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A COMPARISON OF ASYMMETRIC VOLATILITIES ACROSS EUROPEAN STOCK MARKETS AND THEIR IMPACT ON SENTIMENT INDICES

Abstract. *The property of asymmetry is fundamental in the study of financial volatility. In this paper we try to characterize the dynamics of asymmetric volatilities across European stock markets through the use of a modeling method that incorporates a series of GARCH initiatives and the Markov Switching approach. In addition to this, we aim to investigate the manner in which volatility asymmetry influences the evolution of sentiment indexes. Basing our analysis on the MIDAS methodology, (Mi(xed) Da(ta) S(ampling)) we find clear evidence about an existing relation between the two observed variables.*
Keywords: *Asymmetric volatility, Markov Switching, MIDAS regressions, sentiment indices.*

JEL Classification C58, G17, G15

1. Introduction

One of the core scientific research areas in contemporary finance is the relation between financial returns and their volatilities. A strong and growing literature documents on the negative correlation linking returns and conditional variance. As it has been observed in empirical applications, financial markets exhibit the phenomenon of asymmetric volatility which consists in the fact that volatility tends to be higher in market declines than in market escalations.

This phenomenon has been profoundly scrutinized in seminal works like: Black (1976), Christie (1982), Bekaert and Wu (2000), Eraker and Wu (2013) and more recently, Albu et al (2015).

The present paper has two main research objectives. The first is to build on the existing literature and provide an accurate and modern study on the evolution of asymmetric volatilities. For this purpose, we employ a series of models belonging to the GARCH family and the Markov switching method.

The second objective is to evaluate whether the dynamics of the asymmetric volatilities triggers changes in the behavior of sentiment indices. These indices aim to measure the feelings associated with the present state of stock markets. The classical hypothesis of rationality ignores concepts such as feelings or sentiments. Moreover, the efficient market hypothesis also disregards these aspects. In spite of these facts, and though lacking a strong theoretical analysis on the variables that should be included in such approaches, sentiment indexes have appealed to the scientific literature. Until present, the scintific literature focuses on empirical investigations that consider the influences of investor sentiment on the development of the stock market. Bormann (2013) observes that the present literature is divided into two separate types of initiatives. The first uses market variables as proxies for the construction of sentiment indices, while the latter is based on investor sentiment surveys. Key contribution to this area have been put forward by Neal and Wheatley (1998), Klein and Zwergel (2006), Baker and Wurgler (2007) or Lux (2011).

In our methodology we analyze two sentiment indexes, “Sentix” and “ZEW”. Given the fact that these variables have a low frequency, we use the MIDAS approach in order to model the connections between them, and the asymmetric volatilities exhibited in the first part of the study, in a similar pespective to that used in Lupu and Calin (2014 a) or Calin (2015). This method contributes to the existing literature, given the fact that it efficiently captures the effects generated by asymmetric volatilities on these indices, linking the quantitative financial approach to elements of behavioral finance.

The reminder of this paper is organized in the subsequent way. The following section offers a brief review of the present state of the existing literature. Section III presents the data included in this study, while section IV focuses on the methodological aspects of our research. Section V brings forth the results obtained and the last section concludes.

2. Review of the scientific literature

As stated above, the phenomenon of asymmetric volatility (AVP) has been profoundly investigated in the scientific literature. Pioneering works were put forward by Black (1976) and Christie (1982) which characterize the concept in relation to financial leverage. The leverage discussion is continued by Schwert (1989) who does not report a relevant causal link between this parameter and the evolution of the volatilities.

Glosten, Jagannathan and Runkle (1993) document a negative relation between the expected return and the conditional variances of those returns using a GARCH model. Similar approaches are found in Campbell and Hentschel (1992), Koutmos and Booth (1995) or Koutmos (1998). Using models belonging to the GARCH family in volatility investigation is a popular and tractable initiative that has been acknowledged by the scientific literature. Recent contributions in this area can be observed in Lupu (2011), Lupu and Calin (2014 b), Albu et al (2014a) or Albu et al (2014b).

