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Abstract

We study the impact of positive and negative macroeconomic US and European news announcements in different phases of the business cycle on the high-frequency volatility of the EUR/USD exchange rate. The results suggest that in general bad news increases volatility more than good news. The news effects also depend on the state of the economy: bad news increases volatility more in good times than in bad times, while there is no difference between the volatility effects of good news in bad and good times.

JEL Classification: F31, G15, C32.

Keywords: Volatility, News, Nonlinearity, Smooth Transition Models.

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1 Introduction

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 (DeGennaro and Schrieves (1997), Andersen et al. (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006) among others) has shown that news concerning macroeconomic fundamentals increases volatility right after the announcement and, therefore, can partly explain high price volatility.

Recently, there has been active research that tries to shed light on the relationship between the impact of macroeconomic news on financial markets 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 stock market. In general, the 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 addition to stock markets, business cycle effects have been studied by Veredas (2006) in the bond futures market and Faust et al. (2007) and Pearce and Solakoglu (2007) in the foreign exchange market. The findings of Veredas (2006) are in line with the results from equity market, but the findings of Faust et al. (2007) and Pearce and Solakoglu (2007) are not as strong: Faust et al. (2007) find only limited evidence on the state dependence of news effects while Pearce and Solakoglu (2007) find some evidence that the news effects depend on the state of the economy, but do not find asymmetries in the impact of positive and negative news.

In this paper, we study the relationship between the impact of positive and negative macroeconomic news on exchange rate volatility and the state of the business cycle. Our paper contributes to the literature in many 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, which is more comprehensive compared to the ones used in earlier studies. In particular, the news data set includes all the macroeconomic announcements from the USA and all the euro countries obtained from Bloomberg WECO (World economic calendar). Furthermore, besides considering the US business cycle, we study the asymmetries using the 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).

The methodology that we use is more flexible than the ones used in the earlier literature. Most of the 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 then fixing some intervals around the trend, while Andersen et al. (2007) define contractions as beginning when there are three consecutive monthly declines in nonfarm payroll employment. On the other hand, Veredas (2006) 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. We estimate the state dependence in the news effects by using a smooth transition regression model. The main advantage of our approach is that the threshold between the different states is not fixed a priori, but estimated endogenously. Moreover, the model allows the change from one regime (bad times) to another (good times) to be smooth. Therefore, splitting the data beforehand into fixed regimes such as good and bad times is not necessary. Furthermore, the model can be generalized to allow for more than two regimes in a straightforward manner.

We find that in general, macro news do increase volatility significantly, and negative news increase volatility more than positive news. 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. Also, 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. 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 about 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 paper is as follows. Section 2 reviews the related literature and Section 3 describes the data and methodology. The results of the empirical study are presented in Section 4 and Section 5 concludes.

2 News effects and business cycles

The impact of news on exchange rate dynamics has been studied extensively in the recent decades¹. 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 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 headlines of financial newspapers have been studied (for example, by Chan et al., 2001). The results indicate that news causes a jump in the level of the exchange rate and increases the volatility of re-

¹The literature includes DeGennaro and Schrieves (1997), Almeida, Goodhart and Payne (1998), Eddelbütten and McCurdy (1998), Melvin and Yin (2000), Andersen et al. (2003), Chang and Taylor (2003), Bauwens et al. (2005), Dominquez and Panthaki (2006), Laakkonen (2007a) among others.

turns from one hour to two hours after the arrival of information (Andersen and Bollerslev, 1998). The most important macroeconomic announcement seems to be the monthly employment report of the USA (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 theoretically addressed by Veronesi (1999), who suggests 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: "low" meaning recessions and "high" meaning expansions. The investor has to solve the problem of determining the probability $\pi(t)$ of the economy being in the high state (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 arrive, 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 arrive, the expected future asset value increases. However, since the uncertainty $\pi(t)$ increases as well, the price does not increase as much as without the additional uncertainty about the future state of the economy².

While the asymmetries between negative and positive news been examined quite a lot (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. One of the first empirical studies uncovering the state dependence in the news effects was the one of McQueen and Roley (1993). McQueen and Roley (1993) study the effect of macro news on the S&P 500 price movements and measure the business cycle with industrial production³. The levels of 'high', 'medium' and 'low' economic activity are determined by estimating a trend and then fixing certain intervals around the trend. McQueen and Roley (1993) found that good news results in lower stock prices when the state of the economy is 'high', whereas the same surprise in a weak economy is associated with higher stock prices and state that the explanation for this might be the expected cash flows. Positive news in bad times raise expectations about future economic activity and cash flows, but this same information in good times does not lead to higher expected cash flows. The findings of Flannery and Protopapadakis (2002)

²Veronesi's theory concentrates on the impact of news on returns, but we think it can be incorporated also to news effects on volatility due to the positive risk-return relationship derived from Merton's (1973) Intertemporal Capital Asset Pricing Model. See Lanne and Saikkonen (2006) discussion concerning the empirical evidence for the risk-return tradeoff.

