Changes in the Volatility of IBEX35 during the Crisis 2007-2009

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ABSTRACT

This paper investigates the structural break in the volatility of IBEX35. We investigate the volatility of the index over the period 2004-2009. Applying the Quadratic GARCH model and the LLM-test for possible break in the conditional volatility at the end of every month, we detect a structural break test around June 2007, few months after the beginning of financial and economic crisis. We observe different behaviour of conditional volatility in the pre- and post-break sample. The post-break model shows a better forecasting performance than the full sample model.

Keywords: Volatility, Structural Break, GARCH, Stock Markets, IBEX35.

JEL Classification: F3, G1, C5, C12.

Los cambios en la volatilidad del IBEX 35 durante la crisis 2007-2009

RESUMEN

Este trabajo analiza el cambio estructural en la volatilidad del IBEX35. El periodo de estudio abarca desde 2004 hasta 2009. Aplicando el modelo QGARCH y el test LLM para los cambios estructurales con fecha desconocida al final de cada mes, se detecta un cambio alrededor de Junio del 2007, unos meses después del comienzo de la crisis. Se observan diferencias en el comportamiento de la volatilidad antes y después del cambio estructural. Las predicciones de la volatilidad del IBEX35 obtenidas con el modelo con el cambio estructural impuesto son mejores que las predicciones obtenidas con el modelo sin cambio estructural impuesto.

Palabras Clave: Volatilidad; Cambio Estructural; GARCH; Mercados Financieros; IBEX35.

Clasificación JEL: F3, G1, C5, C12.

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1. INTRODUCTION

Volatility of stock prices and its forecasting play an important role in many areas of business life.

Changes in volatility and especially an increase in the level of volatility of financial markets can impact the economic activity through many channels. Investors may equate the higher volatility with higher risk and may alter or postpone their investments. Since shares are a part of household wealth, an increase in volatility may depress the consumer confidence and private consumptions.

The level of volatility in financial markets can also influence corporations’ investment decisions and banks’ willingness and ability to extend credit. Sharp changes in the level of financial market volatility can also be of concern to policymakers since it can threaten the viability of financial institutions and the smooth functioning of financial markets (see Becketti and Sellon (1989) for further discussion). Not to mention is the importance of volatility and volatility forecasting in asset pricing and risk management. Blanchard (2009) discusses the impact of increased volatility in the time of the crises, concentrating on the current economic situation. He points out that the main objective of the policy makers in the time of the severe contraction and the uncertainty indicators at the near of all-time heights should be to reduce the uncertainty using all the available tools bringing among others the volatility of financial markets to the normal levels.

The volatility of financial variables is a dynamic process that changes over time. The changes in volatility can be driven by the arrival of new information that changes the expected returns on stock due to changes in local or global economic environment.

Another factor driving the volatility can be changing traded volume or sociological or psychological factors like panic or fears that drive the stock prices from their fundamental values.

Technological progress that allows the quicker and more precise carrying out the transactions on the stock markets is another factor that makes the volatility to increase.

Finally the changes in volatility can be a consequence of stronger transmission of shocks due to increased interdependence and interconnectivity of stock markets coming from removing the barriers of trading in different markets (e.g. introduction of Euro significantly contributed to the increase in correlation among European stock markets (see Cappiello et al. (2006)).

The underlying process for volatility must be well specified to give the correct predictions about the development of volatility levels. This requires that the parameters of the model are stable over time. Parameters instability is an evidence of model misspecification. The structural break test is a useful tool for investigating the stability of the parameters of the model.

In this paper we concentrate on IBEX 35, the index of the blue chips traded on the Spanish stock market. Initiated in 1992, the IBEX 35 is a market capitalization weighted index of the 35 most liquid Spanish stocks in the Madrid Stock Exchange. We consider the daily quotations of the index over the period January 2004-May 2009, which account for three years of tranquil period and strong positive development of the market and two and a half of the recent economic and financial crises.