Hasanhodzic and Lo (2011) offer an analysis that reconsiders the pioneering study of Black (1976). The authors show that financial leverage does not alter the link between stock prices and volatility. Xiang and Zhu (2015) consider the FTSE-100 as a basis for the investigation of asymmetric volatility in the case of what they define as extreme sells. The authors state that a relevant concept in the characterization of asymmetric volatility is the asymmetric liquidity. Other interesting contributions are present in Eraker and Wu (2013), Jackwerth and Vilkov (2014), Engle and Mistry (2014) or Albu et al (2015).

In the present paper we aim to test the link between the above characterized asymmetric volatility and the evolution of sentiment indices. The specific literature in this field germinated from the study of Neal and Wheatley (1998) who mix three market rations in order to discuss market sentiment. Simetrical iniatives can be observed in more recent contributions such as Finter et al. (2010).

Klein and Zwergel (2006), Heiden et al. (2011) or Lux (2011) explore certain characteristics of the *Sentix* index, while Lahl and Hüfner (2004) debate several statistical features of the *ZEW* indicator.

3. Data

We collected daily prices for the following Western and Eastern European market indices: CAC40 Index, UKX Index, FTSEMIB Index, DAX Index, WIG Index, BET Index, BGTR30 Index, PX Index and BUX Index. Their statistical properties are presented in Figure 1, in which we exhibit empirical distributions for daily log-returns and a superimposed normal distribution.

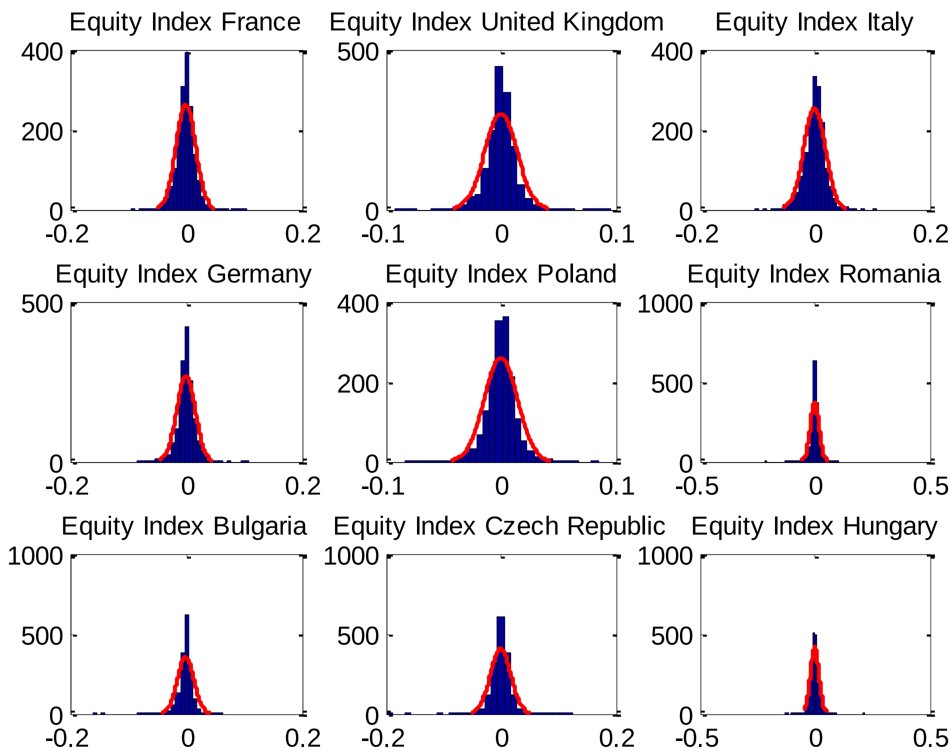

Figure 1 – Histograms for log-returns of all stock market indices

The differences between the series of volatilities that are meant to measure the existence of asymmetries in the dynamics stock indices should be part of the behavior of investors in these markets. We therefore consider the dynamics of Sentix and ZEW indices for the period under analysis. These indices have monthly frequencies and we use their realizations for the same period (September 2007 until December 2014). Statistical properties of the first difference of these series of indices are exhibited in Figure 2, since the levels are not stationary.

