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

by

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Abstract

We study the impact of positive and negative news in different phases of business cycle by using high-frequency volatility of the USD/EUR exchange rate and macroeconomic announcements from the US and Europe. The results suggest that in general bad news increase volatility more than good news. The news effects also depend on the state of the economy: bad news increase volatility more in good times than in bad times, but good news increase volatility as much in bad times than in good times.

Key Words and Phrases: Volatility, News, Nonlinearity, Smooth Transition Models

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 increase 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 been concentrating mainly on the stock markets. McQueen and Roley (1993), Flannery and Protopapadakis (2001), Conrad et al. (2002), Adams et al. (2004), Boyd et al. (2005) and Andersen et al. (2007) all report findings to support the state dependence of announcement effects in the stock markets. In general, the bad news seem 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 bond futures and Faust et al. (2007) and Pearce and Solakoglu (2007) in the foreign exchange markets. The findings of Veredas (2006) are in line with the results from equity markets, 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 between 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 earlier 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 USD/EUR 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 by using the European business cycle indicator. Surely it is reasonable to concentrate on the US business cycle when studying only the US stock markets, but also the studies which use assets from several countries have so far focused only to US news and US business cycles.

Yet, 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 using different kinds of criterion: 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 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 or below 50; 3) expanding or 4) contracting if it is between them and increasing or decreasing. We estimate the state dependence in the news effects by using a smooth transition regression model. The advantages of the model are that the threshold between the different states is not fixed a priori, but estimated and the model allows the change from one regime (bad times) to another (good times) to be smooth. Therefore, splitting the data beforehand into good and bad times (or in between) is not necessary. Furthermore, the model can be generalized to allow for more than two regimes in a straightforward manner.

The biggest contribution of this paper, however, is that in terms of the foreign exchange markets, we are the first to show support to 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. To our knowledge, there are only two papers so far that have studied the state dependence of news effects in these markets. Both papers of Faust et al. (2007) and Pearce and Solakoglu (2007) study the news impacts on exchange rate returns[2], but find only limited evidence on the state dependence of the asymmetric news effects.

We found that in general, the 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. We found that news effects seem to be 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. So, the results are also in line with the previous studies from equity markets.

The plan of the paper is as follows. Section 2 reviews the related literature and Section 3 describes the data and methodology. In Section 4 the results of the empirical study are presented and Section 5 concludes.

2 News effects and business cycles

The impact of news on exchange rate dynamics has been studied extensively in recent decades[3]. The earliest studies in the 1980s used daily return data and simple

[2]Pearce and Solakoglu (2007) also examines the news effects on exchange rate volatility.

[3]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

regressions, and did not get very promising results (see e.g. Aggarwal and Schirm 1998). Since the 1990s the availability of high-frequency data, numerous variations of GARCH-models (Bollerslev et al. 1992), and the methods of filtering intraday volatility periodicity and other market anomalies (Andersen and Bollerslev 1997) have enabled better methods for studying the impact of news on exchange rate volatility.

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 returns from an 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). Also the asymmetries between different groups of news have been examined. Negative news having stronger effect on financial market instruments than positive news is one of the best known results (for example Andersen et al. 2003).

Even if the effects of different types of news have been studied extensively, the empirical literature testing the asymmetries between the news signs and the business cycle has not been very active, partly because time series are required to cover the different states of the economy. This issue has been theoretically addressed by

et al. (2005), Dominquez and Panthaki (2006), Laakkonen (2007a) among others.

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 economy[4].

[4]Veronesi'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)

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 macronews on the S&P 500 price movements and measure the business cycle with industrial production[5]. The levels of 'high', 'medium' and 'low' economic activity are determined by estimating a trend and then fixing some 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. Very similar findings conclude the studies of Flannery and Protopapadakis (2001) and Adams et al (2004). Flannery and Protopapadakis (2001) 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. The study of Flannery and Protopapadakis (2001) differs from the others also because they simultaneously estimate the impact of macroeconomic announcements on level and conditional volatility of daily equity returns by using GARCH models. Adams et al (2004) use the intraday stock index data and study

discussion concerning the empirical evidence for the risk-return tradeoff.