We consider the IBEX 35 due to many reasons - first of all we are interested in the volatility of the Spanish stock market. Secondly comparing to FTSE and DAX, the leading indexes from London and Frankfurt, the IBEX 35 was characterized by the higher volatility over the time of the crises (1.9528% for the second part of the sample, comparing to 1.8654% for London and 1.9013%).

Finally the integration of the Spanish stock market with the world economy and the exposure of Spanish companies to Latin America make the volatility of the index not only sensitive to the national territory but also induces a high exposure to the news coming from Eurozone, USA and Latin America.

Cuñado et al. (2004) analyze the changes in volatility of the monthly returns of the Spanish stock market over 1941-2001. They detect the structural break around 1972, coinciding with the opening of the Spanish economy. They observe higher level of volatility and lower persistence from 1972 to 2001 mostly attributable to the increased growth of trading volume brought about by the economic development of the Spanish economy.
Gil-Alana et al. (2008) examine the stochastic volatility of the Spanish stock market over the period 2001-2006. They use the long memory model that takes into account the existence of the endogenous structural break. When a single break point is allowed they find a possible break around April 2003.

In this paper we analyze the volatility of the index using Quadratic GARCH (QGARCH) model of Sentana (1995). This model not only allows for asymmetry in the conditional volatility but also makes this effect depending on the size of the shocks, which can be especially important in the period of financial crises. This model proves to be a useful tool in modelling conditional volatility. Franses and van Dijk (1996) employed random walk, GARCH, TARCH and QGARCH models to examine the volatility forecasting performance in four developed countries including Dutch, German, Italian, Spanish and Swedish. using the weekly returns over the period 1986 to 1994 and find that QGARCH outperforms the other models. To investigate the possible structural break in the conditional volatility we use the LM-based structural break tests of Andrews (1993) and Andrews and Ploberger (1994) which as shown by Smith (2008) have a superior performance comparing to tests based on iterative cumulative sums of squares algorithm.

Using the before mentioned techniques we detect a structural break in the volatility of IBEX 35 around the end of June 2007, few months after the financial meltdown started. The post break sample is characterized by the higher unconditional volatility and stronger reaction to negative returns, especially those of significant size, comparing to the pre-break sample.

The paper is structured as follows - in the next section we discuss the structural break test applied to volatility of index returns, discuss the models applied and present the loss functions used to evaluate the forecasting performance. Section 3 discusses the evolution of IBEX35 over the period of interests and presents the statistics of the data. Section 4 concentrates on the empirical results of the structural break tests and estimation of the models. Next section discusses the forecasting performance of the models. Section 6 concludes.

2. METHODOLOGY

In this section we discuss the volatility model applied in this paper, the news impact curve (NIC) used to show different impact of positive and negative shocks on the volatility, the structural break test used to detect the possible change in the volatility of the stock index and the evaluation of the forecasting power of the volatility model.

2.1. GARCH model

Given the daily quotations of the index \( P_t \) we define continuously compounded returns as \( r_t = \ln(P_t) - \ln(P_{t-1}) \). We filter the series of returns using an appropriate ARMA filter eliminating the deterministic component of the series. The purely stochastic series of returns are defined as \( r_t = \sigma_t \varepsilon_t \), where \( \varepsilon_t \) is an i.i.d. series with given distribution, mean of zero and unit variance.

The Generalized Autoregressive Conditional Heteroscedastic (GARCH) models, introduced by Engle (1982) and Bollerslev (1986), have been proposed to capture the empirical properties of financial time series like changing volatility and volatility clustering. The simplest \( GARCH(1, 1) \) model is defined as

\[
\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2
\]  

(1)

This model forecasts the variance of date \( t \) return as a weighted average of a constant, past variance and past shock.

In the standard GARCH model the effect of the shock on volatility only depends on the size of the shocks - positive and negative shocks have the same impact on conditional volatility.

Black (1976) observes the tendency of stock market volatility to fall when there is “good news” and to rise when there is “bad news” Engle and Ng (1993) propose tests to examine this
different impact of positive and negative returns on volatility (Sign Bias, Negative Size Bias and Positive Size Bias tests).