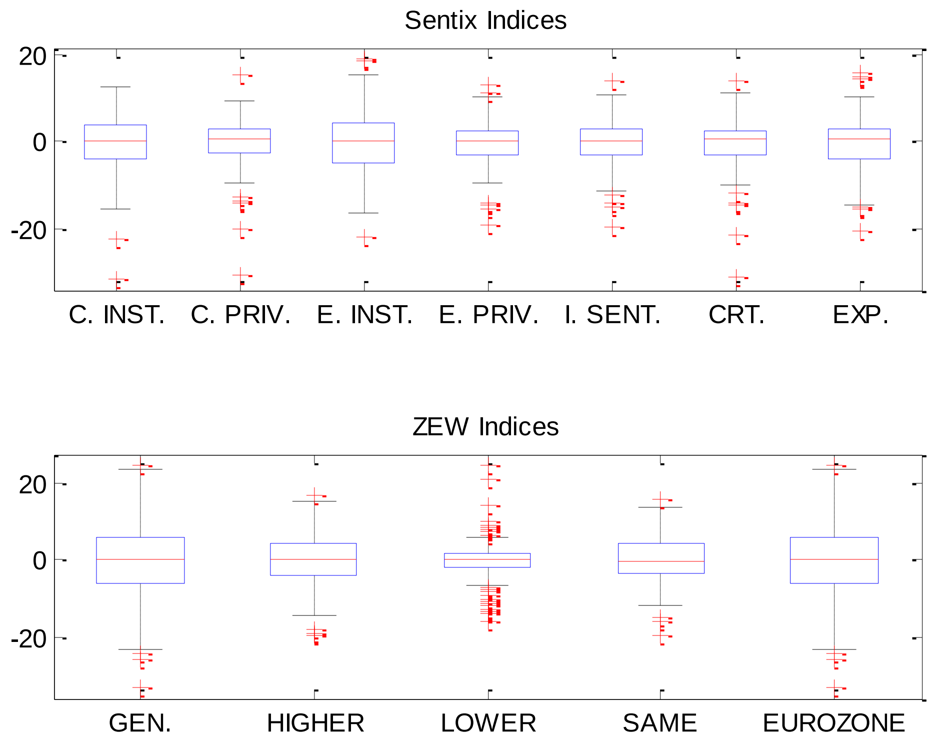

Figure 2 – Statistical properties of The ZEW and Sentix Sentiment indices for the whole sample period

4. Research methodology

Our analysis consists in the computation of the differences between GARCH estimated volatilities and the volatilities estimated by fitting the other three volatility models. The models employed in this section are: GARCH with SKEWED errors, EGARCH and GJR-GARCH.[1] These differences will be used as a measure of the dynamics of asymmetry for each index. These asymmetries will be analyzed through the use of a Markov Regime Shifting analysis on one hand and from this point we will

[1] For an ample discussion on GARCH modeling see for example Călin et al. (2014) or Lupu and Lupu (2007)

try to analyze the extent to which these volatilities could explain the dynamics of sentiment indices across Europe.

For the first analysis we present here the methodology of Markov Switching models as explained in the studies of Kim and Nelson (1999), Tsay (2002) or Alexander (2008).

The logic of the model is based on the assumption of the existence of a process characterized by the following equation:

$$y_t = \mu S_i + \epsilon_t \tag{1}$$

Where $S_m = 1 \ldots n$ and ϵ_t is considered to follow a normal distribution. The above equation states that if we consider *n* states, those states will generate n values for μ and n values for the σ^2 associated to the normal distribution.

In the case of a two state approach, the model expressed by equation 1 has the following form:

Considering a two state approach, the model is characterized by the following set of equations:

$$the\ first\ state: y_t = \mu_1 + \epsilon_t \quad \epsilon_t \sim (0, \sigma_1^2) \tag{2}$$

$$the\ second\ state: y_t = \mu_2 + \epsilon_t \quad \epsilon_t \sim (0, \sigma_2^2) \tag{3}$$

A tractable solution for the estimation of the Markov Switching model is the maximum likelihood method. Its formulation is given by the following equation: [2]

$$\ln L = \sum_{t=1}^{T} ln\left(\frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{y_t - \mu S_m}{2\sigma^2}\right)\right) \tag{4}$$

In order to conduct the sentiment analysis, we use the MIDAS methodology in which the sentiment indices will be used as dependent variables, with low frequency, while the differences in volatilities will be employed as explanatory variables, being characterised by high frequency.

