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Macroeconomic News Effects on the Stock Markets in Intraday Data

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Abstract

The aim of the paper is to compare reactions of two stock markets, the German and the French, to releases of macroeconomic fundamentals emanating from Germany and the U.S. We examine the reaction of intraday returns and volatility of the CAC40 and the DAX indices to macroeconomic surprises. We find that both American and German macroeconomic releases cause an immediate response in returns and volatility of the German and the French stock market sampled at a five-minute frequency. The reaction to the American macroeconomic surprises is stronger than to the German ones.

Keywords: intraday returns, macro surprises, news effect, periodicity, volatility

JEL Classification: C13, C14, C22, G14

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1 Introduction

A considerable amount of literature has documented the importance of macroeconomic news about fundamentals in pricing of financial instruments (see e.g. Cutler, Poterba and Summers 1989, McQueen and Roley, 1993, Andersen, Bollerslev and Cai 2000). Macroeconomic news is said to have a short-lived, but strong effect on financial returns (Andersen and Bollerslev 1998). Recently, researchers have shown an increased interest in modeling the reaction to macro news with intraday data. While the reaction of the FOREX market to macro announcements in intraday framework is exhaustively examined (e.g. Andersen et al., 2003, Bauwens et al., 2005, Melvin and Yin, 2000, Laakkonen and Lanne, 2013), the literature examining the behavior of the stock markets in the presence of macroeconomic surprises is still limited.

Several attempts have been made to examine this issue on the European stock markets. Albuquerque and Vega (2009) show that the reaction to American macroeconomic releases dominates the reaction to Portuguese macroeconomic news. Hanousek, Kocenda and Kutan (2009) estimate the impact of EU macroeconomic fundamentals on main stock indices in Central Europe (Bohemian PX50, Polish WIG20 and Hungarian BUX) and find that that the effect of macro announcements from economies of EU countries is limited. Harju and Hussain (2011) examine four major European equity markets' indices (German DAX, French CAC40, Swiss DMI and British FTSE100) in the presence of American announcements and find that news releases have a similar impact on European investors' behavior – both equity returns and volatility are sensitive to American macro surprises. Będowska-Sójka (2011) examines the reaction of the Polish and the German stock markets to domestic, neighbor-country and American releases. She shows that the American releases influence both stock markets; the German (domestic) macro news has an impact on the German stock market, while in the case of the Polish stock market neither reaction to domestic nor to neighbor-country releases is observed. The study by Entorf, Gross and Steiner (2011) is devoted to examining the impact of two announcements of business-cycle forecasts in Germany, German ZEW Economic Sentiment and the Ifo Business Climate indicator. They found the significant response of the DAX returns and volatility to both ZEW and Ifo releases (Entorf, Gross and Steiner, 2011).

It has been widely pronounced in the literature that intraday returns are characterized by strong intraday periodicity in volatility (Andersen, Bollerslev 1997). Therefore in modelling the reaction to macro releases two approaches are most popular: a one-step procedure in which the intraday periodicity in volatility is estimated together with macro surprises (Baillie and Bollerslev, 1990, Laakonnen and Lanne, 2009), and a two-step procedure in which returns filtered from periodicity are introduced into a model with macro effects' variables (Baillie et al., 2000, Conrad and Lamla, 2010).

Our analysis contributes to the existing works in several ways. We examine the reaction of two European stock markets, the French and the German, to the U.S. and German macro news. German macro news is perceived as domestic in the case of the DAX index and neighbor-country in the case of the CAC40 index. We choose these

two indices, because there exists a strong interdependence between these markets and the reaction to American macro releases on both markets is similar (see e.g. Hanousek, Kocenda and Kutan, 2009, Będowska-Sójka, 2010, Harju and Hussain, 2011).
We use intraday data of the CAC40 and the DAX indices sampled at five-minute frequency and study the reaction to twelve macroeconomic fundamentals. This frequency of data allows us to model the immediate reaction to macro surprises. The choice of fundamentals is determined by the timing of releases both in the U.S. and in Germany and the availability of expectations of macro fundamentals. The French macro announcements are released mainly out of session time and therefore they are not included in the study. Będowska-Sójka (2011) finds that some of the German macro releases influence the German stock market. We continue the previous research and examine if the reaction to domestic releases changes over time. More importantly, by including the CAC40 index in the analysis we are able to assess if the neighbor-country macro releases have an impact on the French stock market.
Two complementary approaches are used in our study in order to examine the reaction to macroeconomic news. In the first, we model the reaction in volatility within FFF regression and introduce each macro news as a separate variable. In the second, we filter periodicity with FFF regression and model filtered returns with ARFIMA-FIGARCH models, where aggregated macro surprises from two countries are included. In this case we are able to estimate the response both in the returns and in volatility and compare the impact of surprises from each economy.
We find that in our sample the German fundamentals' releases increase the mean in the CAC40 index, whereas the American fundamentals' releases decrease the returns of both series. With respect to volatility, the German announcements have a very similar impact on the German and the French main indices' volatility, but the impact of these announcements in a five-minute period is weaker than the impact of American releases.
The rest of the paper is organized as follows: in Section 2 we describe the data, in Section 3 we show the periodicity patterns observed in CAC40 and DAX and present some aspects of periodicity filtering with flexible Fourier form. We show also the descriptive statistics of filtered data. In Section 4 we present the results of the one-step estimation within FFF regression, while in Section 5 we apply the two-step estimation and use conditional volatility models. In the Section 6 we conclude.