[5]They also did robustness checks by using the capasity utilization and unemployment rate as business cycle indicator.

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 resent papers often study different asset 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. Very similar findings present Andersen et all (2007), who 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 market do: good macronews has positive impact in recessions, but negative impact in expansions. Andersen et all (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 large and negative. As Boyd et al. (2005), Andersen et al. (2007) suggest that cash flow effect dominates during contractions and discount effect dominates in expansions. Faust et al. (2007) study the joint movements of exchange rates and US and foreign term structures around the macronews announcements, but find only little evidence of time-variation in responses.

The studies that are more similar to ours are the ones of Conrad et al (2002), Veredas (2006) and Pearce and Solakoglu (2007), which focus to study the asymmetric reactions to positive and negative news in the different phases of business cycles. Conrad et al. (2002) studied the question 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 the individual stocks, and concluded that the markets react more strongly to bad news in good times and that the reaction to good news is not greater in bad times than in good times. Veredas (2006) studies the question by using 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 most similar study to ours is the recent paper by Pearce and Solakoglu (2007), where they study 10 years (1986-1996) of DEM/USD and JPY/USD data and study 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 depended on the state of the economy, and 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 quotes[6] for the USD/EUR (United States Dollar against Euro) exchange rate from 1st January 1999 to 31st December 2004 (Figure 1) 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.

[Figure 1]

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

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 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 seasonality, 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 seasonality, 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 seasonality. 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 compared to the examined group of filtering methods.

The idea[7] 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 random error term $Z_{t,n}$:

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

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

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

There are two components left on the right-hand side of equation (2). The first is the component for the intraday volatility, which will be modeled using trigonometric functions; and the other component is the error term, which includes the extra volatility in the markets, such as the volatility caused by new information. The FFF regression model can be written as

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

[7] Iin the equations t denotes day and n the 5-minute interval.

where $f_{t,n} = 2 \ln \frac{|R_{t,n} - \bar{R}|}{\hat{\sigma}_t / N^{1/2}}$. Besides the sinusoids[8], 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. $\varepsilon_{t,n}$ 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: $\tilde{s}_{t,n} = \frac{T \cdot \hat{s}_{t,n}}{\sum_{t=1}^{[T/N]} \sum_{n=1}^{N} \hat{s}_{t,n}}$. 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 FFF model is estimated for the entire data set, the intraday seasonality pattern is assumed to stay constant over the data sample. Unfortunately this in 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 seasonality 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. The correlogram for the original returns is presented in grey, and the correlogram for the filtered returns is presented in black. As can be seen, the FFF

[8]The value $P =$ 9 was chosen by the AIC and the BIC.

method is capable of filtering the intraday seasonality in volatility.

[Figure 2]

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]

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. The reason is that all the macro figures do not seem to be important enough for a survey forecast to be collected. For example the figures from smaller euro-area countries like Finland do not have forecast. Since the figures that having forecast available are probably the most important ones, we can 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 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, for example 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 negative (dollar appreciates), and negative if the return is positive (dollar depreciates). Table 2 presents the number of observations in the different categories of news.

[Table 2]

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 otherwise[9]. However, it

[9]Most studies that study the impact of news on financial market returns use the actual surprice

has been reported that the impact of news lasts from an hour to two hours (Andersen et al. 2003). Therefore, we follow Andersen and Bollerslev (1998), and estimate the decay structure of the volatility response pattern of news using a third order polynomial:

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

where $n = 1, 2, ...25$ 5 minute intervals. This captures the average decay structure quite well and forces the impact to zero after two hours (when $n = 25$). 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, as depicted in Figure 3.