The MIDAS methodology, Mi(xed) Da(ta) S(ampling) developed by Andreou, Ghysels, and Kourtellos (2013), allows the modeling of the possible linkages between variables with high frequencies and other variables with low frequencies. The modeling background relies on the hyperparameterizing a polynomial lag structure witch leads to the ADL-MIDAS (p_Y^Q, q_X^D) regression given by the equation.[3]

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[2] All computations are performed in Matlab. The Markov Regime Shifting analysis is realized with the use of the code developed by Marcelo Perlin.

[3] The MIDAS estimations are obtained using the Matlab toolbox put forward by Hang Qian, which is an evolution of the MIDAS program developed by Eric Ghysels and available on the Matlab File Exchange

$$Y^{q}_{T+1} = \mu + \sum_{j=0}^{p^{Q}_{Y}-1} \alpha_{j+1} Y^{Q}_{t-j} + \beta \sum_{j=0}^{q^{D}_{X}-1} \sum_{i=0}^{N_D-1} w_{i+j*N_D}(\theta^D) X_{N_D-i,t-j} + u_{t+1} \quad (5)$$

Our estimations incorporate a weighting method described by an exponential Almon lag polynomial with two parameters.

$$w_j(\theta^D) = w_j(\theta_1, \theta_2) = \frac{exp\theta_1 j + \theta_2 j^2)}{\sum_{j=1}^{m} exp(\theta_1 j + \theta_2 j^2)} \quad (6)$$

Following the methodology introduced by Andreou, Ghysels, and Kourtellos (2013) we are able to generate a linear specification for the high-frequency variable (here X^{D}_{t} -the differences in volatility) on the low-frequency variable (here Y^{Q}_{t} – representing the sentiment index values.)

5. Results and discussion

Statistical properties for the three types of differences that measure the asymmetries across the European stock market indices are presented in the boxplots from Figure 3.

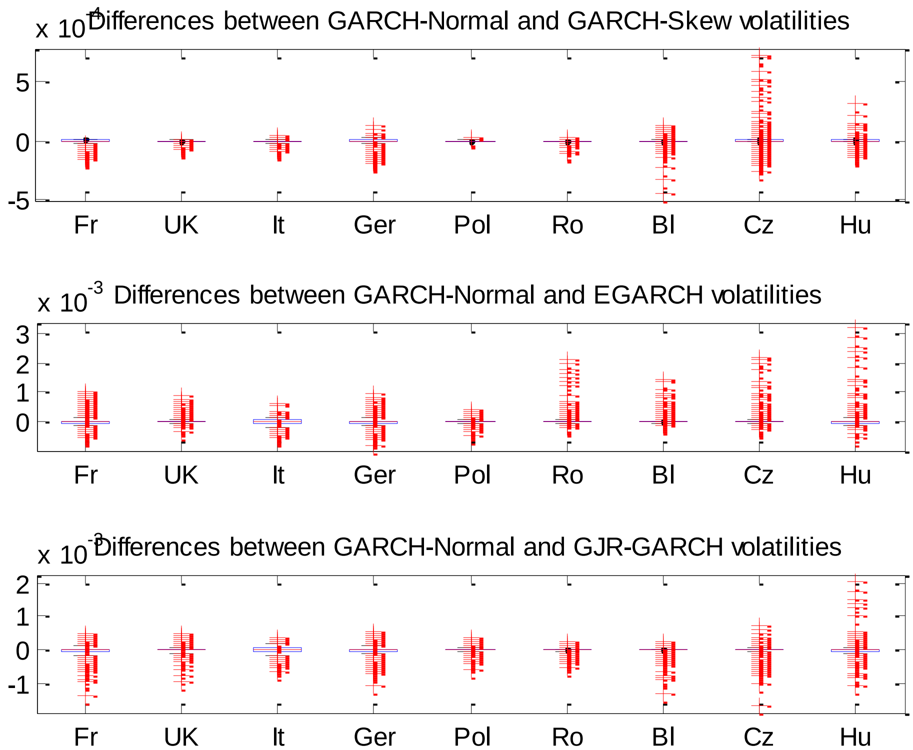

Figure 3 – Statistical properties of differences in volatilities fitted with normal errors against those for which asymmetric models were used

We notice that the distribution of these series of differences have heavy tails for all the countries, with a larger range for the case of Czech Republic and Hungary. For Romania the differences for the first and third case are quite stable and seem to be comparable to the normal distribution, while the second differences show that these distances have larger range than the developed countries.