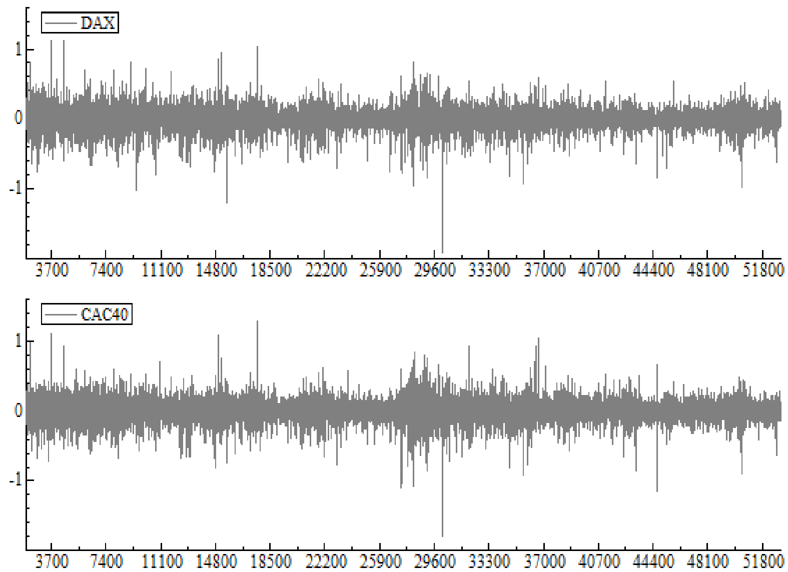
2 Data

2.1 The return series

The sample consists of five-minute CAC40 and DAX prices in the period of 4.5.2009 – 21.4.2011 (506 days). We use the percentage logarithmic returns. The overnight returns are excluded from the sample as they have different statistical properties than other intraday returns (see e.g. Hasbrouck, 2007, Albuquerque and Vega, 2009,

Lahaye, Laurent and Neelly, 2011). Both the CAC40 and the DAX indices are quoted from 9am to 5.30pm, which after excluding overnight return gives us 101 five-minute returns per day (altogether 51106 observations). We use the data available at database www.stooq.pl. The estimation and charts are made in OxMetrics 6.0, in particular G@RCH 6 software and Ox codes (Laurent 2010).
The return series for both indices are depicted in Figure 1.

Figure 1: Intraday 5-minute DAX and CAC40 returns from 4.05.2009 to 21.04.2011.



The descriptive statistics for both returns series are presented in Table 1.

Table 1: Descriptive statistics of raw returns of indices: CAC40 and DAX returns in the period from 04.05.2009 to 21.04.2011

	Mean	Standard deviation	Min	Max	Skewness	Excess kurtosis
CAC40	-0.0002	0.1097	-1.7978	1.2745	-0.2913	7.7312
DAX	-0.0002	0.1032	-1.8979	1.1337	-0.4205	9.0712

The sample mean of both series is not distinguishably different from zero and standard deviations are quite close in both indices. The empirical distribution is skewed to the left with more asymmetry in the DAX returns. Also the excess curtosis is higher in case of the DAX. Hence the empirical distributions of both series are definitely not Gaussian.

2.2 The macro surprises

The publications of important macro fundamentals are usually preceded by the releases of the fundamentals' expectations, which are generated from surveys conducted among the managers or financial analysts. Macro news (macro surprise) is defined as a difference between realization of macro fundamental and its expectation (see e.g. Almeida, Goodhart and Payne, 1998, Andersen et al., 2003).
The macroeconomic dataset consists of twelve fundamentals, half of them announced in the United States and half in Germany. The announcements from the U.S. are commonly considered in the literature, partly because of the importance of the American economy and partly because of its timing, as they are released at the time when European stock exchanges are open. Only few of the announcements from the German economy are released within the time of stock markets activity. From the broad categories of macro news from the American and the German economy we consider only these announcements for which the data of expected and released values of macro fundamentals are available, under condition that they are released within the session time of the stock markets. The fundamentals together with the time of releasing are summarized in Table 2. The chosen macro news represents the real economy indicators, inflation, economic sentiment and production.
Because units of measurement of macroeconomic variables differ, we use standardized news as proposed by Balduzzi, Elton and Green (2001). Within the econometric models we consider both standardized surprises and the indicator variables in order to control for macro surprise effect. The calculation of standardized surprises is described in Section 4.

Table 2: Macroeconomic fundamentals used in the study and timing of their releases in Germany and United States (CET time)

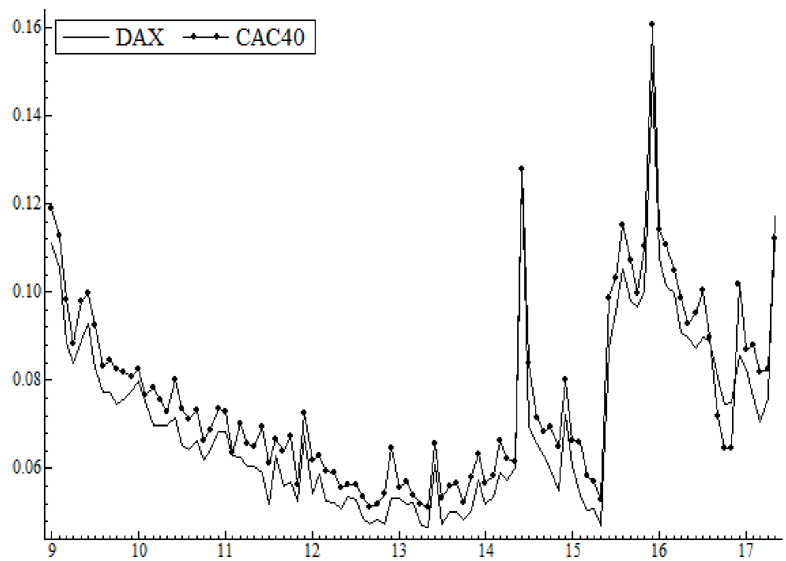
Announcement	Germany	United States
Consumer Price Index CPI	14:00	14:30
Industrial Production IP	12:00	15:15
Unemployment Rate UN	9:55	14:30
Durable Goods Order DGO	12:00	14:30
Economic Sentiment Indicator ES	11:00*	16:00**
Purchasing Manager Index (manufacturing) PMI	9:30***	15:45****

