et al., 2005; Dominquez and Panthaki, 2006; Laakkonen, 2007a among others) has shown that announcements of macroeconomic figures typically cause a jump in asset prices and significantly increase volatility right after the announcement. The issue of news accuracy is of particular importance for macroeconomic news because it is widely known that the first released estimate of a macroeconomic indicator, such as the gross domestic product (GDP) often deviates considerably from the 'final'

[1] This Chapter is a joint work with Professor Markku Lanne. A version of this Chapter has appeared in the HECER Discussion Paper series No. 262 / 2009 and is submitted to Journal of Empirical Finance.

estimate. The figures can be revised for years and the difference between the first and final estimates can be substantial. For example, according to Swanson and van Dijk (2001) it takes at least 12 months for the seasonally adjusted US producer price index and industrial production figures to reach the 'correct' value. Also, there is a large literature confirming that the revisions of macroeconomic figures are somewhat predictable (e.g. Swanson and van Dijk, 2001).

While the literature on the effects of news announcements on financial returns and their volatility is voluminous, there appears to be very little research addressing the consequences of the precision of news announcements. Krueger and Fortson (2003) measured information precision by a linear time trend, which was assumed to capture the increasing precision of news releases over time, and found only limited evidence in favour of the relevance of US employment news accuracy for daily Treasury bond prices. On the other hand, the results of Hautsch and Hess (2007) suggest that more precise news on the US nonfarm payroll has a stronger impact on the intraday prices of Treasury bond futures than less precise news. Hautsch and Hess (2007) state that because the first revision of the previous month's figure (released at the same time as the present month's figure) reveals the measurement error in the previous period, it may help traders to assess the accuracy of the currently released news. Therefore, they measure the precision of an announcement by using the one-step-ahead conditional variance forecast of an ARMA-GARCH model fitted to the time series of revisions of US nonfarm payroll. In particular, the reliability of the announced figure is expected to decrease when the expected revision variance increases. They also study the asymmetries between positive and negative news, and find that the Treasury bond futures market reacts significantly more strongly to negative than positive news, and more strongly to precise 'bad' news than to imprecise 'bad' news.

In this essay, we study the relevance of the precision of news announcements concerning 20 macroeconomic indicators for the effect on the volatility of the euro against United States dollar (EUR/USD) exchange rate returns. We consider three ways of defining the precision of news. First, because the revision of the previous month's figure is always announced at the same time as the first estimate of the present month's figure, we follow Hautsch and Hess (2007) and assume that the size of this revision is a signal to investors of the accuracy of the present month's figure. We study whether investors react differently to standardized news surprises, when the standardized absolute revision of the previous month's figure is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. In other words, our first measure of precision is conditional on the previous revision.

The different macroeconomic indicators deviate considerably by the magnitude of revisions. Some indicators are often revised quite considerably (e.g. nonfarm payroll) while others undergo hardly any revision at all (e.g. confidence figures). These differences allow us to study the importance of the overall accuracy of news announcements on volatility. We study this issue by comparing investors' reactions to standardized news on macro indicators, whose mean standardized absolute revision (the first revision of the previous month's figure) is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. Hence, our second measure of precision is unconditional. We also analyze the conditional and unconditional measures jointly to see whether there are differences in investors' reactions to precise and imprecise announcements of indicators that are usually precise or imprecise.

Ex ante, investors do not actually know which announcements are accurate, and they try to resolve this issue by using prior information. Whether they are successful in predicting the accuracy of the announcements can be determined by means of the 'final correct' figures that become available after several revisions. Specifically with such data, we can compute ex post news surprises that should yield similar results as the ex ante measures if investors' signals of news accuracy are efficient. Moreover, by comparing the two precision measures, we can infer whether investors are trying to predict the first release or final figures.

In the previous literature, the paper that comes closest to ours, is Hautsch and Hess (2007). However, while Hautsch and Hess (2007) argue that investors' reaction to news depends on the relative precision of the announced data compared to the precision of the investors' beliefs, we study if the precision of announcements have direct effects on investors' reactions to news. Also, as mentioned above, we study the issue from several different viewpoints, while they only concentrate on the similar ex ante conditional measure of precision as we do. To our knowledge, neither the ex ante unconditional nor the ex post measures have been used earlier in the literature. Finally, while Hautsch and Hess (2007) only use the news on US nonfarm payroll, our data contains 20 US macroeconomic indicators, and the results are therefore more general, albeit the US nonfarm payroll is probably the most important macro indicator. Our paper also differs from the previous literature in that we study the relevance of news accuracy on exchange rate volatility, while the two earlier papers consider Treasury bond returns.

The results show that when using the revision of the previous month's figure in defining the accuracy of the news releases, the announcements that are more precise, increase volatility significantly more than imprecise ones. Also, the macro indicators that are usually more precise increase volatility significantly more than those usually imprecise. When considering the conditional and unconditional measures of accuracy simultaneously, we find that investors are reacting to both measures of precision. The conditional measure of precision seems to be relevant for investors, since news on the high-precision indicators increase volatility significantly more than news on low-precision indicators only when the announcement is also conditionally precise. On the other hand, among the unconditionally precise or imprecise news, the conditional precision does not cause asymmetric reaction to news, as it does when the indicators are not classified to precise and imprecise by using the unconditional measure. This indicates that the size of the revision of the previous month's figure is not the only signal the investors are using, but that investors react to both, conditional and unconditional measure of precision.

We also find that announcements that ex post turned out to be more precise, increase volatility more than those that turned out to be imprecise. Thus the precision of the previous revision seems to provide an efficient signal of current precision. Moreover, the results suggest that investors try to predict the first-release rather than final figures.

The plan of the Chapter is as follows. Section 5.2 describes the data and the Flexible Fourier Form method, which is used to filter the intraday seasonality from the data. Section 5.3 presents the different measures of precision and the estimation results. Finally, Section 5.4 concludes.

5.2 Data and Methodology

5.2.1 Exchange Rate Data

The original data set contains the five-minute quotes[2] of the EUR/USD exchange rate from 1 January 1999 to 31 December 2004, and it was obtained from Olsen and Associates. The prices are formed by taking the average of the bid and ask quotes, and the returns are computed as the differences of logarithmic prices.

As the foreign exchange market activity slows down decidedly during weekends and certain holiday non-trading periods, it is standard in the literature to explicitly exclude a number of days from the raw five-minute return series. Following Andersen and Bollerslev (1998), we exclude the weekends and certain holidays by always leaving out the returns from 21:05 GMT the night before to 21:00 GMT that evening. Andersen and Bollerslev (1998) state that this definition of a "day" retains intact the intraday periodic volatility structure. The following holidays are excluded from the data: Christmas, New Year, Good Friday and Easter Monday. Besides these holidays, three days are left out from the data because of lack of observations (10 May 1999, 21 Dec 2000, 24 Dec 2000). Daylight savings time is also taken into account, as is standard in the literature.

The five-minute returns exhibit strong intraday periodicity because of the different trading times in the global 24-hour foreign exchange markets. This has to be taken into account in modeling news effects, and one way of doing this is to use a filtered return series. Of the alternative filtering methods proposed in the literature, we choose the Flexible Fourier Form (FFF) model of Andersen and Bollerslev (1997) that uses different frequencies of sine and cosine functions to capture the periodicity. This choice is motivated by Laakkonen (2007b), who studied the consequences of data filtering on the results obtained by using filtered returns. She concluded that for the purpose of studying the impact of news on volatility, the FFF method performs the best among a number of commonly employed filtering methods because it produces the smallest bias in the estimated news coefficients compared to other filtering methods.