The next step consisted in the calibration of the Markov Regime Shifting models with two states for the dynamics of the differences in volatilities. The probabilities for the changes from one state to the other (transition probabilities) were used to compute the moments when shifts are present and we built charts that present these dynamics across all countries and for each of the three categories of differences. Figure 4 below shows these regime shifts moments across all equity indices.

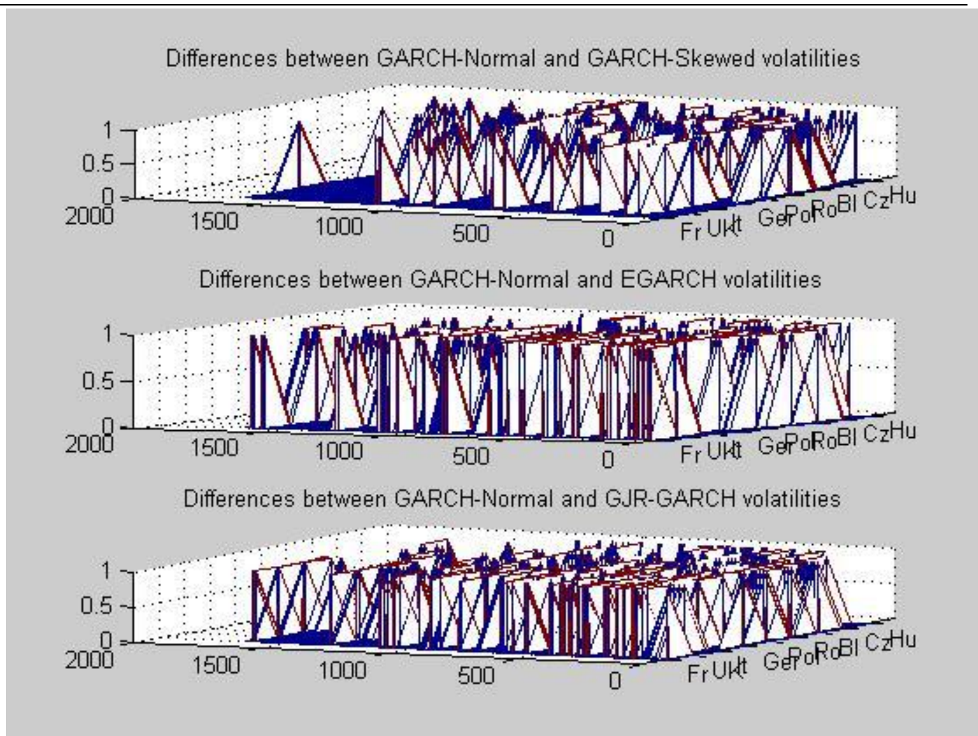

Figure 4 – Presentation of common regime shifting moments across all stock market indices

We can notice the fact that blocks of common moments are formed for the situations when regime shifts are recorded in the dynamics of the differences between differences in volatilities. If we decide to consider these differences as asymmetries in volatilities across all equity markets in Europe we can say that these asymmetries tend to co-move, i.e. to exhibit similar dynamics for the time series in our analysis, which may correspond to accepting that behavior in these markets is driven by the same factors.

Another manner to present the extent to which stock markets exhibit simultaneous regime shifts is developed in Figure 5. We can observe here the frequency of how many regime shifts were perceived in the same time (same day) for each set of asymmetries. We can notice that even though many of the shifts were rather individual, there are plenty of situations with common shifts across the series of returns.