[Figure 3]

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

element (the announced figure less the forecast) as a news variable rather than a dummy variable that does not take to account the size of the news. However, Andersen et al. (2003, 2007) argue that the mere presence of an announcement, not so much the size of the corresponding surprise, tend to boost volatility.

for our purposes. In our analysis we need a continuous measure of the business cycle. According to Veredas (2006) the ISM index is better than other measures like GDP or industrial production used by McQueen and Roley (1993), since being based on expectations, it is the most forward-looking measure available of the market. 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". 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. The business sentiment of the European markets are measured by the IFO Business Sentiment (Germany). The survey is very similar to 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]

3.4 Smooth Transition Regression Model

For studying the asymmetric news effects we use the two-regime Smooth Transition Regression (STR) model defined as follows[10]:

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

where $y_{t,n} = 2\ln\dfrac{\left|\tilde{R}_{t,n} - \bar{R}\right|}{\hat{\sigma}_t/N^{1/2}}$. We continue to follow the Flexible Fourier Form framework (see section 2.1 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, $\mathbf{x}'_{t,n} = (a, x_{1t,n}, ..., x_{kt,n})$, which includes a constant and news variables, and parameter vectors for the linear part $\boldsymbol{\phi}$ and for the nonlinear part $\boldsymbol{\theta}$ of the model. Yet, $\varepsilon_{t,n}$ is the error term of the model. Furthermore, the transition function $G(\gamma, c, h_{t,n-1})$ is the general logistic function of the form,

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

[10]This section is strongly based on the section 4.2 in Granger and Teräsvirta (1993).

where $h_{t,n-1}$ denotes the continuous transition variable[11], γ slope parameter and c threshold parameter. Due to the functional form of the transition function, the model is called logistic STR ($LSTR$) model. 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 controls for the location of the transition function.

The most common choices for K are $K = 1$ ($LSRTR1$) and $K = 2$ ($LSTR2$).The transition function is bounded in between zero and one. If $K = 1$, the parameters $\boldsymbol{\phi} + \boldsymbol{\theta} G(\gamma, c, h_{t,n-1})$ 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 attains its minimum value. An alternative to the $LSTR2$ model is the so called exponential STR ($ESTR$), 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 a good approximation of the $LSTR2$ model, when $c_1 \simeq c_2$ and γ is not too large.

[11]The transition function value depends on the lagged transition variable. In our case, however, the data frequency is 5 minutes, while the business cycle variable (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 basically the same as todays value.

We will consider the following two models:

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

and

$$y_{t,n} = \phi_0 + \phi_1 Npos_{t,n} + \phi_2 Nneg_{t,n} + [\theta_0 + \theta_1 Npos_{t,n} + \theta_2 Nneg_{t,n}]\, G(\gamma, c, h_{t,n-1}) + \varepsilon_{t,n}, \tag{8}$$

where $N_{t,n}$ denotes 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 (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.

3.5 Linearity Testing

We start by testing for linearity against STR-type nonlinearity. The identification problem that under the null hypothesis γ and c are not identified (Luukkonen et al. 1988) is circumvented by approximating the transition function by a third order Taylor approximation. Luukkonen et al. (1988) suggest estimating by ordinary least squares the following model,

$$y_{t,n} = \boldsymbol{\beta}_0' \mathbf{x}_{t,n} + \sum_{j}^{3} \boldsymbol{\beta}_j' \mathbf{x}_{t,n} h_{t,n-1}^{j} + u_{t,n} \tag{9}$$

For our models (7) and (8), $\mathbf{x}_{t,n} = (1, N_{t,n})$ and $\mathbf{x}_{t,n} = (1, Npos_{t,n}, Nneg_{t,n})$, respectively. The null hypothesis of linearity is then $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$, and the LM type test statistics is computed as follows,

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

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 the model (9). Under linearity LM follows approximately the $F(3m, T-4m-1)$ distribution.