³They also did robustness checks by using the capacity utilization and unemployment rate as business cycle indicators.

and Adams et al. (2004) are similar. Flannery and Protopapadakis (2002) use the NYSE-AMEX-NASD market index and find that macro information matters more in times of high economic activity than in the other states of the economy. Adams et al. (2004) use the intraday stock index data and study the effect of PPI and CPI on stock returns and find that the news response is strong when the economy is strong and when the news is bad.

The more recent papers often study different assets simultaneously. Boyd et al. (2005) study the impact of unemployment news on the daily S&P 500 stock index and bond prices, and define the state of the economy by using the NBER business cycle definitions. The results of Boyd et al. (2005) suggest that an announcement of rising unemployment is good news for stocks during economic expansions and bad news during economic contractions. On the other hand, Boyd et al. (2005) find that bond prices rise when there is bad unemployment news during expansions, but do not respond significantly during recessions. The authors hypothesize that higher unemployment predicts lower interest rates and lower corporate profits, and conclude that the relative importance of these two effects vary over the business cycle, explaining the empirical findings. Andersen et al. (2007) present very similar findings. They also study a broad set of asset classes, but also use the assets from different countries. The main results of the study are that bond markets do not react news state dependently but stock markets do: good macro news has positive impact in recessions, but negative impact in expansions. Andersen et al. (2007) state that this leads to different stock-bond correlation across the business cycle: during expansions the stock-bond correlations are small and positive, during contractions they are large and negative. Faust et al. (2007) study the joint movements of exchange rates and US and foreign term structures around the macro news announcements, but find only little evidence of time-variation in responses.

The studies that are more similar to ours in that they focus on the asymmetric reactions to positive and negative news in the different phases of the business cycle are the ones of Conrad et al. (2002), Veredas (2006) and Pearce and Solakoglu (2007). Conrad et al. (2002) studied the asymmetries in the case of stock markets albeit concentrating on the state of the stock market rather than business cycles. They examined the impact of earnings announcements on individual stocks, and concluded that the markets react more strongly to bad news in good times while the reaction to good news is not greater in bad times than in good times. Veredas (2006) used US Treasury ten-year bond futures and 15 macroeconomic fundamentals and ISM index as a proxy for business cycle. His findings are very similar to those of Conrad et al. (2002): bad news has a stronger effect in good times than in bad times, and good news has little effect in bad times. Therefore, the results of both of the papers are somewhat supportive of Veronesi (1999). The closest to ours is the recent paper by Pearce and Solakoglu (2007), where they use ten years (1986-1996) of DEM/USD and JPY/USD data to examine the news effects on mean return and volatility. Pearce and Solakoglu (2007) follow McQueen and Roley (1993) in defining the regimes and find that there was evidence that the responses to some news events depend on the state of the economy, and even more evidence

that volatility effects were state dependent. However, they did not find any clear pattern that news responses would be stronger in the good or bad times: some news items had greater impact in the low state, and some news items in the high state. Also, Pearce and Solakoglu (2007) state that the estimated effects of news appeared to be symmetric with respect to sign.

3 Data and Methodology

3.1 Exchange Rate Data

The original data set contains 5-minute quotes⁴ of the EUR/USD (Euro against United States Dollar) exchange rate from 1st January 1999 to 31st December 2004 and it has been 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 differences of logarithmic prices. The return series is depicted in Figure 1.

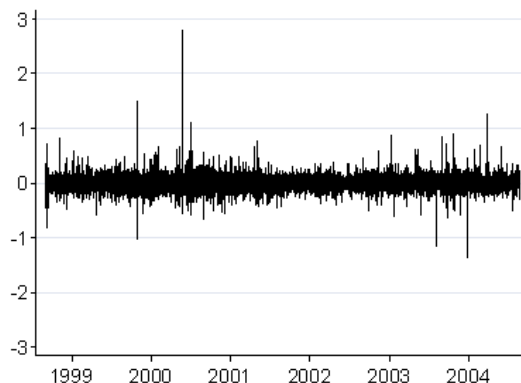


Figure 1 5-minute EUR/USD returns from 1 Jan 1999 to 31 Dec 2004

As the activity in the foreign exchange market 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 the holidays, three days are excluded from

⁴According to many studies, the 5-minute returns strike the best balance between the disadvantages of the microstructure noise (when sampling too frequently) and losing important information (when sampling too infrequently). See the discussion e.g. in Andersen et al. (2007).

the data because of lack of observations. The 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 different trading times in the global 24-hour foreign exchange markets. This has to be taken into account in modeling the news effects. Of the alternative models of filtering the periodicity, we chose the Flexible Fourier Form (FFF) model method 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.