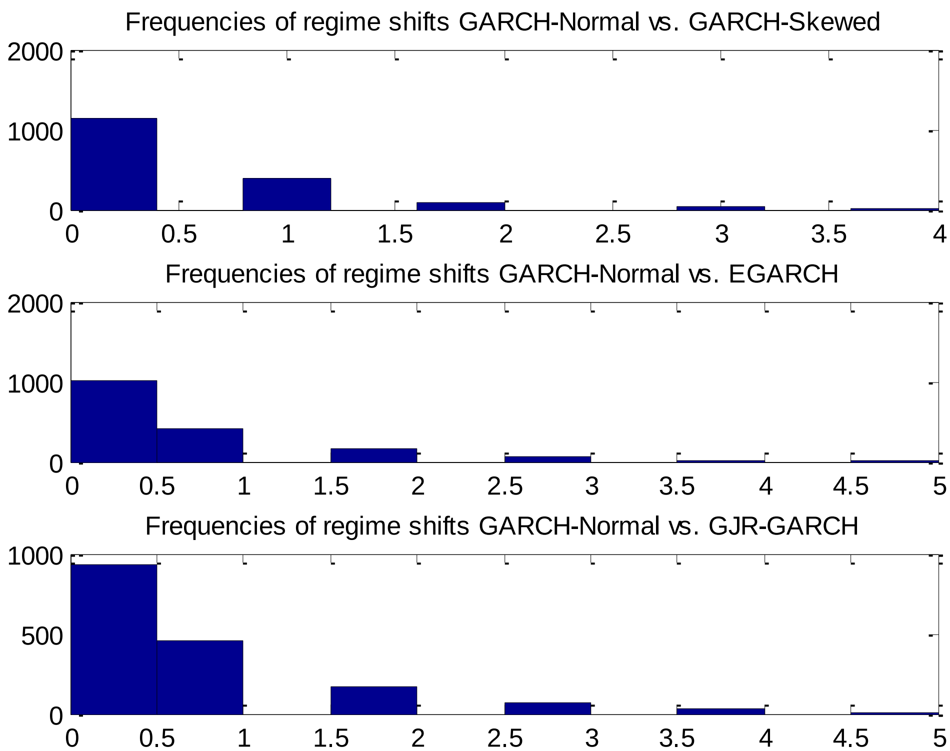

Figure 5 – Histogram of regime shifts for asymmetries across all European markets

In figures 6 and 7 we provide some results concerning the MIDAS regressions t-stats for the first differences of volatilities. We can notice the fact that for France and UK, we observe large t-statistics for almost all the Sentix indicators in our analysis, which means that in this cases the asymmetries, measured by the differences in volatilities fitted with different GARCH models, succeed to explain the sentiment indicators via the MIDAS regression presented in the Methodology section.