The FFF method is based on the following decomposition:

$$R_{t,n} - \bar{R}_{t,n} = \sigma_t \cdot s_{t,n} \cdot Z_{t,n} \tag{5.1}$$

2 According to many studies, five-minute returns strike the best balance between the disadvantages of microstructure noise (when sampling too frequently) and the loss of important information (when sampling too infrequently). For a discussion, see Andersen et al. (2007).

where $R_{t,n}$ denotes the five-minute returns, $\bar{R}_{t,n}$ is the expected five-minute returns and $Z_{t,n}$ is an i.i.d (with mean zero and unit variance) innovations, σ_t represents daily volatility and $s_{t,n}$ is intraday volatility[3].

Squaring both sides of (5.1), taking logs, approximating $\bar{R}_{t,n}$ with the sample mean $\bar{R}$ and eliminating the daily volatility component σ_t from the return process, we end up with the following expression,

$$2\log\frac{|R_{t,n}-\bar{R}|}{\hat{\sigma}_t/N^{1/2}} = \log\left(s_{t,n}^2\right)+\log\left(Z_{t,n}^2\right) \tag{5.2}$$

where following Andersen and Bollerslev (1997), we replace σ_t by $\hat{\sigma}_t$ predicted by a GARCH(1,1) model for the daily volatility. N denotes the number of five-minute intervals in one day (288 in a 24-hour market). Andersen and Bollerslev (1997) suggest a parametric representation of the intraday volatility $s_{t,n}$ and estimate the smooth cyclical volatility pattern by using trigonometric functions. The FFF regression model is the following,

$$\begin{aligned} f_{t,n} = {} & \alpha+\delta_1 n+\delta_2 n^2+\sum_{l=1}^{L}\lambda_l I_{l;t,n} \\ & + \sum_{p=1}^{P}\left(\delta_{c,p}\cos\left(\frac{p2\pi}{N}n\right)+\delta_{s,p}\sin\left(\frac{p2\pi}{N}n\right)\right)+\varepsilon_{t,n}, \end{aligned} \tag{5.3}$$

where $f_{t,n} = 2\log\frac{|R_{t,n}-\bar{R}|}{\hat{\sigma}_t/N^{1/2}}$. Besides the sinusoids[4], a second order polynomial in the intraday interval, n, and the error term of the model $\varepsilon_{t,n}$, the model also contains indicator variables $I_{l;t,n}$, which are used to control for weekday effects and outliers. The estimate of intraday volatility $\hat{s}_{t,n}$ is obtained as $\hat{s}_{t,n} = \exp(\hat{f}_{t,n}/2)$, where $\hat{f}_{t,n}$ are the fitted values from model (5.3). This estimate $\hat{s}_{t,n}$ is normalized so that the mean of the normalized periodicity estimate $\tilde{s}_{t,n}$ equals one: $\tilde{s}_{t,n} = \frac{T\cdot\hat{s}_{t,n}}{\sum_{t=1}^{T/N}\sum_{n=1}^{N}\hat{s}_{t,n}}$ where T is the number of observations in the entire sample and T/N denotes the number of days in the data. To get the filtered returns, the original returns $R_{t,n}$ are divided by the normalized estimate $\tilde{s}_{t,n}$, i.e., $\tilde{R}_{t,n} = \frac{R_{t,n}}{\tilde{s}_{t,n}}$. See Andersen and Bollerslev (1997, 1998) for further details of the method.

If the intraday periodicity pattern is assumed to remain constant over the sample period, the FFF model is estimated for the entire data set. Unfortunately this is not likely to be the case. Laakkonen (2007b) studied the properties of the intraday returns filtered with different methods. She found that all the examined filtering methods were capable of filtering the intraday seasonality only if the filtering was done in subsets of data. Yet, she concluded that the filters performed better the shorter was the subset, which indicates that the intraday volatility pattern was time varying. If the FFF model is estimated only once by using the entire sample period, there are significant periodical autocorrelation left in the absolute

3 In the equations t denotes the day and n the five-minute interval.

4 The value $P = 9$ was selected by using the Schwarz information criteria.

filtered returns. To be able to filter all the periodicity in volatility, the data has to be filtered in subsets. Laakkonen (2007b) states that to be able to filter all the periodicity in volatility, for this particular data set the FFF model has to be re-estimated every week.

The autocorrelation coefficients of absolute filtered and original returns for 1500 five-minute lags, i.e., the autocorrelogram for five days, is depicted in Figure 5.1. It is seen that there is still some autocorrelation left in the filtered absolute returns, although much of the intraday periodicity has been filtered out. In the empirical analysis of Section 5.3, the remaining autocorrelation will have to be taken into account in computing the covariance matrix of the errors of the regression models.

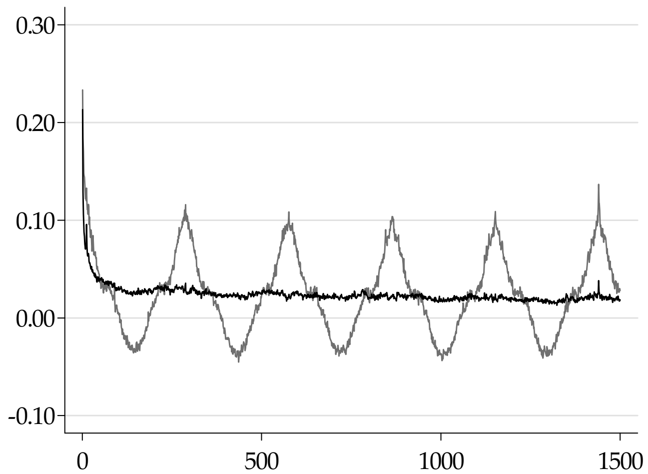

FIGURE 5.1 Autocorrelogram of the original and filtered absolute returns
The figure shows the five day correlogram at lags from 0 to 1500 of the filtered five-minute absolute EUR/USD returns (black line) compared to original absolute returns (grey line). The intraday periodicity was filtered by using the Flexible Fourier Form method.

Some descriptive statistics of the original and filtered return series are presented in Table 5.1. Mean and standard deviation of the return series are not effected dramatically by filtering. However, filtering does have an effect on skewness and kurtosis. The distribution of financial return series is usually very leptokurtic compared to the normal distribution, which indicates the overabundance of great returns compared to the normal distribution. The distribution of the EUR/USD returns is also positively skewed, which suggests that there are more great positive than negative returns. The distribution of the filtered returns is more symmetric: due to filtering, skewness falls from 0.78 to -0.15. Also, the extra kurtosis of the distribution falls from 65.9 to 40.9. Although the distribution of the returns seems to be closer to the normal distribution after filtering, neither the original nor filtered returns are normally distributed.

TABLE 5.1 Key statistical figures

Table presents the key statistical figures for the original and for the filtered returns. The returns were filtered with the Flexible Fourier Form method.

	Returns	Filtered returns
Mean	$5.0E-05$	$6.6E-05$
Standard Deviation	0.0432	0.0434
Skewness	0.781	-0.154
Kurtosis	65.94	40.92
Minimum	-1.35	-1.69
Maximum	2.79	1.68

5.2.2 Macroeconomic Announcement Data

The macroeconomic news data set includes the scheduled releases of 20 US macroeconomic indicators from the years 1999-2004 published in the Bloomberg World Economic Calendar (WECO). Table 5.2 presents the number of the releases of different macro indicators in our data set. Most of the indicators are released once a month, but some of them more often than monthly.

The data comprise the announcement date and time to an accuracy of one minute, the released estimate of the present month's figure of a macro indicator k ($k = 1, 2, ..., 20$), henceforth denoted $A_{t,n;k}$, the market forecast for the figure[5], henceforth denoted $F_{t,n;k}$ and the first revised estimate for the previous month's figure of indicator k , henceforth denoted $A^1_{t,n;k}$.

Besides the Bloomberg announcement data, we use the real time data set of the Federal Reserve Bank of Philadelphia for five macro indicators: nonfarm payroll, consumer price index, housing starts, industrial production and capacity utilization. The data set contains all the revised figures beginning from the first-release figure $A_{t,n;k}$ up to the 'final correct' estimate released m months after the first release, denoted as $A^m_{t+m,n;k}$.