The idea behind the method is that the volatility of the return process $R_{t,n}$ is measured by the demeaned absolute returns, and it can be decomposed into the daily volatility component σ_t , the intraday volatility component $s_{t,n}$ and the *innovation* $Z_{t,n}$:⁵

$$|R_{t,n} - E(R_{t,n})| = \frac{\sigma_t}{N^{1/2}} s_{t,n} Z_{t,n} \quad (1)$$

The expected return $E(R_{t,n})$ is then estimated by the mean return \bar{R} and the daily volatility component is eliminated by dividing the left hand side by $\frac{\hat{\sigma}_t}{N^{1/2}}$, where $\hat{\sigma}_t$ is the GARCH(1,1) estimate of daily volatility. After replacing the expected return by mean return, eliminating the daily component, squaring and taking logs, equation (1) becomes

$$2 \ln \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}} = 2 \ln(s_{t,n}) + 2 \ln(Z_{t,n}) \quad (2)$$

There are two components on the right-hand side of equation (2). The first component means intraday volatility, which will be modeled using trigonometric functions; and the other component is the *innovation* $Z_{t,n}$, which includes the rest of the volatility in the markets, such as the volatility caused by new information. The FFF regression model is

$$\begin{aligned} f_{t,n} = & \alpha + \delta_1 \frac{n}{N_1} + \delta_2 \frac{n^2}{N_2} + \sum_{k=1}^D \lambda_k I_k(t, n) \\ & + \sum_{p=1}^P \left(\delta_{c,p} \cos \left(\frac{p2\pi}{N} n \right) + \delta_{s,p} \sin \left(\frac{p2\pi}{N} n \right) \right) + \varepsilon_{t,n}, \end{aligned} \quad (3)$$

⁵In the equations t denotes day and n the 5-minute interval. N denotes the number of 5-minute intervals during one day (288 in the 24 hour market).

where $f_{t,n} = 2 \ln \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. Besides the sinusoids⁶, the model contains the intercept α and the normalizing factors $\frac{n}{N_1}$ and $\frac{n^2}{N_2}$, where $N_1 = (N + 1)/2$ and $N_2 = (N + 1)(N + 2)/6$. The model also contains the indicator variables $I_k(t, n)$. These variables are used to control for holiday effects, weekday effects, Monday effects etc. and $\varepsilon_{t,n}$ is the error term of the model. 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 of the model (3). This estimate $\hat{s}_{t,n}$ is normalized so that the mean of the normalized seasonality estimate equals one: $\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{\lfloor T/N \rfloor} \sum_{n=1}^N \hat{s}_{t,n}}$ where T is the number of observations in the whole 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 (1998) for further details of the method.

If the intraday periodicity pattern is assumed to stay constant over the data sample, the FFF model is estimated for the entire data set at once. Unfortunately this is not likely to be the case. For example, the trading hours of European markets caused much higher volatility in the early years of euro than they do today. Therefore, to be able to filter all the periodicity in volatility, we have to filter the data in subsets, i.e. to model every week in the data separately.

Figure 2 presents the autocorrelation coefficients of absolute returns for 1500 five minute lags, i.e. the autocorrelogram for five days. As can be seen, the FFF method is capable of filtering the intraday periodicity in volatility, although there are still significant autocorrelation left in the absolute returns.

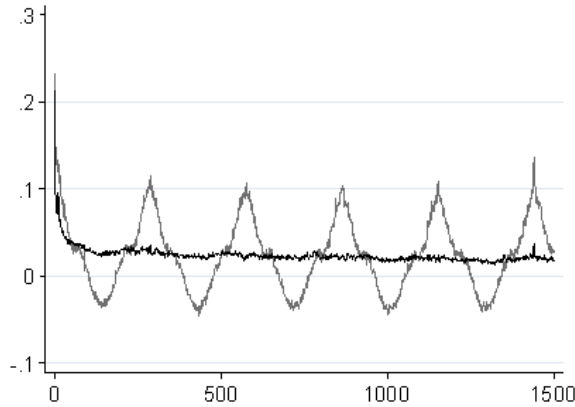


Figure 2 Autocorrelation coefficients of the original and filtered absolute returns

The figure graphs the five day correlogram of the filtered five minute absolute USD/EUR returns (black line) compared to original absolute returns (grey line). The intraday periodicity was filtered by using the Flexible Fourier Form method.

⁶The value $P = 9$ was chosen by using the Akaike and Schwarz information criteria.

The key statistical figures of the original and filtered returns are presented in Table 1. The filtering does not have an effect on the mean and standard deviation of the returns, but decreases both kurtosis and skewness. Even though the distribution of the returns is more close to the normal distribution after the filtering, neither original nor filtered returns do not seem to be normally distributed, because of the excess kurtosis.

Table 1 Key statistical figures

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

	Returns	Filtered Returns
Mean	0.00005	0.00008
Standard deviation	0.0431	0.043
Skewness	0.78	0.06
Kurtosis	65.94	28.94
Minimum	-1.35	-1.56
Maximum	2.78	1.40

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. The announcements are collected for all the euro countries and the USA for the period 1999-2004. The data include the announcement date and time in one minute accuracy, the announced figure and the market forecast of the figure. Unfortunately the market forecast is not available for all of the macro figures. For example the figures from smaller euro countries do not have forecast. Since the figures having forecast available are probably the most important ones, we focus on those.