* Zentrum fűr Europaische Wirtschaftsforschung Economic Sentiment ZEW
** The Conference Board Consumer Confidence Index CBCC
*** Preliminary Manufacturing PMI
**** Chicago PMI

3 Intraday volatility pattern and the methods of periodicity filtering

Intraday data are characterized by periodical patterns observed in volatility, which must be taken into account when modeling news effects (Andersen and Bolleslev, 1998). In the Figure 2 we show the periodical patterns of volatility of the examined stock markets, in which unobserved volatility is proxied by absolute returns. According to stylized facts described in the literature volatility is higher at the beginning and at the end of the trading day and lower in the middle of the day. There are distinct peaks in volatility observed on these two markets, at 14:30 and 16:00 (see Fig. 2).

Figure 2: The averages of absolute DAX and CAC40 returns from 4.05.2009 to 21.04.2011 within five-minute interval from 9:05 till 17:30



Since the papers of Andersen and Bollerslev (1997, 1998) the flexible Fourier form (FFF) has become the most popular parametric method of estimating the deterministic component of volatility. It was introduced originally by Gallant (1981) and used in this approach by Andersen and Bollerlsev in their seminal paper (1997). Our choice of the method of periodicity filtering is motivated by Laakkonen (2007), who showed that for the purpose of studying the impact of news on volatility, the FFF method compared to other methods produced the smallest bias in the estimates for news coefficients (Laakkonen 2007).

3.1 Flexible Fourier form regression

In the flexible Fourier form approach volatility is separated into three components: a periodic component, which reflects daily activity cycle, standard daily volatility clustering and calendar effects (e.g. weekday effect, macro surprise effect). Our sample consists of N equally spaced percentage logarithmic five-minute returns in T days. Therefore $r_{t,n}$ is an intraday return in day t ($t = 1, \ldots, T$) and interval n ($n = 1, \ldots, N$). Andersen and Bollerslev (1998) formulate the following model:

$$r_{t,n} - E\left(r_{t,n}\right) = \frac{\sigma_t s_{t,n} Z_{t,n}}{N^{0.5}} \tag{1}$$

where $E\left(r_{t,n}\right)$ is the unconditional expectation of equally spaced (here five-minute) returns, σ_t is a conditional variance on day t, and $s_{t,n}$ is an intraday periodical component. The innovations $Z_{t,n}$ are assumed to be i.i.d. process independent on the daily volatility process. The expected return is replaced by the sample mean of the five-minute returns, $E\left(r_{t,n}\right) = \overline{r}$, $\widehat{\sigma}_t$ is an a priori estimate of the daily volatility component, N refers to the number of return intervals per day (here $N = 101$). In our approach $\widehat{\sigma}_t$ is calculated as a bipower variation, the robust volatility estimator proposed by Barndorff-Nielsen and Shephard (2004):

$$\widehat{\sigma}_t = \sqrt{\frac{\pi}{2} \frac{N}{N-1} \sum_{n=2}^{N} |r_{t,n-1}||r_{t,n}|}. \tag{2}$$

By squaring and taking logs of both sides of the equation (1) we obtain the following:

$$2\ln \frac{|r_{t,n} - \overline{r}|}{\widehat{\sigma}_t / N^{0.5}} = 2\ln\left(s_{t,n}\right) + 2\ln\left(Z_{t,n}\right) \tag{3}$$

The first component on the right-hand side of the equation (3) refers to intraday volatility and is modeled by the trigonometric functions. The other component is an error term, that includes volatility caused e.g. by news released in the markets.

In the second step, the FFF regression is estimated. As Bollerslev, Cai and Song (2001) show

$$f_{t,n} = 2\ln \frac{|r_{t,n} - \overline{r}|}{\widehat{\sigma}_t / N^{0.5}}$$

can be approached by the trigonometric functions used to describe the intraday periodicity together with variables capturing the effects of announcements releases:

$$f_{t,n} = \mu_1 \frac{n}{N_1} + \mu_2 \frac{n^2}{N_2} + \sum_{p=1}^{p} \left(\gamma_p \cos \frac{2\mu p}{N} n + \delta_p \sin \frac{2\pi p}{N} n \right) + \sum_{i=1}^{I} \phi_i D_{i,t,n} + e_{t,n} \tag{4}$$

where $N_1 = \frac{N+1}{2}$, $N_2 = \frac{2N^2+3N+1}{6}$ are normalizing constants (N_2 normalizing constant is corrected according to the suggestion presented in Laurent (2010)), P

is a tuning parameter determining the order of the Fourier expansion, $D_{i,t,n}$ are the indicator variables that stand for the calendar effects (e.g. weekday effect) and $e_{t,n}$ is an error term. The parameters of equation (4) are estimated with ordinary least squares (OLS). After the estimation the deterministic periodicity factor is defined as:

$$\widehat{s}_{t,n} = \frac{TN \exp\left(\frac{\widehat{f}_{t,n}}{2}\right)}{\sum_{t=1}^{T}\sum_{n=1}^{N} \exp\left(\frac{\widehat{f}_{t,n}}{2}\right)} \tag{5}$$

where $\widehat{f}_{t,n}$ are the fitted values of equation (4). Within equation (5) $\widehat{s}_{t,n}$ estimates are normalized, so that the mean of periodicity components equals one. The filtered returns are then obtained for interval n on day t as

$$\widehat{r}_{t,n} = \frac{r_{t,n}}{\widehat{s}_{t,n}}$$

.