5.3 Empirical Results

In this section, we present the empirical results on the relevance of the precision of macroeconomic indicators on the impact of macro news on EUR/USD volatility. As discussed in the Introduction, we consider three different ways of defining the accuracy of news. In subsection 5.3.1, we concentrate on two ex ante measures. First, *conditional* precision is determined in terms of the extent of the previous month's revision which can be considered a signal that investors use to assess the accuracy of the current announcement. Second, we compare the volatility effects of news announcements of indicators that are usually precise and impre-

5 The market forecast is the median of the survey forecasts that Bloomberg collects from the market agents.

TABLE 5.2 Number of announcements

Indicator	Announcements
Capacity Utilization	70
Change in Nonfarm Payroll	71
Chicago Purchasing Manager Index	71
Consumer Confidence Index	71
Consumer Price Index	72
Durable Goods Orders	71
Factory Orders	71
Gross Domestic Product	71
Housing Starts	71
Import Price Index	69
Industrial production	71
Initial Jobless Claims	307
ISM Manufacturing Index	71
Leading Indicators Index	71
New Home Sales	72
Philadelphia Fed Index	71
Producer Price Index	73
Trade Balance	71
University of Michigan Consumer Confidence Index	133
Wholesale Inventories	71

cise. We call this the *unconditional* measure of precision. Moreover, we examine whether the volatility effects of the typically precise and imprecise indicators depend on the accuracy of the previous month's announcement. In subsection 5.3.2, we present the results based on an ex post measure of accuracy. All the regression models considered below are linear, and they are estimated by ordinary least squares (OLS). Following Andersen and Bollerslev (1998), the autocorrelation in the errors is accounted for by Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 288 lags.

5.3.1 Ex ante Measure of Precision

Because the revision of the previous month's macro figure is always announced along with the present month's figure, we assume that investors use the size of the revision as a signal of the accuracy of the news announcement. Similar assumption was also made by Hautsch and Hess (2007) when studying the Treasury bond markets. Following their approach, we relate accuracy to absolute revisions. In particular, we study whether investors react differently to announced macro figures, when the standardized absolute revision of the previous month's figure is smaller or grater than the sample mean of the standardized absolute revisions of all indicators over the entire sample period. To examine the announcement effects, we consider the following model,

$$y_{t,n} = c + \phi^h \left[S_{t,n} \times D_{t,n}^{high} \right] + \phi^l \left[S_{t,n} \times D_{t,n}^{low} \right] + \varepsilon_{t,n} \tag{5.4}$$

where $y_{t,n} = \log \dfrac{|\tilde{R}_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$ is our measure of exchange rate volatility. The dependent variable is of the same form as in the FFF regression (5.3), but now the raw returns, $R_{t,n}$, are replaced by the filtered returns, $\tilde{R}_{t,n}$. This notation is used throughout this section. Apart from the intercept, c, the explanatory variables include the news variables, $S_{t,n} \times D_{t,n}^{high}$ and $S_{t,n} \times D_{t,n}^{low}$. As usual in the literature, news is defined as standardized absolute surprise $S_{t,n;k} = |A_{t,n;k} - F_{t,n;k}| / \hat{\sigma}_k$, where $A_{t,n;k}$ is a released macro figure of indicator k announced at day t and intraday interval n, $F_{t,n;k}$ is the survey forecast of this figure reported by Bloomberg, and $\hat{\sigma}_k$ is the standard deviation of the absolute surprise of indicator k estimated from the entire sample period. In the empirical analysis, we consider 20 different indicators and combine them into one variable $S_{t,n}$, which takes on a nonzero value whenever there is a news announcement.

The standardized absolute news surprise $S_{t,n}$ interacts with the dummy variables $D_{t,n}^{high}$ and $D_{t,n}^{low}$, which take on value 1 if the first standardized absolute revision $REV_{t,n;k}$ of the previous month's figure is smaller or greater than its sample mean $\overline{REV}$ over all 20 indicators and entire sample period, respectively, and 0 otherwise. $REV_{t,n;k}$ is computed as $REV_{t,n;k} = \left| A_{t,n;k}^1 - A_{t-1,n;k} \right| / \hat{\sigma}_k^{REV}$, where $A_{t-1,n;k}$ is the previous month's announcement of indicator k, $A_{t,n;k}^1$ is its revised estimate released at the same time as $A_{t,n;k}$. The absolute difference is standardized by the standard deviation of the absolute first revisions of indicator k, $\hat{\sigma}_k^{REV}$. A macroeconomic announcement $A_{t,n;k}$ is classified as precise or imprecise if $REV_{t,n;k}$ is smaller ($D_{t,n}^{high} = 1$) or greater ($D_{t,n}^{low} = 1$) than $\overline{REV}$, respectively.

Note that when there are multiple simultaneous announcements, it is possible that both precise and imprecise news are announced at the same time. This happens, e.g., if news of two indicators k_1 and k_2 are announced simultaneously, and $REV_{t,n;k_1} < \overline{REV}$ but $REV_{t,n;k_2} > \overline{REV}$. In this case, $D_{t,n}^{high}$ and $D_{t,n}^{low}$ both take on value 1, and while $D_{t,n}^{high}$ interacts with the standardized surprise of the precise news $S_{t,n} = S_{t,n;k_1}$, $D_{t,n}^{low}$ interacts with the standardized surprise of the imprecise news $S_{t,n} = S_{t,n;k_2}$. On the other hand, if there are multiple precise (or imprecise) news released simultaneously, $S_{t,n}$ is computed as an average of the standardized surprises of different indicators k in the same category of precision (i.e., when there are for instance four simultaneous releases, two precise news announcements $S_{t,n;k_1}$ and $S_{t,n;k_2}$ and two imprecise releases $S_{t,n;k_3}$ and $S_{t,n;k_4}$, $D_{t,n}^{high}$ interacts with $S_{t,n} = \frac{1}{2} \sum_{k=1}^{2} S_{t,n;k}$ and $D_{t,n}^{low}$ interacts with $S_{t,n} = \frac{1}{2} \sum_{k=3}^{4} S_{t,n;k}$).

News announcements have been reported to have long-lasting effects on volatility. For instance, according to Andersen and Bollerslev (1998), the impact lasts from one to two hours. To allow for such prolonged effects, we have to modify model (5.4) to some extent. Specifically, following Andersen and Bollerslev

(1998), the impact of an announcement is assumed to diminish gradually and go to zero after two hours. We first estimate the average news impact pattern by computing the average absolute returns at each five-minute interval following the news announcement minus the average absolute return over the entire sample period. We then estimate the decay structure of the volatility response pattern of news by fitting a third order polynomial to the average news impact pattern. OLS estimation yields the following equation for the average absolute returns following the news announcements,

$$\lambda_m = 0.054\left(1-(m/25)^3\right) - 0.009\left(1-(m/25)^2\right)m + 0.0007\left(1-(m/25)\right)m^2 \tag{5.5}$$

where $m = 1, 2, ...25$ denotes the five-minute interval after the news announcement. The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours, as depicted in Figure 5.2. In the empirical models, the explanatory variables are hence not the news variables as such, but whenever there is an announcement, i.e., $S_{t,n} \neq 0$, in the 25 subsequent 5-minute intervals the corresponding regressor equals $\lambda_1 \times S_{t,n}$, $\lambda_2 \times S_{t,n}, ..., \lambda_{25} \times S_{t,n}$ and zero otherwise.