Most nonlinear GARCH models are motivated by the desire to capture the different effects of positive and negative shocks on conditional volatility or other types of asymmetry.

In this paper we use the QGARCH model introduced by Sentana (1995), which not only allows for asymmetry in the conditional variance but also makes this effect depending on the size of the shock, which in time of high volatility should allow capturing the impact of several extreme market movements.

Sentana (1995) introduces the GQGARCH (Generalized Quadratic GARCH) model defined as

$$
\sigma_t^2 = \omega + \gamma \varepsilon_{t-1} + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \sum_{i=1}^{q} \sum_{j=1}^{q} \alpha_{ij} \varepsilon_{t-i} \varepsilon_{t-j} + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2
$$

The GQGARCH model allows for asymmetry by introducing the lagged values of \( \varepsilon_t \) and the lagged values of the cross-product terms in the conditional variance specification.

In this study we focus on the simplest QGARCH(1,1) specification given as

$$
\sigma_t^2 = \omega + \gamma \varepsilon_{t-1} + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2
$$

that can be rewritten as

$$
\sigma_t^2 = \omega + \left( \frac{\gamma}{\varepsilon_{t-1}} + \alpha \right) \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}
$$

This model can be interpreted as the second-order Taylor approximation to the unknown conditional variance function. Positivity of the variance is achieved if \( \alpha, \beta \geq 0 \) and \( \gamma < 4\alpha \omega \). The model is covariance stationary if \( \alpha + \beta < 0 \).

Asymmetry is introduced by parameter \( \gamma \). If \( \gamma < 0 \) the effect of negative shocks on the conditional variance will be larger than the effect of positive shock of the same size. This effect in turns depends on the size of the shock.

The unconditional variance implied by QGARCH is \( \sigma^2 = \omega/(1 - (\alpha + \beta)) \).

The kurtosis, which governs the thickness of the tails, implied by the model is the function of the asymmetry parameter \( \gamma \).

$$
\kappa = \frac{3 \left[ 1 - \alpha - \beta \right]^2 - \gamma^2 \left( 1 - \alpha + \beta \right) / \omega \right]}{1 - (\alpha + \beta)^2 - 2\alpha^2} \tag{5}
$$

The kurtosis of the QGARCH model is an increasing function of parameter \( \gamma \).

The news impact curves (NIC), introduced by Pagan and Schwert (1990) and discussed by Engle and Ng (1993), measure how new information is incorporated into volatility. The NIC for QGARCH(1, 1) discussed above is given as

$$
NIC = \begin{cases} 
\omega + \beta \sigma_t^2 + \alpha \varepsilon_t^2 + \gamma \varepsilon_t & \varepsilon_t < 0 \\
\omega + \beta \sigma_t^2 + \alpha \varepsilon_t^2 + \gamma \varepsilon_t & \varepsilon_t > 0
\end{cases} \tag{6}
$$

The nice feature of the GARCH models is that they can be easily estimated using the maximum likelihood technique. Using the normal distribution as the underlying distribution of the errors instead of the true distribution we obtain quasi maximum likelihood estimators of the parameters of the model, which as shown by Bollerslev and Wooldridge (1992), are consistent and asymptotically normal, provided that the models for conditional mean and variance are correctly specified.
2.2. Structural break

Structural breaks are important diagnostic tools in econometrics. In the similar way as the mean of economic variables, the heteroscedastic volatility can be affected by structural breaks in the underlying process. When modelling the time-varying volatility we require the parameters describing the data generating process to be stable over time. Otherwise the model can be miss-specified and the volatility forecast can be affected.

Early work of Lamoureux and Lastreps (1990) questions the high level of persistence in the volatility estimated by GARCH models. They analyze 30 stock returns and demonstrate that the persistence was overstated because of the existence of deterministic structural shifts.

Inclan and Tiao (1994) are the first to provide a method of detecting structural breaks in volatility. They propose the Iterative Cumulative Sums of Squares (ICSS) algorithm to detect multiple changes in variance. The ICSS algorithm uses cumulative sums of squares and searches for change points in unconditional volatility systematically at different moments of time.