The market forecast is the median of the survey forecasts that Bloomberg collects from the market agents and it is used in classifying the news as positive and negative. The news item is defined positive when the market forecast is smaller than the announced figure, i.e. the announcement was underestimated. Negative news on the other hand means that market 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 if the unemployment has increased more than expected). Therefore, we classified the news to positive and negative also in an alternative way. The news is classified as positive if the next five minute return following the news announcement is positive (dollar appreciates), and negative if the return is negative (dollar depreciates). Table 2 presents the number of observations in the different categories of news.

Table 2 Number of news announcements in different categories

Table presents the number of announcements observations in each news category. The first news category $N_{t,n}$ 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. $Npos_{t,n}$ and $Nneg_{t,n}$ represent positive and negative news categories, when the classification to positive and negative news was based on the difference between the announced figure and market forecast. $Npos_{-r_{t,n}}$ and $Nneg_{-r_{t,n}}$ divide the macro news to positive and negative by the sign of the return following the news announcement.

Variable	News categories	Obs
	All macro announcements	
$N_{t,n}$	for which the market forecast F_{kt} is available: A_{kt}^f	5236
$Npos_{t,n}$	Positive news: $A_{kt}^f - F_{kt} > 0$	2771
$Nneg_{t,n}$	Negative news: $A_{kt}^f - F_{kt} < 0$	2683
$Npos_{-r_{t,n}}$	Positive news: A_{kt}^f when $R_{t+l} < 0$	2432
$Nneg_{-r_{t,n}}$	Negative news: A_{kt}^f when $R_{t+l} > 0$	2556

If we were only interested in the impact that the macro figure has immediately after the announcement, the news variables would be dummy variables that get a value of one five minutes after the news announcement and zero otherwise⁷. However, it has been reported that the impact of news lasts from one to two hours (Andersen et al., 2003). Therefore, we follow Andersen and Bollerslev (1998), and first create the average news impact pattern by computing the average absolute returns following the news announcement less the average volatility over the whole data. 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:

$$\lambda(n) = 0.054 \left(1 - (n/25)^3\right) - 0.009 \left(1 - (n/25)^2\right) i + 0.0007 \left(1 - (n/25)\right) n^2 \quad (4)$$

where $n = 1, 2, \dots, 25$ denotes the 5 minute interval. The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours (when $n = 25$), as depicted in Figure 3. Now, when the macro news has been announced at $n = 0$, the news variable gets the value of $\lambda(n)$ during the first 25 intervals after the announcement and zero otherwise.

⁷Most studies that study 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.

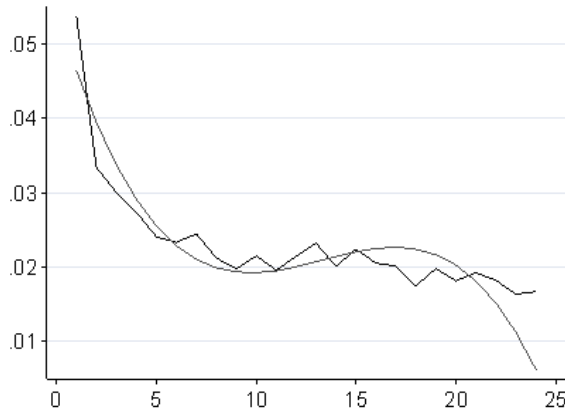


Figure 3 Average news impact pattern and the estimated decay structure

3.3 Business Cycle Indicator

A standard measure of the state of the economy has been the NBER dates of recessions and expansions. However, since this measure only classifies 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 uses the Institute for Supply Management Survey (ISM) index as a measure of the business cycle. The ISM index is constructed from of a survey among 300 people (from 20 manufacturing industries), who are asked to classify the state of the economy as "better", "worse" or "equal" than in the previous month. The survey includes questions related to new orders, production, employment, supplier deliveries and inventories. By averaging the respondents' answers, the index then equals 50 if half of the respondents think the business conditions are better and the other half think they are worse. According to Veredas (2006) the ISM index is better than other measures like unemployment rate or industrial production, since being based on expectations, it is the most forward-looking measure available of the market. Therefore we use this index as a business cycle indicator for the US market.

We use the IFO (Information and Forschung (research)) 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 graphs the time series of the both indices. The correlation between the two indices is positive (0.3835), but not extremely high. While the ISM index reaches the maximum values in the end of the data, 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.