3.2 The characteristics of returns after periodicity filtering

Two issues are to be considered when filtering periodicity with FFF method. The first is that the estimation of FFF regression involve selecting the lag for the Fourier expansion and dummy variables to minimize distortions. Theoretically model selection is based on choosing model that best imitate the shape of periodic pattern with minimal number of parameters (Gençay, Selçuk and Whitcher, 2001). However the choice of parameter P in equation (4) is usually unexplained (e.g. Martens, Chang and Taylor, 2002) or depends on the information criteria (e.g. Laakkonen 2010). We will follow the latter idea and use Bayesian (Schwarz) information criterion. For the initial periodicity estimation we include only dummy variables for weekday effect.

The second issue is related to the characteristics of autocorrelation functions for absolute filtered returns. Laakkonen (2007) shows that if the FFF method is estimated for long series (e.g. few years), significant periodical autocorrelation in volatility might occur. She found that the FFF method was able to capture the intraday periodicity fully only when the filtering was done on subsets of data. Therefore we control the shape of the autocorrelation function of volatility of filtered returns to examine if the FFF method is successful in extracting the intraday periodicity.

The estimates from the FFF regression are presented in Table 3. The value of $p = 7$ and $p = 9$ was selected for CAC40 and DAX returns respectively based on Schwarz information criterion. The parameters standing at variables measuring the weekday effect are not statistically significant (apart from Friday variable in regression for DAX). Therefore in further estimations we omit these variables.

The descriptive statistics of the series after periodicity filtering are presented in Table 4. Filtering the data from periodicity influence slightly the means and standard

Table 3: The estimates of parameters of FFF regression

	DAX		CAC40	
parameter	coefficients	*std.errors*	coefficients	*std.errors*
ϕ_1 (Monday)	-0.0212	0.0368	0.0249	0.0361
ϕ_2 (Tuesday)	-0.0332	0.0327	-0.0117	0.0320
ϕ_3 (Wednesday)	-0.0036	0.0319	0.0163	0.0313
ϕ_4 (Thursday)	-0.0210	0.0342	-0.0158	0.0335
ϕ_5 (Friday)	**-0.0866**	0.0388	-0.0313	0.0381
μ_1	**-4.5037**	0.1583	**-4.1188**	0.1400
μ_2	**2.9724**	0.1511	**2.6259**	0.1321
γ_1	**-0.2778**	0.0489	**-0.2207**	0.0433
δ_1	**-0.1780**	0.0475	**-0.2808**	0.0416
γ_2	**-0.2577**	0.0195	**-0.2470**	0.0183
δ_2	**-0.0981**	0.0270	**-0.1258**	0.0243
γ_3	**-0.1457**	0.0162	**-0.1107**	0.0156
δ_3	0.0005	0.0211	0.0160	0.0195
γ_4	**-0.1353**	0.0154	**-0.1162**	0.0150
δ_4	**0.1269**	0.0186	**0.1120**	0.0175
γ_5	**0.0428**	0.0152	**0.0590**	0.0148
δ_5	**0.1525**	0.0173	**0.1432**	0.0165
γ_6	**0.1179**	0.0151	**0.1567**	0.0147
δ_6	0.0061	0.0166	-0.0032	0.0159
γ_7	**-0.0361**	0.0150	0.0014	0.0147
δ_7	**-0.0948**	0.0162	**-0.0833**	0.0156
γ_8	-0.0262	0.0150		
δ_8	**0.0564**	0.0158		
γ_9	0.0235	0.0150		
δ_9	**0.0973**	0.0156		
T	51106		51106	
k	25		21	

Note: The bolded parameters are statistically significant at $\alpha = 0.05$

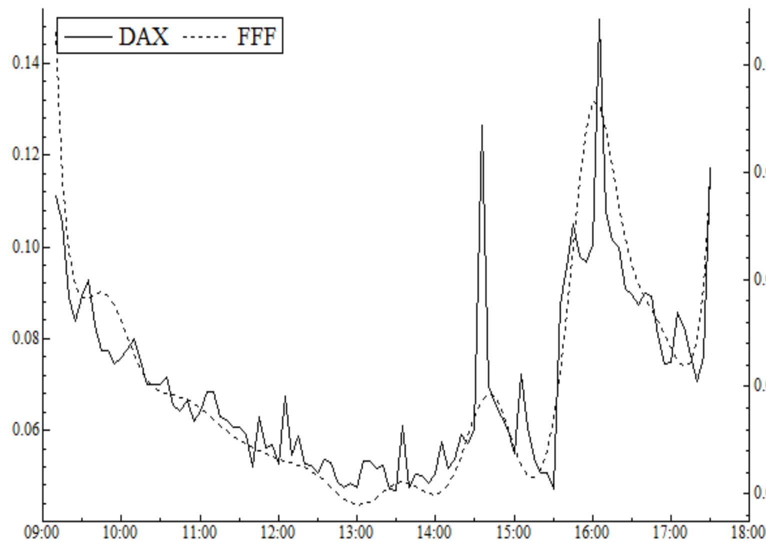
deviations. The distributions are left-tailed as for the raw return series, and the excess curtoses are even higher than for raw series.

We present the average absolute raw returns of DAX and CAC40 together with average absolute filtered returns (see Figure 3 and 4 respectively). The shapes of average absolute returns after filtering are well-fitted to the original shapes. The right-side scale is required for non-parametric periodicity estimators, which are given in a form, that satisfy the standardization condition shown in (5). We also present the autocorrelation function of absolute raw and filtered returns of DAX and CAC40

Table 4: The descriptive statistics of filtered returns: CAC40 and DAX in the period from 04.05.2009 to 21.04.2011

	Mean	Std.dev	Min	Max	Skewness	Excess kurtosis
CAC40, $p = 7$	-0.0001	0.1083	-1.8660	1.4792	-0.2692	8.7594
DAX, $p = 9$	0.0000	0.1018	-2.0323	1.2140	-0.4082	10.4120

Figure 3: The comparison of average absolute returns of DAX and absolute filtered returns from 4.05.2009 to 21.04.2011. The method of filtering is flexible Fourier form (FFF)



DAX stands for average absolute returns of DAX index, whereas FFF stands for average absolute returns of filtered DAX index.