Aggarwal et al. (1999) use the ICSS algorithm to identify the points of change in the variance of ten largest stock markets in Asia and Latin America. They find that the high volatility of emerging markets is characterized by frequent sudden changes in variance, majority of which are associated with important events in each country rather than the global event, with the October 1987 crash as the only global one that has significantly increased volatility of all the stock markets considered.

Testing for breaks when the break date is known is straightforward. However, testing for structural breaks when the break date is unknown is much more complicated. Andrews (1993) and Andrews and Ploberger (1994) construct test statistics based on the supremum or averages of the traditional LM test across a range of different break dates (they propose three test statistics - supLM, aveLM and expLM). These tests do not have the standard distributions and the critical values are calculated by the authors. Hansen (1997) presents a numerical procedure for computing asymptotic p-values of the test statistics.

Smith (2008) compares the performance of the LM-based structural breaks tests of Andrews (1993) and Andrews and Ploberger (1994) and the ICSS break test of Inclan and Tiao (1994). The Monte Carlo simulation results show a tendency to over-reject in the supLM and expLM tests but the empirical rejection frequency for the aveLM test is remarkably close to its nominal size. The ICSS test rejects too frequently to be acceptable even in the quite large samples, but when applied to standardized normally distributed residuals the test has quite good size; the performance of this test degrades significantly when the standardized residuals are leptokurtic.

He also finds that both the LM and ICSS tests have good power to detect breaks in the unconditional level of volatility but only LM-based tests statistics have the ability to consistently detect breaks in volatility dynamics that do not affect the unconditional level of volatility.

Smith concludes that LM-based tests are preferable to the ICSS test. In the empirical part the author detects the structural breaks in 12 different financial time series considering the possible breaks in either unconditional volatility or all the parameters of the volatility specification.

In this paper, following the conclusions of Smith (2008), we apply the LM based tests and the results of Andrews (1993), Andrews and Ploberger (1994) and Hansen (1997) to detect the structural breaks in the volatility of the index returns.

We test for the structural breaks in all the parameters of the volatility equation. Since the model with the structural break at the date \( \tau \) nests the standard model we can easily test for the break in volatility using the likelihood ratio test statistic as presented in Andrews (1993) and Andrews and Ploberger (1994).

They consider a function \( F_n(\tau) \), where \( n \) is the number of observations and \( F(\tau) \) is the value of the likelihood ratio test statistics for the break at the date \( \tau \) versus the model without the break. We assume that \( \tau \) lies between two dates \( T_1 = 0.15 \ast n \) and \( T_2 = 0.85 \ast n \).

We impose the possible break at the end of each month and estimate the following model
\[ \sigma_t^2 = I[\tau](\omega_1 + \gamma_1 \varepsilon_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2) + (1 - I[\tau])(\omega_2 + \gamma_2 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2) \] (7)

where \( I[\tau] \) is an indicator function that takes the value of one for \( t = 1, \ldots, \tau \) and zero otherwise.

Andrews (1993) discusses the asymptotic properties of the test statistic

\[
\sup_{T_1 \leq \tau \leq T_2} F_n = \sup \{ F_n(\tau) \} \tag{8}
\]

and reports asymptotic critical values. In this test, the date of the break \( \tau \) that maximizes \( F_n(\tau) \) will be the estimated date of the break.

Andrews and Ploberger (1994) propose two additional test statistics - \( \exp F_n \) and \( \text{ave} F_n \) that are calculated as

\[
\exp F_n = \ln\left( \frac{1}{n_{\tau}} \right) \sum_{\tau = T_1}^{T_2} \exp(0.5 * F_n(\tau)) \quad \tag{9}
\]

\[
\text{ave} F_n = \frac{1}{n_{\tau}} \sum_{\tau = T_1}^{T_2} F_n(\tau) \quad \tag{10}
\]

where \( n_{\tau} \) is the total number of breaks considered.

The \( p \)-values associated with these statistics are calculated using the numerical approximation proposed by Hansen (1997).