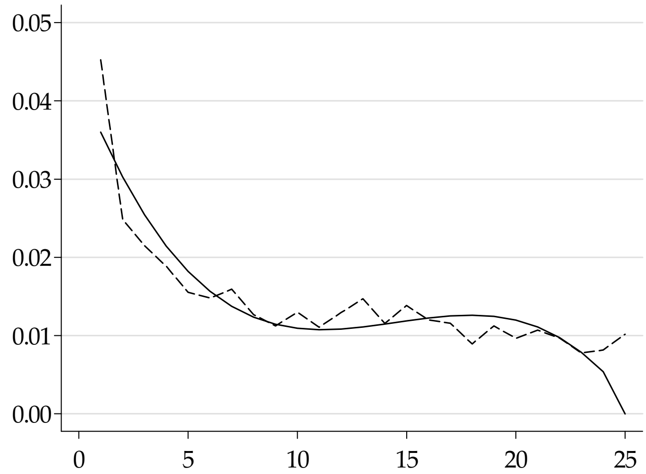

FIGURE 5.2 Decay structure of volatility response pattern after news
The figure presents the mean absolute returns after news announcements (dashed line) and the estimated news impact decay structure (solid line). Decay structure was estimated using the third order polynomial.

The third column of Table 5.3 presents the results of model (5.4). In general, both precise and imprecise news announcements increase volatility significantly. All the coefficients are positive and significant, as expected. Moreover, the news announcements that are more precise, increase volatility significantly more than imprecise ones (p-value of the Wald test for the equality of the coefficients is $2.53E-04$).

Because some indicators are typically revised a lot (e.g. nonfarm payroll) and some only a little or not at all (e.g. confidence figures), investors might take this into account and react differently to those indicators that are generally more precise than others. We study this issue by comparing investors' reactions to news on indicators for which the mean absolute revision (the first revision of the previous month's figure) over the entire sample period is smaller or greater than that of all the indicators[6]. Specifically, we consider the following model,

$$y_{t,n} = c + \phi^{h\_i} \left[S_{t,n} \times D_{t,n}^{high\_ind} \right] + \phi^{l\_i} \left[S_{t,n} \times D_{t,n}^{low\_ind} \right] + \varepsilon_{t,n} \tag{5.6}$$

where with the exception of the dummy variable, the notation is the same as in model (5.4). Dummy variables $D_{t,n}^{high\_ind}$ and $D_{t,n}^{low\_ind}$ take on value of 1 if the sample mean $\overline{REV}_k$ of the first standardized absolute revisions of indicator k is smaller or greater than the sample mean $\overline{REV}$ over all the 20 indicators, respectively, and 0 otherwise. In other words, if $\overline{REV}_k$ is smaller than $\overline{REV}$, indicator k is deemed a high-precision indicator ($D_{t,n}^{high\_ind} = 1$), and otherwise low-precision indicator ($D_{t,n}^{low\_ind} = 1$).

The results of model (5.6) are reported in the fourth column of Table 5.3. The results are very similar to those of model (5.4). Also, the releases of the macro indicators that are usually more precise increase volatility significantly more than those usually imprecise (p-value of the Wald test equals 0.006). Thus news items that are more accurate, conditionally or unconditionally, increase volatility more than inaccurate news items. This indicates that investors pay attention to the quality of news, and act more upon precise news announcements.

It is possible that both the conditional and unconditional measures of precision simultaneously affect investors' confidence in the news. To allow for both effects, we let the dummy variables interact as follows,

$$\begin{aligned} y_{t,n} = c &+ \phi^{h\_i,h} \left[S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{high} \right] + \phi^{h\_i,l} \left[S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{low} \right] \\ &+ \phi^{l\_i,h} \left[S_{t,n} \times D_{t,n}^{low\_ind} \times D_{t,n}^{high} \right] + \phi^{l\_i,l} \left[S_{t,n;k} \times D_{t,n}^{low\_ind} \times D_{t,n}^{low} \right] + \varepsilon_{t,n} \end{aligned} \tag{5.7}$$

Here, for instance, $\phi^{h\_i,l}$ gives the effect of news of a high-precision indicator k ($D_{t,n}^{high\_ind} = 1$) whose previous announcement turned out to be imprecise ($D_{t,n}^{low} = 1$). The difference between $\phi^{h\_i,h}$ and $\phi^{h\_i,l}$, on the other hand, tells us the volatility impact of the accuracy of the previous announcement for high-precision indicators, whereas $\phi^{l\_i,l} - \phi^{l\_i,h}$ is the corresponding figure for news on low-precision indicators. Hence, this model allows us to examine the interactions of conditional and unconditional precision in different ways.

The estimation results of model (5.7) and the p-values of Wald tests of some hypotheses of interest are presented in the last column of Table 5.3. The results suggest that investors take both conditional and unconditional precision simultaneously into account. In particular, while in model (5.4) we saw that the conditional measure of precision is relevant to investors such that they react signif-

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6 University of Michigan Consumer Confidence Index, ISM Manufacturing Index, Philadelphia Fed Index, Consumer Price Index, Producer Price Index, Chicago Purchasing Manager Index and Gross Domestic Product are the indicators that are on average more precise than the others.

icantly more strongly to conditionally precise news than imprecise news, this holds no more when the unconditional measure of precision is taken into account. When considering the high-precision and low-precision indicators separately, we see that investors do not react differently to conditionally precise and imprecise news (the p-values of the Wald tests of $\phi^{h\_i,h} = \phi^{h\_i,l}$ and $\phi^{l\_i,h} = \phi^{l\_i,l}$ equal 0.188 and 0.205, respectively). This might suggest that the unconditional measure of precision is more relevant to investors than the conditional measure. However, when we compare the investors' reactions to unconditionally precise and imprecise news among the conditionally precise and imprecise news, we see that also the conditional precision measure is relevant. In particular, the news on high-precision indicators increase volatility significantly more than news on low-precision indicators only when the news are conditionally precise (the p-values of the Wald tests of $\phi^{h\_i,h} = \phi^{l\_i,h}$ and $\phi^{h\_i,l} = \phi^{l\_i,l}$ equal 0.014, and 0.398, respectively.

All in all, our findings hence indicate that investors not only use the latest revision as a signal of news precision but also simultaneously take the overall accuracy of the different indicators into account. The latter effect was not considered by Hautsch and Hess (2007).

5.3.2 Ex post Measure of Precision

Investors' assessment of the precision of a news announcement is based on information available when the announcement is made. This information may include past and present revision and a measure of the overall precision of a macro indicator, as discussed above. However, investors' assessment may not be precise as a typical macroeconomic figure converges to its 'final correct' value only after a number of revisions. Therefore, it would be interesting to see whether the volatility effects differ between news announcements that are truly accurate and inaccurate. Significant differences would indicate that investors are successful in predicting the accuracy of news. Moreover, considering both ex ante and ex post accuracy simultaneously would allow for judging whether it is the first-release or 'final' values that they are trying to predict. Due to the presence of predictability of revisions documented in the previous literature (see, e.g., Swanson and Dijk (2001) and the references therein), significant volatility effects of news surprises defined by the first-release instead of 'final' figures would indicate investors' inability to take the revision process into account.

To measure ex post accuracy, we use the Philadelphia Fed data for five macro indicators: nonfarm payroll, consumer price index, housing starts, industrial production and capacity utilization, discussed in Section 2.2. To divide the news into accurate or inaccurate, we have to decide which is the proper number of revisions after which the figure has reached the 'final correct' value. According to Swanson and Dijk (2001), it takes at least 12 months for US industrial production and produces prices to reach the correct values. We define the 'final correct' value to be the one released 24 months after the first release, i.e. $A^{24}_{t+24,n;k}$.

We consider models analogous to those in Section 5.3.1. First, to study the differences in the volatility impact of ex post precise and imprecise news, we

TABLE 5.3 Estimation results

Table presents the parameter estimates of models (5.4), (5.6) and (5.7). The explanatory news variables are the standardized absolute surprises of 20 different macro indicators k. The news surprises interact with dummy variables which divide news to precise and imprecise. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively.