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

1. Test the null hypothesis $H_{01} : \beta_3 = 0$.
2. Test $H_{02} : \beta_2 = 0 | \beta_3 = 0$.
3. Test $H_{03} : \beta_1 = 0 | \beta_2 = 0 = \beta_3 = 0$.

If the rejection is stronger against H_{02} (measured in the p-value), choose $LSTR2$ or $ESTR$. Otherwise choose $LSTR1$ (see Teräsvirta (1994) for details). The p-values of the tests are presented in Table 3. As can be seen, the linearity is highly rejected in all of the models and transition variables. The type of the model that the test sequence above suggests is the $LSTR1$ on the both transition variables.

[Table 3]

4 Empirical results

4.1 Estimation Results

Table 4 presents the estimation results of model (7). As can be seen, the smoothness parameter γ is very large in both of the cases. 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 transition functions against transition variables. As can be noticed, the transition function is very steep and is quite close to switching regression model. One reason for the large γ are the possible estimation problems, since estimating γ requires a large amount of observations in the neighborhood of c.

For the estimation purposes we had to standardize the transition variables to have both positive and negative values. Therefore both transition variables were demeaned, and the values of parameter c do not refer to the actual value of index, but rather to the demeaned index. The means of the transition variables are the following: ISM: 52.6 and IFO: 93.1. Therefore, the estimated values of parameter c refer 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 "good" times, one in the beginning of the data set (1999-2000) and the other in the end of the data set (2004). How long these expansion periods have last, depends on the used 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 2002[12]. 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 54.4 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 coefficients. Parameter $\boldsymbol{\phi}_1$ presents the impact of news in the "lower" regime, or in "bad" times, and $\boldsymbol{\phi}_1 + \boldsymbol{\theta}_1$ presents the impact of news in the "upper" regime, meaning "good times". If $\boldsymbol{\theta}_1$ 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. Therefore we conclude that macroeconomic news increase volatility significantly. We can also see that news effects are state dependent. In both of the cases, the estimates for $\boldsymbol{\theta}_1$ is significantly greater than zero. This implies, that the macro news increase volatility more in good times than in bad times.

[12]Their data ends to year 2002.

[Table 4]

[Figure 5]

[Figure 6]

Table 5 presents the estimation results of the model (8), when the news were classified to positive and negative by using the market forecast. Table 6 presents the estimation results of the model (8), when the news were classified to positive and negative by using the sign of the return following the news announcements. We can first conclude that there are no major changes in the parameters γ and c compared to the estimates of model (7).

Now, the parameters $\boldsymbol{\phi}_1$ and $\boldsymbol{\phi}_2$ present the impact of positive and negative news in "bad" times and $\boldsymbol{\phi}_1 + \boldsymbol{\theta}_1$ and $\boldsymbol{\phi}_2 + \boldsymbol{\theta}_2$ present the impact of positive and negative news in "good" times, respectively. Table 7 summarizes the coefficient values for different news variables for the transition function values $G = 0$ and $G = 1$. First of all, if we use the market forecast to classify the news to positive and negative, the negative news seems to have greater effect than positive news, both in good times and bad times. On the other hand, if we use the sign of the following return to classify the news to positive and negative, the positive news seem to have greater coefficient estimates in the bad times and negative news in good times. However, the differences are quite small in the cases when positive news have greater coefficient estimates than negative news. It has not yet been tested if these differences are statistically significant, but it seems that in general negative news increase volatility more than positive news.

Now, from Tables 5 and 6 we can see, that there seem to be differences between the negative news between the two regimes, while the coefficient for the nonlinear part is insignificant for the positive news. Also, in both of the cases the negative news coefficient value for the nonlinear part is positive. 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 underreact to good news in bad times, due to aversion of uncertainty concerning the state of the economy.

[Table 5]

[Table 6]

[Table 7]

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 USD/EUR 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 are first to uncover evidence on state dependence of the positive and negative news effects in the foreign exchange markets.