2.3. Forecasting and forecast evaluation

As mentioned before forecasting future volatility based on the available information is an important and useful task in many areas of economic life. The expected future volatility of financial market returns is the main ingredient in assessing asset or portfolio risk and plays a key role in derivatives pricing models.

The family of GARCH model proves to be a useful tool for forecasting future volatility. As GARCH models specify the conditional variances as the explicit function of observed values, one-step ahead forecasts are easily obtained. More distant predictions are obtained by repeated substitution.

To select the best for model for conditional volatility based only on the in-sample estimation and model evaluation is only a part of the task. The out-of-sample forecasting ability of the GARCH models is an alternative approach to judge the adequacy of different volatility models.

Considering our \( QGARCH(1,1) \) model \( \sigma_t^2 = \omega + \gamma \varepsilon_{t-1} + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \) we are interested in the forecast of \( \sigma_t^2 \) at future time \( s \) given all the available information at time \( t \). We denote this forecast as \( h_{t+s|t} \). We can evaluate the forecasts recursively as

\[
h_{t+s|t} = \hat{\omega} + \hat{\alpha} \hat{\varepsilon}_{t+s-1|t}^2 + \hat{\beta} h_{t+s-1|t} \quad \tag{11}
\]

where \( \hat{\varepsilon}_{t+s|t} = h_{t+s|t} \) for \( s > 0 \) by definition.

We can work out the formula for conditional forecast in the case of \( QGARCH \) model and obtain

\[
h_{t+s|t} = \hat{\omega} \sum_{i=0}^{s-1} (\hat{\alpha} + \hat{\beta})^{s-1} + (\hat{\alpha} + \hat{\beta})^{s-1} h_{t+1|t} \quad \tag{12}
\]

Notice that this allows us to compute all the forecasts having estimated parameter models and
changes in the volatility of ibex35 during the crisis 2007-2009

$h_{t+1|t}$, $h_{t+1|t}$ is contained in the information set at time $t$ and can be computed from all the available observations and using the estimated model for the conditional volatility.

The “true” and unobservable volatility is needed to evaluate the forecasting performances of the competing GARCH models. As the proxy for the volatility we use the realized volatility. Andersen and Bollerslev (1998) suggest that the high frequency data can be used to compute the unobserved volatility measure. Cumulative intra-day squared returns provide a reduction in noise and a radical improvement in temporal stability relative to classical measure of volatility based on the squared daily returns.

Following the results from Andersen and Bollerslev (1998) we use 1-minute squared returns of IBEX 35 obtained from Bloomberg. The proxy for the daily volatility $\hat{\sigma}_t^2$ is defined as

$$\hat{\sigma}_t^2 = \sum_{i=1}^{511} r_{i,t+1}^2$$

(13)

Comparing the forecasting performance of competing models is one of the most important aspects of forecasting process. In the economic literature different evaluation measures has been proposed. The statistical loss functions used in this study are:

<table>
<thead>
<tr>
<th>Loss Function</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MSE$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T} (\hat{\sigma}_{t+s</td>
</tr>
<tr>
<td>$HMSE$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T} \left( \frac{\hat{\sigma}_{t+s</td>
</tr>
<tr>
<td>$MAE$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T}</td>
</tr>
<tr>
<td>$QLIKE$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T} \left( \ln h_{t+s</td>
</tr>
<tr>
<td>$LL_1$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T} \left( \ln \hat{\sigma}_{t+s</td>
</tr>
<tr>
<td>$LL_2$</td>
<td>$\frac{1}{T} \sum_{s=1}^{T} \left</td>
</tr>
<tr>
<td>$TIC$</td>
<td>$\frac{\sqrt{T} \sum_{s=1}^{T}(\hat{\sigma}_{t+s</td>
</tr>
</tbody>
</table>

$MSE$ assumes that the forecasts face the quadratic loss and threats the prediction errors symmetrically in the same way as $MAE$ does although the penalization in case of $MSE$ is heavier. Bollerslev and Ghysels (1996) suggest that the accuracy should be evaluated using a heteroscedasticity adjusted $MSE(HMSE)$. In this case, the forecast error is scaled by the actual volatility. The $QLIKE$ loss function, suggested by Bollerslev et al. (1994), corresponds to the loss function implied by the Gaussian likelihood.