Variable	**Parameter**	(5.4)	(5.6)	(5.7)
$S_{t,n} \times D_{t,n}^{high}$	ϕ^h	19.42^{**} (1.14)	–	–
$S_{t,n} \times D_{t,n}^{low}$	ϕ^l	12.43^{**} (1.43)	–	–
$S_{t,n} \times D_{t,n}^{high\_ind}$	ϕ^{h_i}	–	20.24^{**} (1.21)	–
$S_{t,n} \times D_{t,n}^{low\_ind}$	ϕ^{l_i}	–	15.40^{**} (1.21)	–
$S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{high}$	$\phi^{h\_i,h}$	–	–	20.41^{**} (1.30)
$S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{low}$	$\phi^{h\_i,l}$	–	–	15.38^{**} (3.52)
$S_{t,n} \times D_{t,n}^{low\_ind} \times D_{t,n}^{high}$	$\phi^{l\_i,h}$	–	–	15.11^{**} (1.72)
$S_{t,n} \times D_{t,n}^{low\_ind} \times D_{t,n}^{low}$	$\phi^{l\_i,l}$	–	–	12.15^{**} (1.49)
Wald test, p-value				
$\phi^h = \phi^l$		$2.5E-04$	–	–
$\phi^{h\_i} = \phi^{l\_i}$		–	0.006	–
$\phi^{h\_i,h} = \phi^{h\_i,l}$		–	–	0.188
$\phi^{h\_i,h} = \phi^{l\_i,h}$		–	–	0.014
$\phi^{h\_i,h} = \phi^{l\_i,l}$		–	–	$4.06E-05$
$\phi^{h\_i,l} = \phi^{l\_i,h}$		–	–	0.946
$\phi^{h\_i,l} = \phi^{l\_i,l}$		–	–	0.398
$\phi^{l\_i,h} = \phi^{l\_i,l}$		–	–	0.205

estimate the following model

$$y_{t,n} = c + \phi^h \left[S_{t,n} \times D_{t,n}^{high\_expost} \right] + \phi^l \left[S_{t,n} \times D_{t,n}^{low\_expost} \right] + \varepsilon_{t,n} \tag{5.8}$$

where, as in the ex ante analysis, $S_{t,n}$ combines the surprises on news of all five indicators. The dummy variables $D_{t,n}^{high\_expost}$ and $D_{t,n}^{low\_expost}$ divide the news into precise and imprecise (high and low precision), respectively. An announcement $A_{t,n;k}$ is deemed precise, if its standardized absolute 'final' revision $REV_{t,n;k}^{24}$ is smaller than the sample mean of all the 'final' revisions over all five indicators and the entire sample period, denoted by $\overline{REV}^{24}$, and imprecise otherwise. $REV_{t,n;k}^{24}$ is given by $REV_{t,n;k}^{24} = \left| A_{t+24,n;k}^{24} - A_{t,n;k} \right| / \hat{\sigma}_k^{24}$, where $A_{t+24,n;k}^{24}$ is the 'final correct' value of macro figure $A_{t,n;k}$, released 24 months after the first release. $\hat{\sigma}_k^{24}$ is the standard deviation of the absolute 'final' revisions of indicator k. If $REV_{t,n;k}^{24}$ is smaller than the sample mean $\overline{REV}^{24}$ ($D_{t,n}^{high\_expost} = 1$), news is classified precise, and otherwise ($D_{t,n}^{low\_expost} = 1$) imprecise[7]. Hence, model (5.8) facilitates studying whether truly accurate news has an impact different from that of inaccurate news. If also ex post more precise news announcements turn out to have a greater impact on volatility, it indicates that the signals investors use to infer the accuracy of news indeed are useful.

Model (5.8) is corresponding to model (5.4) in the previous subsection, and by comparing the results of these two models we can see whether the ex ante and ex post measures of precision yield different results. The coefficient estimates and some test results are presented in the third column of Table 5.4. As can be seen from the results of model (5.8), the coefficient estimates are very similar when using the different definitions of the precision. The estimated coefficient of the precise news is greater than that of the imprecise news in each case, although the difference is not statistically significant.

As pointed out above, the results in Table 5.4 are based on only five macro indicators, while the data set used in Subsection 5.3.1 contains 20 indicators. As a robustness check, we estimated also model (5.4) with the same subset of macro indicators that is used in estimating model (5.8). We found that also in that case the coefficient of precise news is greater than the coefficient of imprecise news, but the difference is not statistically significant (p-value = 0.600). It seems that ignoring the majority of the news announcements leads to greater standard errors, causing nonrejection in the Wald test. This suggests that had we estimated model (5.8) with the data set containing the 20 indicators, we could have found significant differences also with the ex post measures of precision.

So far, we have implicitly assumed that investors try to predict the (potentially false) first release of a macroeconomic indicator, as the news surprise has been defined in terms of that figure and the market forecast. However, another possibility is that they are actually predicting the 'final' value, taking the revision process into account. To find out about the investors' expectations formation, let us consider new surprises defined in terms of the 'final' value instead of the first release. In other words, we define the news surprise as the standardized absolute difference between the 'final' figure $A_{t+24,n;k}^{24}$ and the market expectation $F_{t,n;k}$, i.e. $\tilde{S}_{t,n;k} = \left| A_{t+24,n;k}^{24} - F_{t,n;k} \right| / \hat{\sigma}_k^{\tilde{S}}$, where $\hat{\sigma}_k^{\tilde{S}}$ is the standard deviation of the absolute surprise of indicator k. As in the previous analysis, $\tilde{S}_{t,n}$ combine the surprises of news of all five indicators. As a first step, we estimate the following model,

$$y_{t,n} = c + \phi^{h\_\tilde{S}} \left[\tilde{S}_{t,n} \times D_{t,n}^{high\_expost} \right] + \phi^{l\_\tilde{S}} \left[\tilde{S}_{t,n} \times D_{t,n}^{low\_expost} \right] + \varepsilon_{t,n}, \qquad (5.9)$$

where regardless of the news surprise $\tilde{S}_{t,n}$, everything else is the same as in model (5.8). The estimation results can be compared to those of model (5.8) to see whether the news effects are similar irrespective of the definition of the news surprise. The results of the model (5.9) are reported in the fourth column of Table 5.4. As can be seen from the results of models (5.8) and (5.9), the coefficient estimates are very similar when using the different definitions for the news surprise.

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[7] Note that similarly to ex ante analysis, the dummy variables may take on a value of one simultaneously if there are multiple announcements at the same time of both precise and imprecise indicators.

Next, to examine the relative importance of the first release and the 'final' figure to investors, we include news variables based on both in the following model,

$$
\begin{aligned}
y_{t,n} = c + \phi^{h}\left[S_{t,n} \times D_{t,n}^{high\_expost}\right] + \phi^{l}\left[S_{t,n} \times D_{t,n}^{low\_expost}\right] \\
+ \phi^{h\_\tilde{S}}\left[\tilde{S}_{t,n} \times D_{t,n}^{high\_expost}\right] + \phi^{l\_\tilde{S}}\left[\tilde{S}_{t,n} \times D_{t,n}^{low\_expost}\right] + \varepsilon_{t,n}
\end{aligned} \tag{5.10}
$$

The significance of ϕ^{h} and ϕ^{l} and insignificance of $\phi^{h\_\tilde{S}}$ and $\phi^{l\_\tilde{S}}$ would indicate that investors attempt to predict the first release instead of the final figures, and vice versa. The results of model (5.10) are presented if the last column of Table 5.4, and they suggest that investors are trying to predict the first release rather than the 'final' figure. Here, only the coefficients of the news variables based on surprise $S_{t,n;k}$ are statistically significant. This suggests that rather than the difference between the 'final correct' value $A_{t+24,n;k}^{24}$ and the forecast $F_{t,n;k}$, the unanticipated information that investors react to, is the difference between the first release of the figure $A_{t,n;k}$ and the forecast $F_{t,n;k}$.