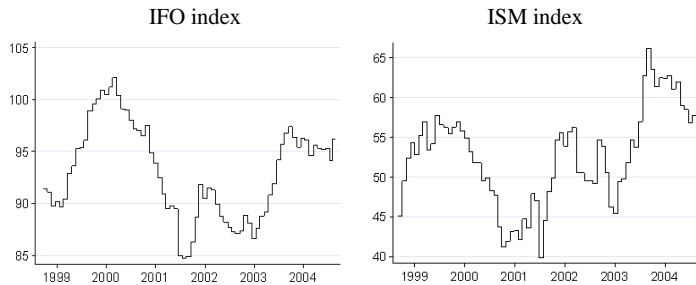


Figure 4 Business sentiment indices for Europe and the USA

3.4 Smooth Transition Regression Model

For studying the asymmetric news effects we use the two-regime Smooth Transition Regression (*STR*) model⁸:

$$y_{t,n} = \phi' \mathbf{x}_{t,n} + \theta' \mathbf{x}_{t,n} G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n} \quad (5)$$

where $y_{t,n} = 2 \ln \frac{|\tilde{R}_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. We continue to follow the Flexible Fourier Form framework (see section 3.1 for details), so the dependent variable is of the same form as in model (3), but now instead of the returns $R_{t,n}$ we have 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, ϕ and θ are parameter vectors and $\varepsilon_{t,n}$ is the error term. Our primary choice for the transition function is the general logistic function of the form,

$$G(\gamma, c, h_{t,n-1}) = \left(1 + \exp \left\{ -\gamma \prod_{k=1}^K (h_{t,n-1} - c_k) \right\} \right)^{-1}, \gamma > 0, \quad (6)$$

where $h_{t,n-1}$ denotes the continuous transition variable⁹, γ slope parameter and c threshold parameter. Due to the functional form of the transition function,

⁸This 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.

⁹The value of the transition function depends on the lagged transition variable. In our case, however, the data frequency is 5 minutes, while the business cycle indicator (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 ISM index is announced.

the model is in this case called 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. Parameter c determines the location of the transition function.

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 ϕ (lower regime, $G = 0$) to $\phi + \theta$ (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: $G(\gamma, c, h_{t,n-1}) = 1 - \exp\{-\gamma(h_{t,n-1} - c)^2\}$, $\gamma > 0$ 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.

We will consider the following two models:

$$y_{t,n} = \phi_0 + \phi_1 N_{t,n} + [\theta_0 + \theta_1 N_{t,n}]G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \quad (7)$$

and

$$\begin{aligned} y_{t,n} = & \phi_0 + \phi_1 N_{pos,t,n} + \phi_2 N_{neg,t,n} \\ & + [\theta_0 + \theta_1 N_{pos,t,n} + \theta_2 N_{neg,t,n}]G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \end{aligned} \quad (8)$$

where $N_{t,n}$ denotes news variable, which includes all news, both positive and negative and $N_{pos,t,n}$, $N_{neg,t,n}$ denote positive and negative news variables, respectively. So, model (7) allows the impact of news to be different in different states of economy, while model (8), in addition, enables the different effect of positive and negative news in each state.

3.5 Linearity Testing

We start by testing for linearity against STR-type nonlinearity. The 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 Luukkonen et al. (1988). They suggest estimating by ordinary least squares the following auxiliary regression,

$$y_{t,n} = \beta'_0 \mathbf{x}_{t,n} + \sum_j^3 \beta'_j \mathbf{x}_{t,n} h_{t,n-1}^j + u_{t,n} \quad (9)$$

For our models (7) and (8), $\mathbf{x}_{t,n} = (1, N_{t,n})'$ and $\mathbf{x}_{t,n} = (1, N_{pos,t,n}, N_{neg,t,n})'$, respectively. The null hypothesis of linearity is then $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$, and the LM type test statistics F is computed as follows,

$$F = \frac{(SSR_0 - SSR_1)/3m}{SSR_1/(T - 4m - 1)}, \quad (10)$$

where SSR_0 is sum of squared residuals from a regression of $y_{t,n}$ on $\mathbf{x}_{t,n}$, SSR_1 is sum of squared residuals from auxiliary regression (9) and m is the number of explanatory variables in (9). Under linearity F follows approximately the $F(3m, T - 4m - 1)$ distribution.

If STR-type nonlinearity is detected, the test of Luukkonen et al. (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 $H_{01} : \beta_1 = 0 | \beta_2 = \beta_3 = 0$.
2. $F2$: Test $H_{02} : \beta_2 = 0 | \beta_3 = 0$.
3. $F3$: Test $H_{03} : \beta_3 = 0$.

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 (see Teräsvirta (1994) for details).

4 Empirical results

In this section we present the empirical results. First, we tested for linearity using the procedure suggested by Teräsvirta (1994). As can be seen from the results in Table 3, the linearity is highly rejected in all of the models and transition variables. The type of the model that the test sequence suggests is the *LSTR1* irrespective of which of the two transition variables is used.