The two logarithmic loss functions $LL_1$ and $LL_2$ proposed by Diebold and Lopez (1996) penalize the forecast errors asymmetrically. $TIC$ (Theil Inequality Coefficient) is a scale invariant measure that always lies between zero and one, where zero indicates a perfect fit.

3. DATA

The figure 1 shows the evolution of IBEX 35 over 2004-2009 and the volatility computed as the rolling standard deviation of monthly intervals. We observe a change in the behaviour of the index from 2007 on. The index is marked by higher and more frequent peaks in the daily returns, which is reflected in an increased volatility of the index. Table 1 shows the summary statistics of the data.
IBEX 2004-2009 and Rolling Standard Deviation (Window Width 1 month)

Figure 1. IBEX 35 returns (upper plot) and the rolling standard deviation (lower plot) over 2004-2009.

<table>
<thead>
<tr>
<th>IBEX 35</th>
<th>Mean</th>
<th>St.Dev</th>
<th>Max</th>
<th>Min</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>ADF test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0102</td>
<td>1.4203</td>
<td>10.11</td>
<td>-9.58</td>
<td>-0.11</td>
<td>12.55</td>
<td>-37.89 (0.000)</td>
</tr>
</tbody>
</table>

Table 1. The main statistics of the data.

The mean is very low and almost zero although the series has the maximum returns of 10.11% and minimum of -9.58%. The skewness is negative which shows that the returns are left-skewed and the kurtosis indicates fat tails in the distribution. The value of the Augmented Dickey Fuller Test (the critical value of -2.8619 at 5% level of significance) shows that the series is stationary.

We apply the ARMA filter (the lowest value of the Schwarz Information Criterion we have obtained for ARMA(1,1)) for estimation of volatility models and evaluation of the forecasts.

We apply the ARCH-LM test of Engle (1982) to the series of residuals $\varepsilon_t$ obtained from the mean equation. For the valued of $q = 1, ..., 5$ we obtain following values of ARCH-LM test statistic – ARCH(1)=37.19 and ARCH(5)=70.55 with the $p-values = 0.0000$ for both tests. Clearly we have the presence of ARCH effects in conditional volatility.

We can further investigate the nature of the ARCH effects by the means of the Sign Bias, Negative Size Bias and Positive Size Bias tests proposed by Engle and Ng (1993).

For the Sign Bias we have obtained the value of the $t$-statistic for the parameter $\gamma_1$ of 3.8203, for the Negative Size Bias of -11.33 and for the Positive Size Bias of 0.3449. There is substantial evidence of asymmetric ARCH effects, coming especially from negative returns.

The first part of the sample 2004 - 2006 covers the period of rapid development of the stock market in Spain, driven by the strong economic growth, full integration in the world economy and the expansion of the Spanish companies outside the country. On the other hand from March 2007 the world, European and Spanish economy experience the most severe, initially financial, but than economic, crises from the Great Depression.

The table 2 below shows the average return and standard deviation of returns for these periods.

The Table 2 shows how differently the index was behaving over the period of interest. The first subsample (2004-2006) is characterized by the positive average returns and low volatility, the second (2007-2009) has a negative average return but at the same time much higher volatility.
The financial and economic crisis 2007-2009 that started with credit crunch in March 2007 brought a lot of volatility to the stock markets across the world and daily movements of the indexes and individual stocks not noticed before.

Over this period IBEX 35 moved seven times above 5% daily return and eight time below the negative 5% return. On 10/10/2008 the index fell by 9.14%, the biggest drop in its history. It was a final chapter of the turbulent week that suffered the decline of 21% of the value of the index. Panic seemed spread to other than financial sectors with heavy punishment of leading energy suppliers and telecoms. On this single day Banco Santander lost 11.95%, Telefonica 9.10%, BBVA 11.37%, Iberdrola 10.57%.