As discussed above, if the ex ante measure provides a good signal of the actual accuracy of a news released that is revealed only later, this could explain the similarity of the results based on ex ante and ex post measure. To study this, we examined whether the ex ante and ex post measures of revision indeed produce similar categories of precise and imprecise news. With the ex post measure of precision, 170 news announcements were classified as precise and 146 announcements as imprecise. Out of the 170 precise announcements, 106 were classified as precise by the ex ante measure of precision. The same ratio of imprecise news was 64 out of 146. So, roughly 60% percent of the precise news and 45% of the imprecise news were classified to the same category regardless of the precision measure. Thus, the ex ante measure of precision gives quite a good approximation to the "true" precision of news.

5.4 Conclusion

In this essay, we study the relevance of the accuracy of news announcements for their impact on the volatility of the EUR/USD exchange rate returns. The sample comprises the five-minute returns from 1999 until 2004, and the news data consists of the announcements of 20 different US macroeconomic indicators.

We define the accuracy of news by both conditional and unconditional measures. Following Hautsch and Hess (2007), in the conditional analysis, we assume that investors use the size of the revision of the previous month's figure as a signal of the precision of the current announcement. More precise news announcements turn out to increase exchange rate volatility significantly more than imprecise announcements. In the unconditional analysis, we examine whether the volatility impact of a news announcement depends on the overall accuracy of an indicator, defined in terms of the average size of its revisions. We find that the announcements of high-precision indicators increase volatility significantly more

TABLE 5.4 Estimation Results

Table presents the parameter estimates of models (5.8), (5.9) and (5.10). We assume that the estimate of a macro figure has reach to its 'correct' value $A^{24}_{t+24,n;k}$ after revising it 24 months. Two alternative definitions for the news surprise is considered. In model (5.8) it is assumed that investors try to forecast the first estimate of a macro figure $A_{t,n;k}$, while in model (5.9) investors try to estimate the 'correct' figure $A^{24}_{t+24,n;k}$. The news surprises interact with dummy variables, which divide the news to precise and imprecise ex post. In model (5.10) both definitions of news surprises are included to model to see for which one of them the investors react to. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively.

Variable	**Parameter**	(5.8)	(5.9)	(5.10)
$S_{t,n} \times D^{expost\_high}_{t,n}$	ϕ^h	18.88^{**} (2.95)	–	15.83^{**} (6.06)
$S_{t,n} \times D^{expost\_low}_{t,n}$	ϕ^l	12.76^{**} (3.03)	–	8.48^{*} (3.89)
$\tilde{S}_{t,n} \times D^{expost\_high}_{t,n}$	$\phi^{h\_\tilde{S}}$	–	18.68^{**} (3.31)	2.67 (6.81)
$\tilde{S}_{t,n} \times D^{expost\_low}_{t,n}$	$\phi^{l\_\tilde{S}}$	–	12.41^{**} (2.79)	6.09 (3.76)
Wald test, p-value				
$\phi^h = \phi^l$		0.194	–	0.340
$\phi^{h\_\tilde{S}} = \phi^{l\_\tilde{S}}$		–	0.183	0.672
$\phi^h = \phi^l = 0$		–	–	$2.59E-04$
$\phi^{h\_\tilde{S}} = \phi^{l\_\tilde{S}} = 0$		–	–	0.241

than those of low-precision indicators.

Finally, when considering the conditional and unconditional measures of accuracy simultaneously, we find that both measures are to some extent relevant in terms of the impact of news on volatility. News on the high-precision indicators increase volatility significantly more than news on low-precision indicators only when the announcement is also conditionally precise. Hence, the conditional measure of precision seems relevant. On the other hand, when considering the high-precision and low-precision indicators separately, we find no difference in the reactions to conditionally precise and imprecise news. This indicates that the size of the revision of the previous month's figure is not the only signal the investors are using.

We complement the ex ante analysis by measuring the precision of news in terms of the 'final correct' figure that only became available after a great number of revisions. To this end, we use the real time data set of the Federal Reserve Bank of Philadelphia, which contains all the revisions of a subset of five macroeconomic indicators. This data set allows us to define an ex post measure of precision as the absolute standardized difference between the final and first-release figures. Our results suggest that the news precise ex post increases volatility more than imprecise news, but the difference is not statistically significant at conventional significance levels. This may be due to fact that because of data limitations, only five indicators are included in the ex post analysis. The real-time data is also used for examining whether investors are capable of taking the revision process into account. When news surprises defined in terms of both first-release and the 'final' figures are included in the same regression model, only the former turn out to have significant volatility effects. This suggests that investors are actually attempting to predict the first-release figures instead of the correct final figures.

REFERENCES

Andersen, T., Bollerslev, T., (1997) "Intraday periodicity and volatility persistence in financial markets" Journal of Empirical Finance 4, 115-158

Andersen, T., Bollerslev, T., (1998) "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies" The Journal of Finance 53, 219-265

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2003) "Micro Effects and Macro Announcements: Real-Time Price Discovery in Foreign Exchange" American Economic Review 93, 38-62

Andersen T., Bollerslev, T., Diebold, F., Vega, C., (2007) "Real-Time Price Discovery in Stock, Bond and Foreign Exchange Markets" Journal of International Economics 73, 251-277

Bauwens, L., Ben Omrane, W., Giot, P., (2005) "News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market" Journal of International Money and Finance 24, 1108-1125

Degennaro, R., Shrieves, R., (1997) "Public information releases, private information arrival and volatility in the foreign exchange market" Journal of Empirical Finance 4, 295–315

Dominguez, K., Panthaki, F., (2006) "What defines 'news' in foreign exchange markets?" Journal of International Money and Finance 25, 168-198

Hautsch, N., Hess, D., (2007) "Bayesian Learning in Financial Markets: Testing for the Relevance of Information Precision in Price Discovery" Journal of Financial and Quantitative Analysis 42

Krueger, A., Fortson, K., (2003) "Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality" Journal of the European Economic Association 1, 931-957

Laakkonen, H., (2007a) "The Impact of Macroeconomic News on Exchange Rate Volatility" Finnish Economic Papers 20, 23-40

Laakkonen, H., (2007b) "Exchange Rate Volatility, Macro Announcements and the Choice of the Intraday Seasonality Filtering Method" Bank of Finland Discussion Papers 23/2007

Swanson, N., Dijk, D., (2001) "Are statistical reporting agencies getting it right? Data rationality and business cycle asymmetry" Journal of Business & Economic Statistics 24, 24-42

Veronesi, P., (2000) "How does Information Quality Affect Stock Returns?" Journal of Finance 55, 807-837

SUMMARY IN FINNISH (YHTEENVETO)

Esseitä makrotalouden uutisten vaikutuksista valuuttakurssien volatiliteettiin

Johdanto

Yksi rahoituksen taloustieteen keskeisistä aiheista on tarkastella uuden informaation välittymistä arvopaperien hintoihin. Elektroniset kaupankäyntijärjestelmät yleistyivät 1990-luvulla ja ovat tarjonneet uusia mahdollisuuksia uutisten vaikutusten empiiriselle tutkimukselle. Parhaimmillaan aineistot kattavat kaikki markkinoilla tapahtuneet osto- ja myyntitarjoukset ja toteutuneet kaupat. Käyttämällä tällaisia tiheästi havaittuja aikasarja-aineistoja, ts. päivänsisäisiä aineistoja, voidaan tarkastella, mitä markkinoilla tapahtuu juuri silloin, kun uutinen julkaistaan. Tämä on tärkeää, koska sijoittajat reagoivat uuteen informaatioon välittömästi, eikä reaktioita välttämättä pysty erottamaan muista päivän markkinatapahtumista johtuvista liikkeistä päiväaineistoa käyttämällä.