According to our results, the macro news increase volatility more in good times than in bad times. Yet, the negative news have 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 markets and also support the theory of Veronesi (1999).

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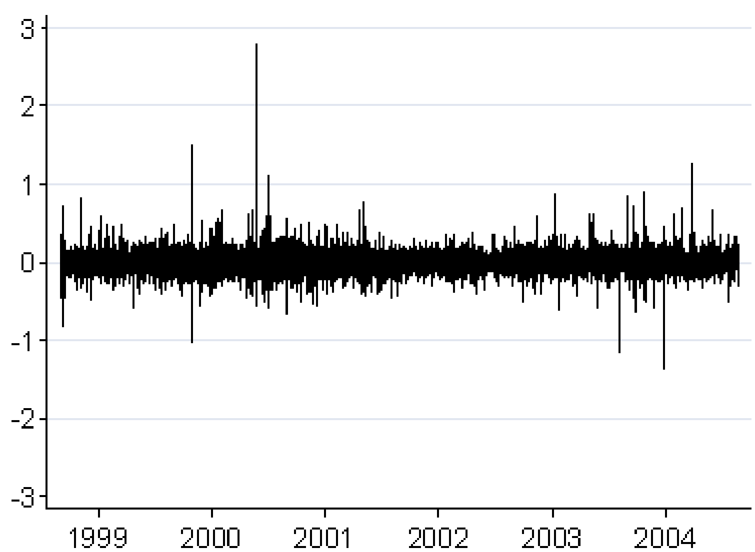

Figure 1 5-minute USD/EUR returns from 1 Jan 1999 to 31 Dec 2004

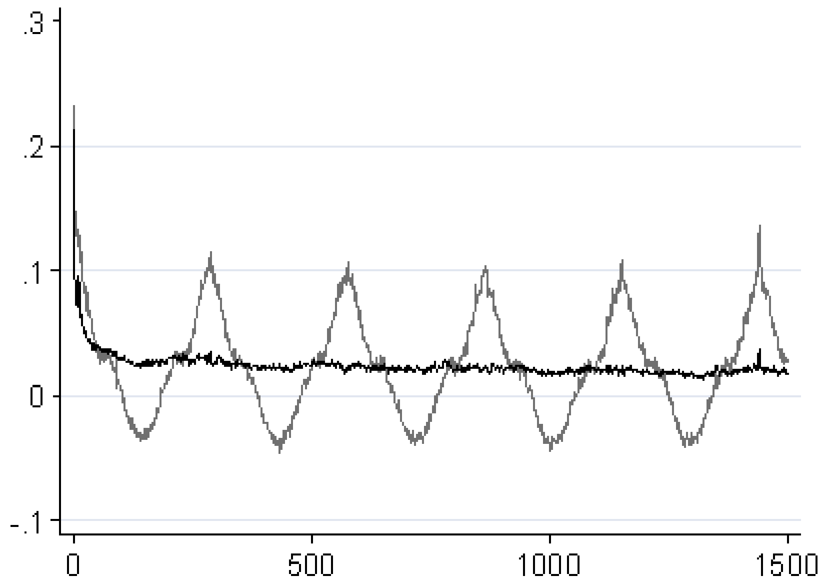

Figure 2 Autocorrelation coefficients of the original and filtered absolute returns

The figures graph 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.