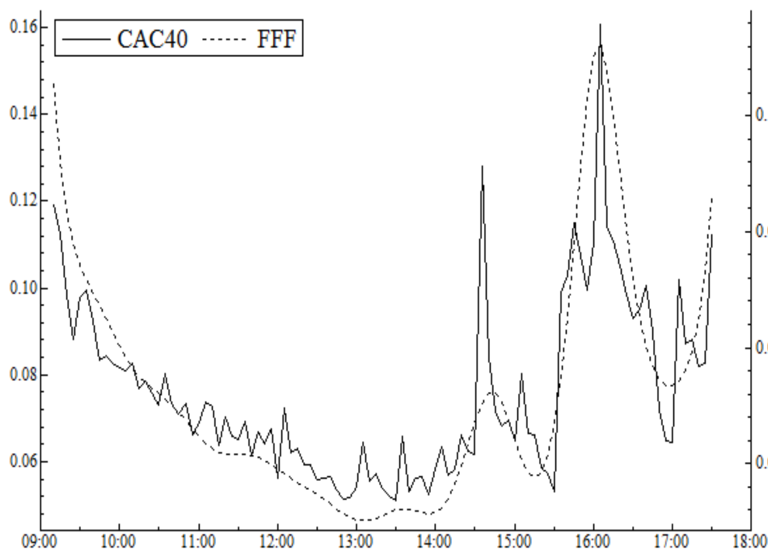
(see Figure 5 and 6 respectively). In the case of absolute raw returns, the peaks in volatility are recognized at lags of multiple 101 (the whole autocorrelation functions are depicted for the number of lags referring to 5 days). After intraday periodicity adjustment, these peaks are no longer observable and the autocorrelation function is characterized by rapid initial decay in first lags followed by very slow rate of decay thereafter. This hyperbolic shape exhibits the persistence in volatility associated with the long memory. This property is an intrinsic feature of the high frequency series (Baillie, Bollerslev and Mikkelsen, 1996). As the autocorrelation functions for absolute filtered returns in both cases decay without significant peaks, we assume that the intraday periodicity pattern is stable over whole sample and therefore estimate FFF regression for the entire data set.

4 The reaction to macro news: one-step estimation

In the one-step estimation we include two different types of the variables $X_{i,t,n}$ standing for macro surprises to the flexible Fourier form:

$$f_{t,n} = \mu_1 \frac{n}{N_1} + \mu_2 \frac{n^2}{N_2} + \sum_{p=1}^{p} \left(\gamma_p \cos \frac{2\mu p}{N} n + \delta_p \sin \frac{2\pi p}{N} n \right) + \sum_{i=1}^{I} \phi_i X_{i,t,n} + e_{t,n}. \quad (6)$$

Figure 4: The comparison of average absolute returns of CAC40 and absolute filtered returns from 4.05.2009 to 21.04.2011. The method of filtering is flexible Fourier form (FFF)



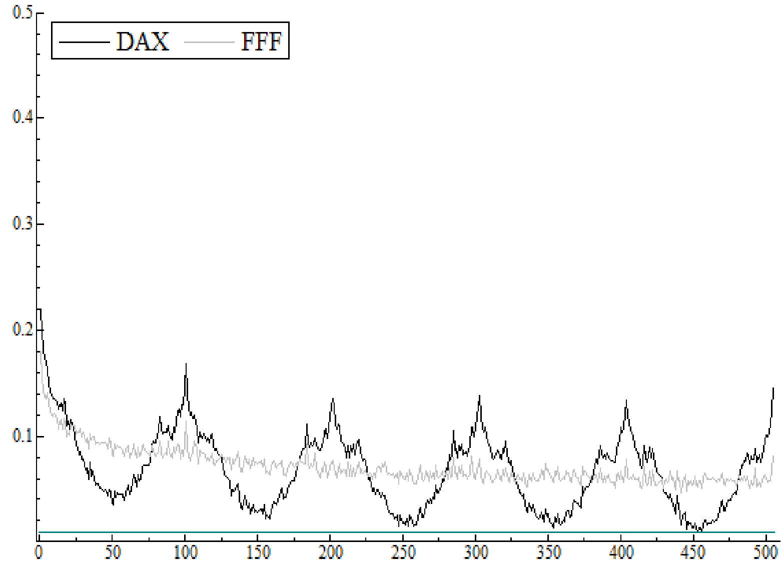
CAC40 stands for average absolute returns of CAC40 index, whereas FFF stands for average absolute returns of filtered CAC40 index.