Table 3 Results of the linearity test against STR-type nonlinearity

Table presents the results of the linearity test against STR type nonlinearity by Luukkonen et al. (1988). The first column describes the news variables used in the test and the second column presents the considered transition variables. The third column presents the p-values of the H_0 hypothesis $\beta_1 = \beta_2 = \beta_3 = 0$. The next three columns present the p-values of the hypotheses H_{01}, H_{02}, H_{03} (see details in section 3.5), and the last column presents the type of the model suggested by the test.

News variable(s)	Trans. variable	F	$F1$	$F2$	$F3$	Model Type
$N_{t,n}$	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
$Npos_{t,n}, Nneg_{t,n}$	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

4.1 Estimation Results

Table 4 presents the estimation results of model (7). As can be seen, the smoothness 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 steep. Figure 5 presents the graphs of the transition functions against transition variables. As can be seen, the transition function is very steep and actually quite close to a switching regression model.

For estimation purposes, we standardized the transition variables to take both positive and negative values by demeaning them. 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 6 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 data set (1999-2000) and the other at the end of the data set (2004). The duration of these expansion periods depends on the transition variable.

Are the suggested 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 2002¹⁰. Andersen et al. (2007) state that their business cycle dates match closely those designated by NBER over postwar period. So, at least the first expansion period seems to match with the other studies. Unfortunately NBER has not published the dates after November 2001, so we cannot compare the 2004 expansion period from their dates. In addition, Veredas (2006) states that 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.

Next we interpret the news variable coefficient estimates. Parameter ϕ_1 is the impact of news in the "lower" regime, or in "bad" times, and $\phi_1 + \theta_1$ is the impact of news in the "upper" regime, meaning "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 5% significance level. Therefore we conclude that macroeconomic news increases volatility significantly. We can also see that 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.

¹⁰Their data ends in 2002.

Table 4 Estimation results, all news

Table presents the parameter estimates of the Smooth Transition Model (7), where the impact of macroeconomic news was studied in different phases of business cycle. The German IFO index and the ISM Manufacturing index were used as transition variables. The Newey West standard errors (288 lags) are in the brackets and the bolded figures are statistically significantly different from zero at the five percent significance level.

	IFO index	ISM index
ϕ_0	-2.208 (0.008)	-2.131 (0.007)
ϕ_1	22.033 (0.514)	22.590 (0.504)
θ_0	0.119 (0.015)	-0.219 (0.017)
θ_1	4.653 (1.034)	3.337 (1.069)
γ	368.7 (70.38)	2949.1 (42.22)
c	3.284 (0.011)	4.351 (0.001)

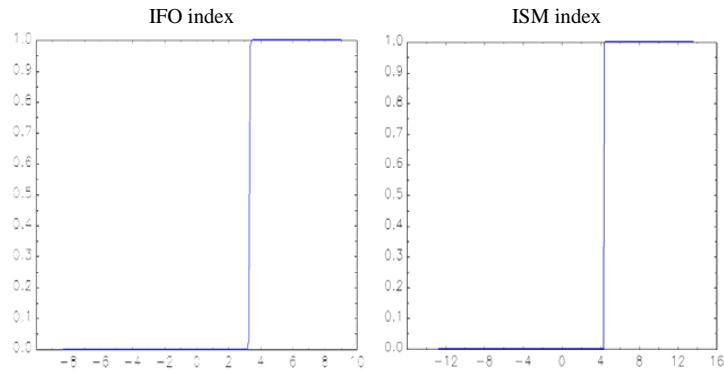


Figure 5 Transition function vs. transition variable

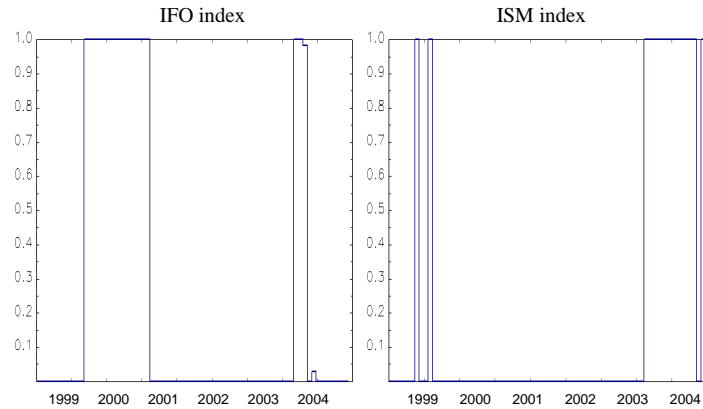


Figure 6 Transition function vs. time

Table 5 presents the estimation results of model (8), where the news are divided to positive and negative based on two classification methods. We can first conclude that there are no major changes in the parameters γ and c compared to the estimates of model (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 for the nonlinear part is insignificant for the positive news. This implies that there seem not to be 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. Also, the results support the theory of Veronesi (1999), which suggests 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 5 Estimation results, positive and negative news

Table presents the parameter estimates of the Smooth Transition Model (8), where the impact of positive and negative macroeconomic news was studied in different phases of business cycle. The news was classified as positive and negative by using the Bloomberg market forecast (first panel) and by using the sign of the return following the news (second panel). The German IFO index and the ISM Manufacturing index were used as transition variables. The Newey West standard errors (288 lags) are in the brackets and the bolded figures are statistically significantly different from zero at the five percent significance level.