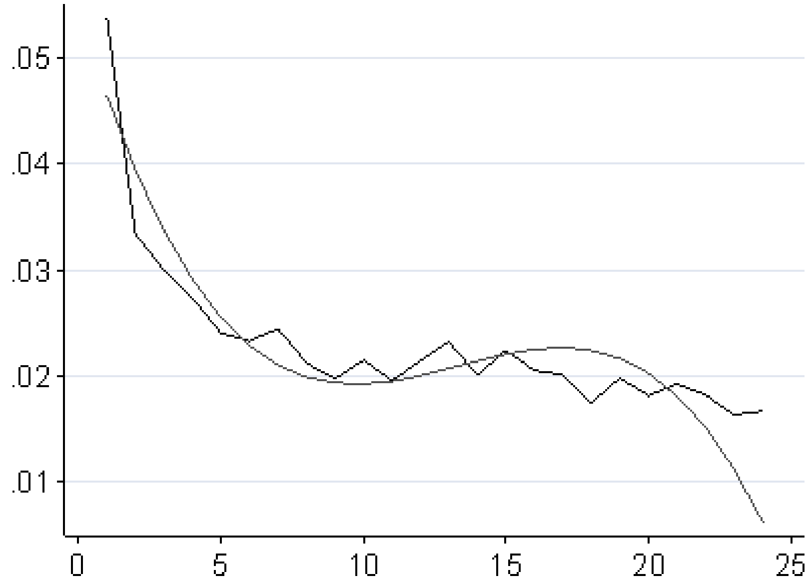

Figure 3 Average news impact pattern and the estimated decay structure

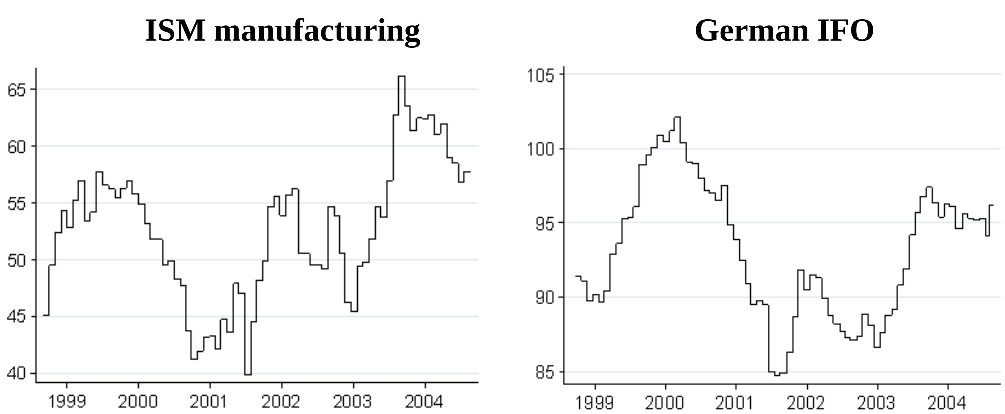

Figure 4 Business sentiment indices for Europe and the USA

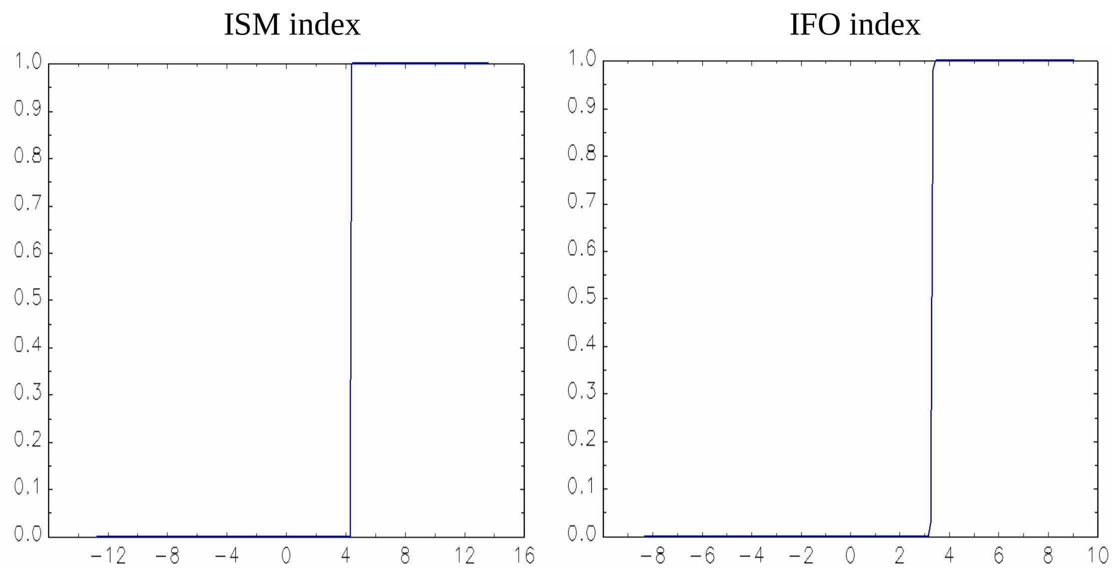

Figure 5 Transition function vs. transition variable

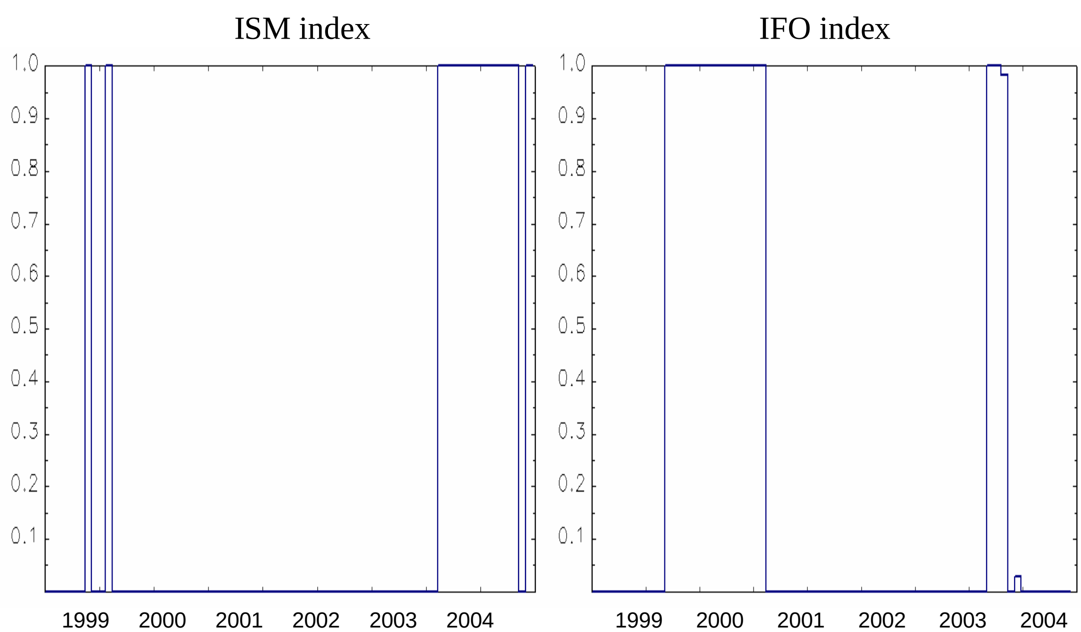

Figure 6 Transition function vs. time

Table 1 Key statistical figures

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

Table 2 Number of news announcements in different categories

Table presents the number of announcements observations in each news categories. 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 market forecast is available. Pos and Neg 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. Pos_r and Neg_r divide the macro news to positive and negative by using the sign of the return following the news announcement.

Variable	News categories	Obs
All	All macro announcements for which the market forecast F_{kt} is available: A_{kt}^{f}	5237
Pos	Positive news: $A_{kt}^{f} - F_{kt} > 0$	2383
Neg	Negative news: $A_{kt}^{f} - F_{kt} < 0$	2291
Pos_r	Positive news: A_{kt}^{f} when $R_{t+1} < 0$	2503
Neg_r	Negative news: A_{kt}^{f} when $R_{t+1} > 0$	2404

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 present the p-values of the hypothesis $\beta_1 = \beta_2 = \beta_3 = 0$. The last columns present the type of the model suggested by the sequence of hypotheses H_{01}, H_{02}, H_{03}.