In the first approach we use the standardized surprises (hereafter SURP), whereas in the second the indicator variables are included (INDV). Following Balduzzi et al. (2001) the standardized surprises are calculated as the difference between the actual and expected value of fundamentals, divided by the deviations from the actual values in the sample. In the model (SURP) $X_{i,t,n}$ is calculated as:

$$X_{i,t,n} = \frac{|w_i - E(w_i)|}{\sigma_i}. \quad (7)$$

where w_i is the released value and $E(w_i)$ is the expected value of the macro

Figure 5: The autocorrelation function for absolute raw returns (DAX) and filtered returns (FFF)



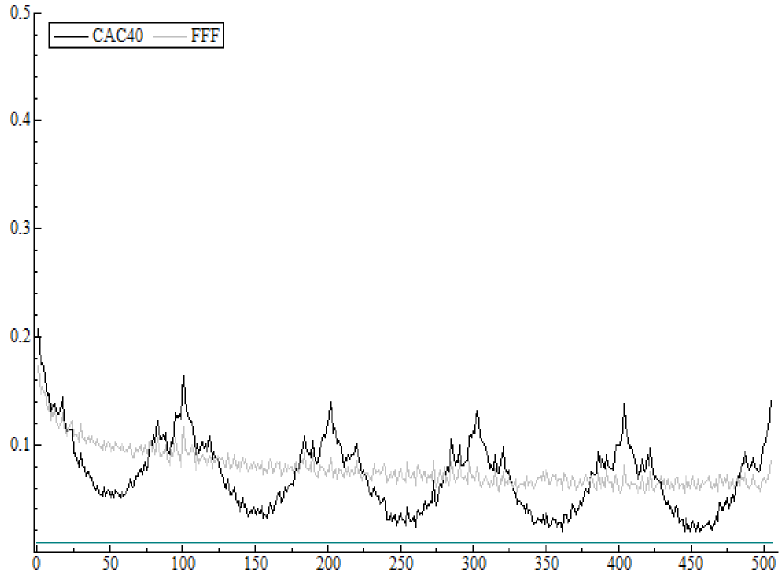
The autocorrelation functions for raw series (DAX) and filtered series (FFF). The 505 lags represent five days.

fundamental based on analytics' consensus, σ_i is the standard deviation of the surprises in the sample. When there is no surprise at a given five-minute interval, the value of variable $X_{i,t,n}$ is zero. The results of the FFF regression for standardized surprises are presented in Table 5.

This regression allows us to consider the reaction to macro surprises in the first five-minute interval after the announcement. For both series, DAX returns and CAC40 returns, the same American announcements increase volatility of returns. These are: unemployment rate UN, durable goods order DGO and economic sentiment EC. The peaks in volatility observed on 14:35 and 16:05 which are clearly visible in average absolute returns (Figure 3) are to some extent caused by the releases examined in the study. When we consider announcements from the German economy, three macro surprises increase volatility of DAX and CAC40 indices. These are industrial production IP, durable goods order DGO and economic sentiment ES.

We also present the estimates from flexible Fourier form regression with indicator variables (INDV). These variables represent the news arrival and are equal to unity when the macro surprise occurs ($w_i \neq E(w_i)$) in the first five-minute interval after the release, or are zero otherwise. The estimated coefficients presented in Table 6 show that four out of six American announcements have an impact on volatility of DAX and CAC40 indices – these are unemployment rate UN, durable goods order

Figure 6: The autocorrelation function for absolute raw returns (CAC40) and filtered returns (FFF)



The autocorrelation functions for raw series (CAC40) and filtered series (FFF). The 505 lags represent five days.

DGO, economic sentiment EC and – in addition to the results from former regression – consumer price index CPI. In the case of domestic (DAX) or neighbor country (CAC40) macro surprises the same announcements are statistically significant as in the regression with standardized news.

The signs of estimates from the models with standardized surprises (Table 5) and dummy variables (Table 6) are identical. The most powerful announcement in the short run is the American unemployment rate. The parallel variable from the group of the German announcements, the German unemployment rate, produces no significant impact. This can be caused by the fact that the whole-country unemployment report is preceded by reports from German lands and therefore macro surprise in the final release declines. Among the German announcements, ZEW releases occur to be the most influential. Although the sample period is different from one used in the previous study (Będowska-Sójka 2011), results obtained for the DAX regression with dummy variables confirm our earlier findings.

Table 5: The estimates of flexible Fourier form regression with standardized news (SURP)

Index	DAX				CAC40			
Ann.	United States		Germany		United States		Germany	
Xi	coeff.	JRSE	coeff.	JRSE	coeff.	JRSE	coeff.	JRSE
CPI	1.0932	0.6239	0.2391	0.6384	1.0757	0.5641	0.3632	0.7485
IP	-0.1267	0.5955	**1.1197**	0.3748	0.5192	0.3294	**1.2538**	0.2613
UN	**3.4393**	0.7062	-0.2486	0.5808	**2.5562**	0.6135	0.2099	0.2835
DGO	**2.0618**	0.4961	**0.8410**	0.3983	**2.4886**	0.3991	**0.9063**	0.3787
ES	**2.1339**	0.3885	**1.7217**	0.2951	**1.9552**	0.3814	**1.5966**	0.3592
PMI	-0.2050	1.0680	-0.1299	0.5000	0.5775	0.4835	0.0596	0.4436
$\frac{n}{N_1}$	**-14.0286**	1.2640			**-14.9174**	1.2550		
$\frac{n^2}{N_2}$	**9.1364**	0.8385			**9.74404**	0.8316		
T	51106				51106			

Note: The five-minute DAX and CAC40 returns are from 9:10 , May, 4, 2009, through 17:30, April, 21, 2011 for a total of 506 days. The total number of observations is 51106. The intraday periodicity is estimated with FFF regression. The estimated parameters are presented together with jackknife robust standard errors (CJRSE) of MacKinnon and White (1985). The bolded parameters are statistically significant at $\alpha = 0.05$.