	Market forecast		Sign of the return	
	IFO	ISM	IFO	ISM
ϕ_0	-2.198 (0.008)	-2.120 (0.007)	-2.212 (0.008)	-2.135 (0.007)
ϕ_1	16.057 (0.658)	16.566 (0.636)	21.570 (0.635)	22.554 (0.628)
ϕ_2	16.285 (0.679)	16.702 (0.652)	22.335 (0.631)	22.956 (0.611)
θ_0	0.122 (0.015)	-0.217 (0.017)	0.120 (0.015)	-0.214 (0.017)
θ_1	1.871 (1.288)	-0.081 (1.362)	2.263 (1.237)	-0.317 (1.300)
θ_2	5.811 (1.293)	4.986 (1.379)	5.337 (1.266)	2.918 (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 6 summarizes the estimates for the positive and negative news variables when the transition function takes on values $G = 0$ and $G = 1$. Clearly, in bad times, the difference between the positive and negative news is not statistically significant. 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 to positive and negative: the p-values are 0.128 (IFO index) and 0.081 (ISM index) when the classification is based on the sign of the return.

Table 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 F-tests for the equality of positive and negative news. In the $Npos_{t,n}$ and $Nneg_{t,n}$ the positive and negative news are classified by using the Bloomberg market forecast, and in the $Npos_{-r_{t,n}}$ and $Nneg_{-r_{t,n}}$ the positive and negative news were classified by using the sign of the return following the news.

	IFO	ISM
$Npos_{t,n}$ Bad times	16.057	16.566
$Nneg_{t,n}$ Bad times	16.285	16.702
$Npos_{t,n} = Nneg_{t,n}$, p-value	0.833	0.896
$Npos_{-r_{t,n}}$ Bad times	21.570	22.554
$Nneg_{-r_{t,n}}$ Bad times	22.335	22.956
$Npos_{-r_{t,n}} = Nneg_{-r_{t,n}}$, p-value	0.401	0.650
$Npos_{t,n}$ Good times	17.928	16.485
$Nneg_{t,n}$ Good times	22.096	21.688
$Npos_{t,n} = Nneg_{t,n}$, p-value	0.017	0.008
$Npos_{-r_{t,n}}$ Good times	23.833	22.237
$Nneg_{-r_{t,n}}$ Good times	27.672	25.874
$Npos_{-r_{t,n}} = Nneg_{-r_{t,n}}$, p-value	0.128	0.081

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 autocorrelation of order q . The tests for no remaining nonlinearity and parameter constancy closely resemble the linearity test described in section 3.5. In both tests the dependent variable is the model residual, and in the parameter constancy test the time index is used as 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; the test statistics values vary from 281 to 2860.7. This comes not as a surprise, considering the autocorrelation structure of the absolute filtered returns in Figure 2.

Table 7 present the p-values of the remaining nonlinearity test. F_{NL} tests for the linearity and the $F1_{NL}$, $F2_{NL}$, and $F3_{NL}$ tests help to select the type of the STR model (as the $F1$, $F2$ and $F3$ tests in Section 3.5). As can be seen, the null hypothesis of linearity is rejected. The alternative model in the test for remaining nonlinearity is an additive STR model, where instead of two

regimes there are three regimes (low, middle, high). Therefore, we estimated the model also by allowing a third regime. The estimated coefficient values do not seem to be reasonable in view of the results of the two-regime model¹¹. Also, we had computational difficulties with some of the news variables and transition variables. The probable reason for the unreasonable results and the computational difficulties 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 c 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 as an “outlier” regime and the data are better described with the two regime model. One potential problem with the test for no remaining nonlinearity is that it also has power against remaining autocorrelation (Teräsvirta 1994). Hence, our finding remaining nonlinearity could be spurious. The fact that the test rejects the hypothesis of no remaining nonlinearity also after the three regime model (with p-value 0.007) only strengthens this suspicion.

Table 7 Diagnostics: remaining nonlinearity

Table presents the p-values of the test of the remaining nonlinearity, where the alternative has an additive structure. The residuals are from the Smooth Transition Model (7), where the German IFO index and the ISM Manufacturing index were used as transition variables.