News variable(s)	**Transition variable**	**LM**	H_{01}	H_{02}	H_{03}	**Model Type**
All	ISM	1.54E-08	1.20E-03	1.02E-02	5.15E-06	LSTR1
	IFO	7.12E-11	1.28E-03	3.30E-01	2.85E-10	LSTR1
Pos, Neg	ISM	5.01E-08	3.10E-04	3.89E-02	2.04E-05	LSTR1
	IFO	8.21E-10	3.10E-03	2.91E-01	1.59E-09	LSTR1
Pos_r, Neg_r	ISM	5.87E-08	2.79E-03	2.35E-02	4.35E-06	LSTR1
	IFO	6.54E-09	1.02E-03	6.85E-01	1.49E-08	LSTR1

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.

	ISM	**IFO**
ϕ_0	**-2.131**	**-2.208**
	[0.007]	[0.008]
ϕ_1	**22.590**	**22.028**
	[0.504]	[0.514]
θ_0	**-0.219**	**0.119**
	[0.017]	[0.015]
θ_1	**3.337**	**4.656**
	[1.069]	[1.035]
γ	3198.2	342.6
	[42.22]	[62.29]
c	4.351	3.285
	[0.001]	[0.010]

Table 5 Estimation results: positive and negative news A

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. The news is positive if the announced figure is greater than the forecasted one, and negative if the forecast is greater than the announced figure. 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.

	ISM	IFO
ϕ_0	**-2.119**	**-2.197**
	[0.007]	[0.008]
ϕ_1	**18.458**	**17.942**
	[0.646]	[0.670]
ϕ_2	**19.410**	**19.476**
	[0.663]	[0.678]
θ_0	**-0.218**	**0.123**
	[0.017]	[0.015]
θ_1	1.498	2.480
	[1.382]	[1.296]
θ_2	**5.481**	**4.678**
	[1.359]	[1.324]
γ	2850.7	2807.1
	[41.00]	[130.7]
c	4.351	3.286
	[0.001]	[0.002]

Table 6 Estimation results: positive and negative news B

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 sign of the return following the news announcement. The news is positive if the next five minute return following the news is negative (dollar appreciates) and negative if the return is positive. 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.

	ISM	IFO
ϕ_0	**-2.135**	**-2.212**
	[0.007]	[0.008]
ϕ_1	**22.926**	**22.295**
	[0.612]	[0.631]
ϕ_2	**22.603**	**21.562**
	[0.629]	[0.635]
θ_0	**-0.214**	**0.120**
	[0.017]	[0.015]
θ_1	-0.415	2.311
	[1.301]	[1.240]
θ_2	**2.842**	**5.365**
	[1.298]	[1.265]
γ	3481.9	1978.7
	[42.28]	[167.0]
c	4.351	3.285
	[0.001]	[0.004]

Table 7 Estimation results: summary

Table presents the summary of the news variable coefficient estimates of the smooth transition model (7) and (8), where the impact of positive and negative macroeconomic news was studied in different phases of business cycle. The German IFO index and the ISM Manufacturing index were used as transition variables.

	ISM	IFO
All: ϕ_1	22.59	22.028
All: $\phi_1+\theta_1$	25.927	26.684
Pos: ϕ_1	18.458	17.942
Neg: ϕ_2	19.41	19.476
Pos: $\phi_1+\theta_1$	19.956	20.422
Neg: $\phi_2+\theta_2$	24.891	24.154
Pos_r: ϕ_1	22.926	22.295
Neg_r: ϕ_2	22.603	21.562
Pos_r: $\phi_1+\theta_1$	22.511	24.606
Neg_r: $\phi_2+\theta_2$	25.445	26.927