Table 6: The estimates of flexible Fourier form regression with dummy variables (INDV)

Index	DAX				CAC40			
Ann.	United States		Germany		United States		Germany	
Xi	coeff.	JRSE	coeff.	JRSE	coeff.	JRSE	coeff.	JRSE
CPI	**1.7034**	0.3838	0.3858	0.7096	**1.8738**	0.3759	0.0868	0.6837
IP	0.2332	0.5389	**1.0888**	0.4479	0.5501	0.4602	**1.0229**	0.3666
UN	**4.5723**	0.3716	-0.1255	0.8362	**3.6231**	0.5176	0.2625	0.5401
DGO	**2.4571**	0.5180	**0.8693**	0.3863	**2.9583**	0.3543	**1.0867**	0.4154
ES	**2.2614**	0.4250	**1.7370**	0.3837	**1.7087**	0.5557	**1.7294**	0.3767
PMI	0.1203	0.8151	0.0628	0.4200	0.7128	0.4791	0.2766	0.3933
$\frac{n}{N_1}$	**-14.0002**	1.2940			**-14.9114**	1.2560		
$\frac{n^2}{N_2}$	**9.1182**	0.8572			**9.7412**	0.8326		
T	51106				51106			

Note: The five-minute DAX and CAC40 returns are from 9:10 , May, 4, 2009, through 17:30, April, 21, 2011 for a total of 506 days. The intraday periodicity is estimated with FFF regression. The estimated parameters are presented together with jackknife robust standard errors (JRSE) of MacKinnon and White (1985). The bolded parameters are statistically significant at $\alpha = 0.05$.

5 The reaction to macro news: two-step estimation

5.1 Methodology

In the second approach we estimate the joined impact of macro news from the U.S. and the German economy, both on the conditional mean and the conditional variance. We construct two aggregated indicator variables in order to measure the joined impact. These variables are equal to unity at the time of the macro surprise releases (within the first five-minute interval), if any of the above-listed macro surprises occurs and zero otherwise. One variable is for the releases from the German economy, and the other for releases from the U.S. Our aim is to answer, if the macro fundamentals influence the markets' mean and volatility immediately following the information releases.
As the hyperbolic decay of the autocorrelation function of the absolute filtered returns indicates the long memory, the conditional variance of the filtered return series is modeled with a fractionally integrated process. We choose the FIGARCH model of Baillie et al. (1996) (other examples of FIGARCH modelling in intraday data are: Baillie, Cecen and Han, 2000, Conrad and Lamla, 2010). The series used in this part of the study are the returns filtered with FFF method.
At this stage we are interested in the reaction of indices both in level and in volatility. Therefore we allow for explanatory variables in the form of indicative variables in the conditional mean and in the conditional variance equations.
The conditional mean equations are modeled with the ARFIMA process with two indicator variables, $X_{i,t,n}$, standing respectively for the German ($i = 1$) and the American ($i = 2$) macro releases:

$$\Psi(L)(1-L)^{\delta}\left(\widehat{r}_{t,n} - \mu_{t,n} - \sum_{i=2}^{2}\alpha_i X_{i,t,n}\right) = \Theta(L)a_{t,n} \tag{8}$$

$$a_{t,n} = \varepsilon_{t,n}\sigma_{t,n} \tag{9}$$

where $\widehat{r}_{t,n}$ is filtered intraday return, $\varepsilon_{t,n}$ is i.i.d. process with Student t distribution. The innovations are modeled with the FIGARCH(p,d,q) process:

$$(1-L)^d\Phi(L)a_{t,n}^2 = \omega + B(L)\left(a_{t,n}^2 - \sigma_{t,n}^2\right) \tag{10}$$

with lag polonymials $\Phi(L) = 1 - \sum_{i=1}^{q}\phi_i L^i$, $B(L) = 1 - \sum_{i=1}^{q}\beta_i L^i$, and $0 \leq d \leq 1$ being the fractional differencing parameter.
Similarly to the conditional mean equation, in the conditional variance equation we allow for two indicator variables standing for the presence of the macro surprises. The conditional variance equation is following:

$$B(L)\sigma_{t,n}^2 = \omega + \sum_{i=1}^{2}\omega_i X_{i,t,n} + \left(B(L) - (1-L)^d\Phi(L)\right)a_{t,n}^2 \tag{11}$$

For any $0 < d < 1$ the FIGARCH process is not covariance stationary, since its unconditional variance does not exist, nonetheless it is strictly stationary (Fiszeder 2009). A crucial issue in specifying a proper FIGARCH model is to examine if all the parameters of the FIGARCH process ensure non-negativity of the conditional variance. An in-depth discussion on the properties of the FIGARCH model can be found in (Conrad, Haag, 2006). Since in the Section 5.2. FIGARCH(1,d,1) models are presented, we show the necessary and sufficient conditions for non-negative conditional variance given in Conrad and Haag (2006) for this particular specification. These conditions ensure that all ψ_i coefficients in the ARCH(∞) representation of the FIGARCH process are nonnegative. The FIGARCH model has the following ARCH(∞) representation:

$$\sigma_k^2 = \frac{\omega}{\beta_1} + \left(1 - \frac{(1-L)^d \Phi(L)}{B(L)}\right) a_k^2 = \frac{\omega}{\beta_1} + \sum_{j=1}^{\infty} \psi_j a_{k-j}^2 \tag{12}$$

where for the sake of convenience we change the notation for the subindex from t, n to $k = 1, \ldots, TN$. For the (1,d,1) model the ARCH coefficients can be derived recursively as $\psi_1 = d + \phi_1 - \beta_1$ and $\psi_j = \beta_1 \psi_{j-1} + (f_j - \phi_1)(-g_{j-1})$ for $j \geq 2$, where $f_j = \frac{j-1-d}{j}$ and $g_j = f_j g_{j-1}$ with $g_0 = 1$. The conditional variance of the FIGARCH(1,d,1) is nonnegative if (Conrad, Haag, 2006, Corollary 1, p.421):

- Case (1): for $0 < \beta_1 < 1$, either $\psi_1 \geq 0$, $\phi_1 \leq f_2$, or for $j > 2$ with $f_{j-1} < \phi_1 \leq f_j$, it holds that $\psi_{j-1} \geq 0$;

- Case (2): for $-1 < \beta_1 < 0$, either $\psi_1 \geq 0$, $\psi_2 \geq 0$, and $\phi_1 \leq f_2 \frac{\beta_1 + f_3}{\beta_1 + f_2}$ or for $j > 3$ with $f_{j-2} \frac{\beta_1 + f_{j-1}}{\beta_1 + f_{j-2}} < \phi_1 \leq f_{j-1} \frac{\beta_1 + f_j}{\beta_1 + f_{j-1}}$, it holds that $\psi_{j-1} \geq 0$ and $\psi_{j-2} \geq 0$.