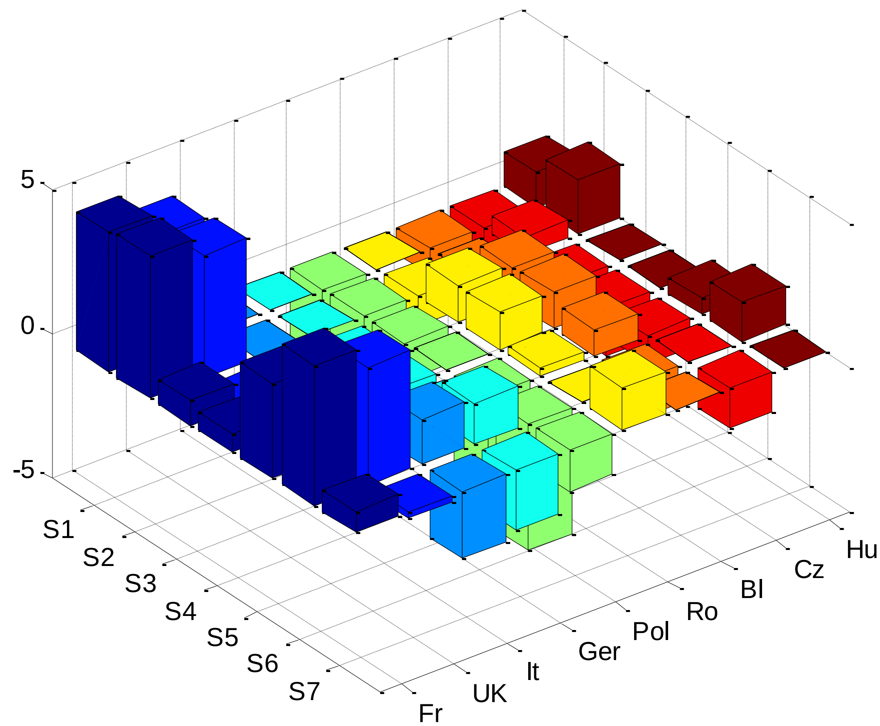

Figure 6 – T-statistics for the MIDAS regressions of Sentix Indices on the differences in volatilities resulted from GARCH with normal errors and GARCH with skewed errors

In the case of the ZEW indices, we notice more significant results for UK, Italy, Germany for the more developed economies and some reaction in the case of Bulgaria, Czech Republic and Hungary. The significant connections between European sentiment indicators and the asymmetries detected by the difference between volatilities seem to be more significant in the case of France and UK and less significant for the countries from Eastern Europe.

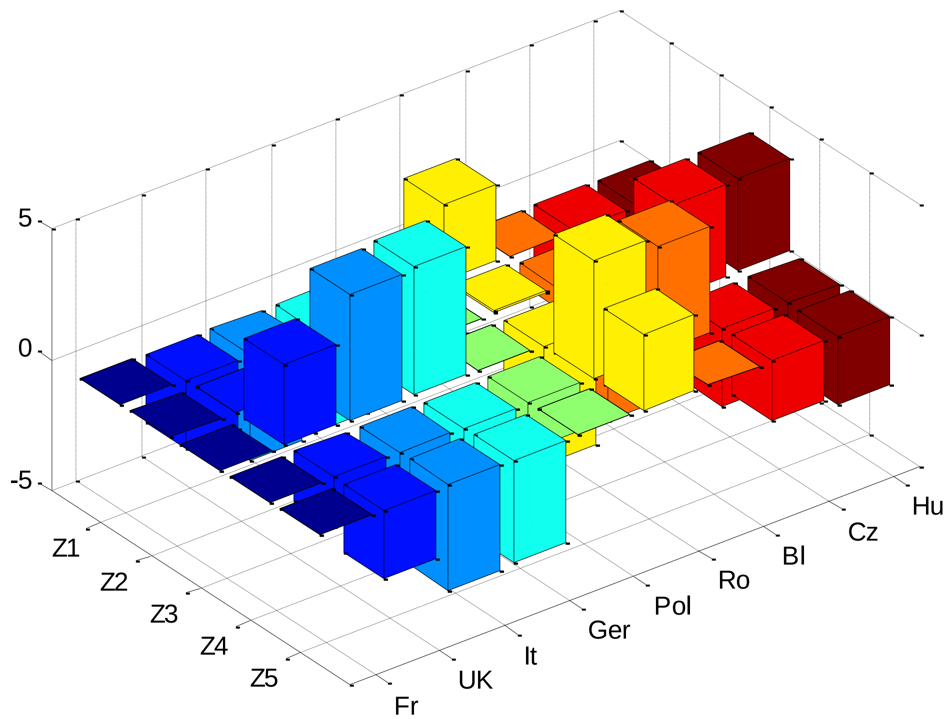

Figure 7 – T-statistics for the MIDAS regressions of ZEW Indices on the differences in volatilities resulted from GARCH with normal errors and GARCH with skewed errors

6. Conclusions:

This paper starts from two research questions. First of all we focused on the topic of asymmetric volatilies in European finanial markets. We then build on these results and try to investigate a possible connection between the assymetric volatility and the dynamics of two Sentiment Indices.

Firstly we observe that in the cases analysed the distributions of the differences obtained exhibit heavy tails. Moreover, our results indicate the fact that asymmetries in volatilities tend to co-move in the case of European equity markets.

The MIDAS method reveals the fact that in the case of France and UK the evolution of the Sentix indicator is influenced by the asymmetric volatilities. The ZEW indices are also extremely sensitive to these volatilities in the cases of UK, Italy, and Germany. Reactions are also reported for Bulgaria, Czech Republic and Hungary.

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