Valuuttamarkkinat ovat maailman suurimmat ja nopeasti kehittyvät markkinat, joiden dynamiikan ymmärtäminen on tärkeää mm. sijoittajille, rahoitusinstituutioille ja talouspoliittisille päättäjille. Tämä vaitöskirjatutkimus tarkastelee uutisten vaikutusta valuutakurssin volatiliteettiin lyhyellä aikavälillä keskittyen erilaisiin epäsymmetrisyyksiin erilaisten uutisten välillä. Aineistona käytetään viiden minuutin välein havaittua euron ja USA:n dollarin välistä valuuttakurssia vuosilta 1999 - 2004 ja uutisina USA:n, Japanin, Ison-Britannian ja euroalueen makrotalouden tunnuslukuja (esim. bruttokansantuote, kuluttajien luottamusindeksi, työttömyysindeksi).

Tutkimus koostuu neljästä esseestä. Ensimmäisessä tutkitaan, miten uutisten vaikutuksesta saatavat empiiriset tulokset riippuvat tutkimuksessa käytetystä ekonometrisestä menetelmästä, jolla aineistosta poistetaan päivänsisäisiä kausivaihteluita. Kolmessa muussa esseessä tutkitaan eri tavoin uutisten mahdollisia epäsymmetrisiä vaikutuksia valuuttakurssin volatiliteettiin. Toisessa esseessä tarkastellaan eroja positiivisten ja negatiivisten uutisten vaikutusten välillä. Kolmannessa esseessä taas puolestaan tutkitaan, onko uutisten vaikutus erilainen talouden nousu- ja laskusuhdanteissa. Neljännessä esseessä tarkastellaan uutisten vaikutuksen riippuvuutta uutisten tarkkuuteen. Varsinaisia tutkimuksia edeltää johdantoluku, joka esittelee tutkimusten kysymyksiin liittyviä talousteoreettisia lähtökohtia ja aiheeseen liittyvää kirjallisuutta.

1. Essee

Vuorokauden ympäri avoinna olevat valuuttamarkkinat ovat aktiivisimmillaan USA:n ja Euroopan markkinoiden aukioloaikoina, jolloin myös volatiliteetti on keskimäärin voimakkaampaa kuin muina vuorokauden aikoina. Kun markkinoiden aukioloajoista johtuvat vaihtelut toistuvat päivästä toiseen, siitä aiheutuu volatiliteetin aikasarjaan päivänsisäisiä kausivaihteluita, jotka näkyvät U:n muotoisena päivittäin toistuvana autokorrelaatiorakenteena. Markkinoiden aukioloajoista johtuvat erot volatiliteetin tasossa täytyy filtteröidä (puhdistaa) aineistosta, jotta uutisten vaikutukset volatiliteettiin pystytään identifioimaan. Mikäli aineistoa ei filtteröidä, ei ole selvää, johtuuko volatiliteetin muutos uutisen julkaisemisesta vai siitä, että volatiliteetti on muutenkin keskimäärin voimakkaampaa siihen aikaan päivästä, jolloin uutinen julkaistaan.

Tiheästi havaittujen päivänsisäisten aineistojen käyttö on nykyään yleistä empiirisissä tutkimuksissa, minkä vuoksi myös erilaisten filtteröintimenetelmien kehittäminen on ollut aktiivista. On kuitenkin mahdollista, että volatiliteetin filtteröinnissä käytetyt menetelmät eivät välttämättä suoriudu tehtävästään hyvin. Filtteröinti ei välttämättä poista päivänsisäistä kausivaihtelua kokonaan tai saattaa poistaa sen lisäksi myös jotain muuta (esimerkiksi uutisten vaikutuksia). On myös mahdollista, että filtteröinti muodostaa aineistoon uusia piirteitä (esimerkiksi poikkeuksellisen suuria tai pieniä havaintoja), jotka saattavat tuottaa mittavirhettä ja johtaa virheelliseen päättelyyn siitä, kuinka suuri vaikutus uutisilla on volatiliteettiin.

Ensimmäisessä esseessä tarkastellaan päivänsisäisen kausivaihtelun puhdistusmenetelmien eroja ja tutkitaan, miten erilaiset filtteröintimenetelmät vaikuttavat uutisten vaikutuksesta saatuihin tilastollisiin tuloksiin. Menetelmien eroja tutkitaan sekä empiirisesti että simulointikokeiden perusteella, ja tulosten mukaan niiden välillä voi olla suuriakin eroja. Tärkein havainto on, että kaikki menetelmät poistavat kausivaihtelun volatiliteetista vain, jos aikasarja filtteröidään jaksottain (esimerkiksi kaikki aineiston vuodet erikseen). Tulos viittaa siihen, että volatiliteetin kausivaihtelu muuttuu ajassa, koska eri jaksoille estimoitu kausivaihtelu on parempi sovite havaitulle kausivaihtelulle kuin koko aineistolle kerrallaan estimoitu kausivaihtelu. Lisäksi sekä filtteröintimenetelmä että estimoinnissa käytettyjen periodien pituus vaikuttavat selvästi uutisten vaikutusta kuvaavien kertoimien estimaattien suuruuteen. Koska tutkija itse päättää molemmat näistä, on asiaan kiinnitettävä huomiota luotettavien tulosten takaamiseksi. Simulointikokeen tulokset taas paljastavat, että kaikki käytetyt menetelmät tuottavat alaspäin harhaisia estimaatteja uutisten vaikutusten kertoimiin. Harhan suuruus riippuu kuitenkin jonkin verran käytetystä menetelmästä, ja harhan pienuuden perusteella tulokset suosivat Flexible Fourier Form -menetelmää kolmen vertailtavan filtteröintimenetelmän joukosta.

2. Essee

Toisessa esseessä tutkitaan eri maiden makrotalouden uutisten vaikutusta euron ja USA:n dollarin välisen valuuttakurssin volatiliteettiin. Tulosten mukaan USA:n makrotalouden uutisten vaikutus EUR/USD valuuttakurssin volatiliteettiin on huomattavasti voimakkaampi kuin euroalueen uutisten vaikutus. Euroalueen maiden makrotalouden uutisten vaikutuksen suuruus seuraa aika tarkasti maan taloudellista kokoa: mitä suurempi maa, sitä voimakkaampi vaikutus sen uutisilla on. Euroalueen suurimpien maiden (Saksan ja Ranskan) makrotalouden uutisilla on jopa suurempi vaikutus EUR/USD volatiliteettiin kuin makroluvuilla, jotka kuvaavat koko euroalueen talouden tilaa yhteensä, kun taas pienimpien maiden (Suomen ja Irlannin) makrotalouden uutisilla ei ole tilastollisesti merkittävää vaikutusta volatiliteettiin. Ison-Britannian makrotalouden uutisilla on yhtä suuri vaikutus EUR/USD volatiliteettiin kuin suurimpien euroalueen maiden uutisilla, kun taas Japanin makrotalouden tilaa kuvaavat luvut eivät vaikuta EUR/USD volatiliteettiin tilastollisesti merkitsevästi.

Tutkimuksessa tarkastellaan lisäksi erilaisia epäsymmetrisyyksiä positiivisten ja negatiivisten uutisten vaikutuksissa. Positiivisten ja negatiivisten uutisten vaikutusten eroja on tutkittu kirjallisuudessa runsaasti, mutta empiiriset tulokset näyttävät kuitenkin olevan jonkin verran ristiriitaisia. Osassa tutkimuksista on havaittu, että negatiivisilla uutisilla on voimakkaampi vaikutus valuuttakurssien volatiliteettiin kuin positiivisilla uutisilla, kun taas toisissa tutkimuksissa tällaista epäsymmetriaa ei ole havaittu.