Transition variable	F_{NL}	$F1_{NL}$	$F2_{NL}$	$F3_{NL}$
IFO index	0.006	0.297	0.001	0.698
ISM index	0.007	0.282	0.001	0.765

Table 8 present the p-values of the parameter constancy test of Eitrheim and Teräsvirta (1996). In Table 8, $F1_{PC}$ refers to test where on the first power of the time index was included to the auxiliary regression, whereas also second and third powers of the time index are included to the tests $F2_{PC}$ and $F3_{PC}$, respectively. As can be seen, the test rejects the parameter constancy, which means that some kind of time-varying Smooth Transition Model could be more adequate for the data. However, due to the interactive nature of these three tests, the rejection could also be caused by the remaining autocorrelation. The outcome of trying to fix the remaining nonlinearity problem could support this view. Also, we think that it is quite unreasonable to assume that the definition of the good and bad times could have changed during the six year data period. On the other hand, it could also be possible that the structural changes in the data are causing the slowly decaying autocorrelation structure, as was suggested by Lamoureux and Lastrapes (1990). However, Andersen and Bollerslev (1998), who study the properties of a high-frequency data very similar to ours, claim that the long-memory characteristics of the returns series are related to the data generating process itself, rather than being induced by infrequent structural shifts.

¹¹These results are available upon request.

Table 8 Diagnostics: parameter constancy

Table presents the p-values of the test of the parameter constancy. The residuals are from the Smooth Transition Model (7), where the German IFO index and the ISM Manufacturing index were used as transition variables.

Transition variable	$F1_{PC}$	$F2_{PC}$	$F3_{PC}$
IFO index	2.2E-15	2.6E-34	2.7E-44
ISM index	2.4E-07	4.6E-49	1.5E-58

All in all, the diagnostic tests suggest that there is still some regularity in the data. 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 to 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.

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. Yet, 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. Our results are well in line with the earlier results from the equity and bond markets, and they also support the theory of Veronesi (1999).

References

- [1] Adams, G., McQueen, G., Wood, R., (2004) “The Impact of Inflation News on High Frequency Stock Returns“ *The Journal of Business* 77, 547–574
- [2] 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
- [3] Andersen, T., Bollerslev, T., (1997) “Intraday periodicity and volatility persistence in financial markets“ *Journal of Empirical Finance* 4, 115-158

- [4] 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
- [5] 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
- [6] 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
- [7] 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
- [8] Boyd, J., Hu, J., Jagannathan, R., (2005) “The Stock Market’s Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks“ *RThe Journal of Finance* 60, 649-672
- [9] 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
- [10] Chang, Y., Taylor, S., (2003) “Information arrivals and intraday exchange rate volatility” *International Financial Markets, Institutions and Money* 13, 85–112
- [11] Conrad, J., Cornell, B., Landsman, W.R., (2002) “When Is Bad News Really Bad News?“ *The Journal of Finance* 57, 2507-2532
- [12] 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
- [13] Dominguez, K., Panthaki, F., (2006) “What defines ‘news’ in foreign exchange markets?“ *Journal of International Money and Finance* 25, 168-198
- [14] 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.
- [15] Eitrheim, O., Teräsvirta, T., (1996), “Testing the adequacy of smooth transition autoregressive models“ *Journal of Econometrics* 74, 59-75
- [16] 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

- [17] Flannery, M., Protopapadakis, A., (2002) “Macroeconomic Factors Do Influence Aggregate Stock Returns“ *The Review of Financial Studies* 15, 751-782
- [18] Granger, C.W.J., Teräsvirta, T., (1993) “Modelling Nonlinear Economic Relationships, *Advanced Texts in Econometrics*“ Oxford University Press
- [19] Laakkonen, H., (2007a) “The Impact of macroeconomic news on exchange rate volatility“ *Finnish Economic Papers* 20, 23-40
- [20] Laakkonen, H., (2007b) “Exchange Rate Volatility, Macro Announcements and Choice of the Intraday Seasonality Filtering Method“ *Bank of Finland Discussion Paper* 23/2007
- [21] 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
- [22] Lanne, M., Saikkonen, P., (2006) “Why is it so difficult to uncover the risk-return tradeoff in stock returns?“ *Economic Letters* 92, 118-125
- [23] Luukkonen, P., Saikkonen, P., Teräsvirta, T., (1988) “Testing linearity against smooth transition autoregressive models“ *Biometrika* 75, 491-499
- [24] McQueen, G., Roley, V.V., (1993) “Stock Prices, News and Business Conditions“ *The Review of Financial Studies* 6, 683-707
- [25] Melvin, M., Yin, X., (2000) “Public information arrival, exchange rate volatility and quote frequency“ *The Economic Journal* 110, 644-661
- [26] Merton, R.C., (1973) “An intertemporal capital asset pricing model“ *Econometrica* 41, 867-887
- [27] Pearce, D., Solakoglu, N., (2007) “Macroeconomic news and exchange rates“ *Journal of International Financial Markets, Institutions and Money* 17, 307-325
- [28] Teräsvirta, T., (1994) “Specification, estimation, and evaluation of smooth transition autoregressive models“ *Journal of the American Statistical Association* 89, 208-218
- [29] Veredas, D., (2006) “Macroeconomic surprises and short-term behavior in bond futures“ *Empirical Economics* 30, 843-866
- [30] Veronesi, P., (1999) “Stock market overreaction to bad news in good time: A rational expectations equilibrium model“ *Review of Financial Studies* 12, 975-1007