Alternatively, Bollerslev and Mikkelsen (1996) provide the following inequality constraints (p. 159): $\beta_1 - d \leq \phi_1 \leq \frac{2-d}{3}$ and $d\left[\phi_1 - \frac{(1-d)}{2}\right] \leq \beta_1 (\phi_1 - \beta_1 + d)$.
After model estimation we use both approaches in examining if the stationary conditions for FIGARCH models are satisfied.

5.2 Empirical results

First we estimate pure ARFIMA-FIGARCH models without additional variables. To capture the leptokurtosis in the filtered returns series, the innovation term has Student t distribution with ν degrees of freedom. The parameters in the conditional variance equations are statistically significant with the values that satisfy the stationary conditions presented in Section 5.1. The fractionally integrated parameters in both equations, the conditional mean and the conditional variance, are also statistically significant.
Next we estimate the ARFIMA-FIGARCH models with indicative variables measuring the joined impact of releases. The values of the parameter estimates in

Table 7: The estimates of ARFIMA(0,δ,0) – FIGARCH(1,d,1) with indicator variables standing for the macro announcements in the German and the American economy

	CAC40 no an	CAC40 an	DAX no an	DAX an
The conditional mean equation				
δ	**-0.0071**	**-0.0071**	**-0.0085**	**-0.0084**
	0.0034	*0.0034*	*0.0034*	*0.0034*
α_1 German ann.		**0.0280**		0.0157
		0.0100		*0.0094*
α_2 American ann.		**-0.0357**		**-0.0322**
		0.0101		*0.0094*
The conditional variance equation				
ω_0	**0.0004**	**0.0004**	**0.0003**	**0.0003**
	0.0000	*0.0000*	*0.0000*	*0.0000*
ω_1 German ann.		**0.0045**		**0.0044**
		0.0015		*0.0014*
ω_2 American ann.		**0.0177**		**0.0135**
		0.0038		0.0029
d	**0.3477**	**0.3328**	**0.3638**	**0.3483**
	0.0114	*0.0112*	*0.0109*	*0.0108*
φ	**0.3413**	0.**3261**	**0.3806**	**0.3601**
	0.0196	*0.0207*	*0.0227*	*0.0248*
β	**0.6050**	**0.5800**	**0.6369**	**0.6068**
	0.0203	*0.0228*	*0.0221*	*0.0261*
ν (Student df.)	**6.3130**	**6.4335**	**5.4018**	**5.4656**
	0.9123	*0.9456*	*0.8263*	*0.8754*
Log L	45903.4	45956.87	49996.7	50047.12

Note: The estimated parameters together with standard errors (in italics). The bolded parameters are statistically significant at $\alpha = 0.05$. "*no an*" means that the indicative variables are not included in the equations, "*an*" means the model with announcement variables is estimated. Parameters α_i and ω_i stand for the announcement effect of the German or American macro surprises respectively in the conditional mean and the conditional variance equation. v stands for the degree of freedom in Student t distribution. Log L is a value of logarithm of maximum likelihood function.

both equations do not change significantly when we allow for indicative variables. The estimated parameters, namely α_1, α_2, ω_1, ω_2, for both indices have the same signs. In the mean equation for CAC40 returns we find a significant positive effect of the German macro surprises and a negative effect of the U.S. surprises. In the conditional variance equation for CAC40 index the estimated parameters of aggregated indicator variables from both economies are positive and highly significant. It means that volatility of index returns increases in five-minute intervals after the release of macro surprises.

In the model for DAX returns the American macro surprises decrease first five-minute

return, whereas the German macro surprises have no effect on the conditional mean. Both aggregated releases from the German and the U.S. economy increase volatility. However, similar to the results obtained in model for CAC40 returns, the impact of American macro surprises on conditional volatility is definitely stronger than that of German macro news. This finding offers additional information to that obtained from the FFF regression.
The results of this part of study show that in the very short period after the macro release, there is the reaction to American macro surprises in returns and volatility. This result corroborates earlier findings on the other markets. We observe also the reaction to the German macro surprises - they increase volatility on the German and the French stock market. Although to some extent the results are dependent on the specificity of the sample period, this study is confirming the results obtained for the DAX index presented by Będowska-Sójka (2011) for different sample period.

6 Conclusions

In the paper we examine and compare the reaction of the French and the German blue chip indices to the macro surprises from two economies, the German and the American. Within flexible Fourier form one-step estimation we show that the German macro surprises have a very similar impact on the German and French main indices' volatility. In our group of fundamentals the most powerful announcement is the American unemployment rate. Among the German announcements, ZEW releases occur to be the most influential. We show that when modeling the absolute returns with the FFF regression, both approaches, with indicator variables and standardized surprises, give similar results.
In the two-step estimation within ARFIMA-FIGARCH models with aggregated macro surprises from two economies, we find that the German macro surprises increase the mean of the French index. Both German and American macro surprises increase volatility of the French and the German index. Although the results confirm the previous findings in the literature that the American announcements have an impact on volatility, we show that the effect of German macro news is also significant not only on the domestic market, but also in the French stock market which is perceived as a neighbor-country market. However, the impact of German releases is weaker than the impact of the American ones.

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