Tutkimuksen yksi keskeisin tulos on, että positiivisten ja negatiivisten uutisten vaikutusten välillä ei ole eroja, mutta mikäli markkinoille tulee yhtä aikaa sekä positiivisia että negatiivisia uutisia, on vaikutus volatiliteettiin merkittävästi suurempi kuin siinä tapauksessa, että markkinoille tulee pelkästään positiivisia tai negatiivisia uutisia. Tämän epäillään johtuvan siitä, että sijoittajien on vaikea päätellä onko uutisten yhteisvaikutus valuuttakurssin arvoon positiivinen vai negatiivinen, mikäli talouden indikaattorit antavat ristiriitaisia signaaleja talouden tilasta. Volatiliteetin nousu voisi tietysti johtua myös pelkästään siitä, että kaupankäynti lisääntyy voimakkaasti silloin kun uutisia julkaistaan useampi kerrallaan. Tutkimuksessa havaittiin kuitenkin myös, että volatiliteetti kasvaa enemmän siinä tapauksessa, että julkaistaan pelkästään yksi makrotalouden uutinen kuin silloin, kun markkinoille tulee yhtä aikaa useampi kuin yksi uutinen ja kaikki uutiset ovat samansuuntaisia (joko positiivisia tai negatiivisia). Tämä viittaisi siihen, että uutisten vaikutus volatiliteettiin ei riipu niinkään uutisten määrästä, vaan ennemmin signaalin selkeydestä, ja näin ollen volatiliteettia aiheuttaa ennemmin markkinoilla kohonnut epävarmuus kuin uuden informaation johdosta lisääntynyt kaupankäyntivolyymi.

3. Essee

Kolmannessa esseessä jatketaan positiivisten ja negatiivisten uutisten vaikutusten erojen tarkastelua tutkimalla ovatko vaikutukset erilaiset taloussuhdanteiden eri vaiheissa. Talouden tilan mittarina käytetään kahta indeksiä: Saksan IFO (Information und Forshung) -indeksiä ja USA:n teollisuuden ISM (Institute for Supply Management) -indeksiä, jotka ovat kyselytutkimuksiin perustuvia teollisuuden ja liike-elämän tilaa kuvaavia indeksejä. Tulosten mukaan uutisten vaikutus volatiliteettiin on voimakkaampi talouden "hyvinä" aikoina kuin "huonoina" aikoina. Lisäksi, negatiiviset uutiset vaikuttavat "hyvinä" aikoina voimakkaammin kuin "huonoina" aikoina, kun taas positiivisten uutisten kohdalla tällaista eroa ei havaita.

Havaitun kaltaista epäsymmetrisyyttä uutisten vaikutuksessa selitetään teoriakirjallisuudessa sijoittajien halulla turvautua talouden tilan epävarmuudelta. Sijoittajat vaativat preemion arvopaperin hintaan suojaamaan talouden tilan epävarmuudelta, joka johtaa sijoittajien ylireagoimiseen huonoihin uutisiin hyvinä aikoina ja alireagoimiseen hyviin uutisiin huonoina aikoina. Jos sijoittaja olettaa talouden tilan olevan huono, mutta markkinoille tuleekin hyviä uutisia, ei sijoittaja suostu maksamaan arvopaperista niin paljon korkeampaa hintaa kuin sen arvo oikeasti olisi hyvien uutisten jälkeen. Hintaa laskee sijoittajan vaatima preemio lisääntyneestä epävarmuudesta talouden oletustilaan nähden ristiriitaisten uutisten jälkeen. Jos sijoittaja toisaalta uskoo talouden tilan olevan hyvä, mutta uutiset ovat negatiivisia, laskee arvopaperin hinta enemmän kuin sen todellinen arvo laskisi pelkän huonon uutisen vuoksi. Syynä tähän on se, että arvon laskemisen lisäksi sijoittaja vaatii jälleen preemion talouden epävarmuutta vastaan, koska ei negatiivisten uutisten jälkeen olekaan enää varma talouden tilan hyvyydestä.

4. Essee

Makrotalouden tunnuslukujen erityispiirre muihin markkinauutisiin verrattuna on, että niiden ensimmäiset julkaisut ovat tyypillisesti vasta arvioita todellisesta arvosta. Tarkat arvot voidaan laskea usein vasta monen kuukauden tai joskus jopa vuosien kuluttua, ja lopulliset tarkat luvut poikkeavat monesti huomattavastikin ensimmäisistä arvioista. Uusia arvioita luvuista julkaistaan kuukausittain (tai neljännesvuosittain riippuen indikaattorista) ja edellisten kuukausien lukujen uudet arviot julkaistaan yleensä yhtä aikaa kuin kuluvan kuukauden luvun ensimmäinen arvio. Väitöskirjan neljännessä esseessä tarkastellaan, riippuuko sijoittajien reaktiot uutisiin siitä, ovatko ne tarkkoja vai epätarkkoja.

Tarkkuutta mitataan kolmella tavalla, joista ensimmäisessä uutisen tarkkuus määritellään sen perusteella, onko edellisen kuukauden luvun ensimmäisen arvion ja ensimmäisen revisioidun luvun välinen erotus (ensimmäinen revisio) pienempi vai suurempi kuin koko aineiston ensimmäisten revisioiden keskiarvo. Tämän mittarin oletetaan toimivan signaalina tarkkuudesta sijoittajille siksi, että revisioiden on todettu olevan jossain määrin ennustettavissa. Mikäli edellisen kuukauden työttömyysindeksi osoittautuu epätarkaksi (ensimmäinen revisio suuri), voi tämä siis indikoida kuluvan kuukauden työttömyysindeksin arvon olevan epätarkka. Joidenkin indikaattoreiden lukuja revisioidaan yleensä huomattavasti, kun taas toisia ei välttämättä juuri ollenkaan. Sijoittajat saattavat ottaa tämän huomioon reagoidessaan uutisiin, minkä vuoksi toisessa tavassa mitata tarkkuutta jaotellaan indikaattorit yleisesti ottaen epätarkoiksi ja tarkoiksi. Jos työttömyysindeksin ensimmäisten revisioiden keskiarvo on esimerkiksi pienempi kuin aineiston kaikkien uutisten ensimmäisten revisioiden keskiarvo, määritellään kaikki työttömyysindeksistä julkaistut uutiset tarkaksi. Vaikka edellisen kuukauden luvun ensimmäisen revision suuruus voi olla hyvä signaali sijoittajalle kuluvan kuukauden uutisen tarkkuudesta, ei se kuitenkaan kerro oikeasti, onko kuluvan kuukauden julkaistu luku tarkka vai ei. Näin ollen kolmantena tarkkuuden mittarina tutkimuksessa käytetään ns. "todellista" tarkkuutta. Makrotalouden indikaattorin todellisen arvon arvioidaan olevan tiedossa kahden vuoden kuluttua ensimmäisen arvion julkaisemisesta, joten uutinen määritellään tarkaksi, mikäli ensimmäisen arvion ja kahden vuoden jälkeisen revisioidun luvun välinen erotus on pienempi kuin kaikkien uutisten lopullinen revisio keskimäärin.

Tulosten mukaan tarkat uutiset kohottavat volatiliteettia merkitsevästi enemmän kuin epätarkat uutiset riippumatta käytetystä tarkkuuden mittarista. Tämän oletetaan johtuvan siitä, että tarkat uutiset lisäävät kaupankäyntiä enemmän kuin epätarkat uutiset ja sitä kautta kohottavat myös volatiliteettia enemmän. Koska tulokset ovat samansuuntaiset käytettäessä tarkkuuden mittarina ensimmäistä revisiota ja "todellista" tarkkuutta, vaikuttaa edellisen kuukauden luvun ensimmäinen revisio toimivan hyvänä signaalina "todelliselle" uutisen tarkkuudelle.