Three day later, on 13/10/2008, the index rose by 10.65%, its biggest daily increase since its creation. The markets worldwide surged in value following the efforts of the governments to ease the effects of the financial crises. Over the weekend the G-7 governments agreed on a joint plan to face the crises, consisting in supporting financial institutions and guaranteeing the interbank loans. The main gainers of the day were the big blue chips of the market - Banco Santander rose by 12.35%, Telefonica 9.57%, BBVA 10.16%, Iberdrola 18.80%.

These dramatic changes of the index motivate the investigation of the correct model for volatility of the index.

4. EMPIRICAL RESULTS

In this section we present and discuss the results of empirical estimation of the models. First we discuss the results of the structural test in volatility equation, estimation of the volatility models.
and present the results of volatility forecasting.

4.1. Structural tests in volatility

As mentioned before Andrews (1993) and Andrews and Ploberger (1994) develop tests for structural breaks which are valid for unknown break points and provide asymptotic critical values for these test statistics. Hansen (1997) presents numerical procedures for computing approximate asymptotic \( p \)-values for these statistics.

We allow for structural breaks in all the parameters of the unconditional volatility equation at unknown break point. To capture the asymmetric behavior of volatility we use the QGARCH\((1, 1)\) model proposed by Sentana (1995). We allow for a potential structural break at the end of every month (at time \( \tau \)) between 15\% and 85\% of the sample. For each potential break point \( \tau \) we estimate the conditional volatility specification given as

\[
\sigma_t^2 = I(\tau)(\omega_1 + \gamma_1 \varepsilon_{t-1} + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2) + (1 - I(\tau))(\omega_2 + \gamma_2 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2) \quad (14)
\]

For each potential point of break at time \( \tau \) we define the test statistic as \( F_n(\tau) = -2(l_r - l_u) \), where \( l_r \) and \( l_u \) are maximized valued of the loglikelihood function of the restricted and unrestricted model, respectively.

The Figure 3 shows the values of \( F_n(\tau) \) for each month from October 2004 to June 2008.

![Figure 3. Structural Break test statistics.](image)


<table>
<thead>
<tr>
<th>Stat</th>
<th>supF(n)</th>
<th>ExpF(n)</th>
<th>AveF(n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Table 3. Structural break tests.
We observe a break in conditional volatility of oil prices around June 2007, few months after the financial crisis has started (where the test statistic takes the highest value). We also checked the presence of the structural break using other asymmetric GARCH model. We apply the model proposed by Glosten, Jagannathan and Runkle (1993) (GJR-GARCH), which allows for asymmetric effects of positive and negative shocks on volatility and the Volatility Switching GARCH model of Fornari and Mele (1996), further extension of the GJR-GARCH model that also takes into account the difference between the forecasted and realized volatility, and detect the structural break in June 2007 as well.

Table 4 and Table 5 show the estimated GARCH model for IBEX returns on the date of the break (June 2007) and for the full sample.

<table>
<thead>
<tr>
<th></th>
<th>ω1</th>
<th>α1</th>
<th>γ1</th>
<th>β1</th>
<th>ω2</th>
<th>α2</th>
<th>γ2</th>
<th>β2</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBEX</td>
<td>0.1257*</td>
<td>0.0934*</td>
<td>−0.2072*</td>
<td>0.7331*</td>
<td>0.0703*</td>
<td>0.0695*</td>
<td>−0.2461*</td>
<td>0.9067*</td>
</tr>
<tr>
<td></td>
<td>(0.0314)</td>
<td>(0.0351)</td>
<td>(0.0426)</td>
<td>(0.0620)</td>
<td>(0.0260)</td>
<td>(0.0191)</td>
<td>(0.0514)</td>
<td>(0.0202)</td>
</tr>
</tbody>
</table>

Table 4. The results of the estimation of the conditional variance equation, in parenthesis the standard error, * significant at 5% level of significance, Q(5) and Q(10) are the values of the Ljung-Box test statistic for the presence of correlation at lag 5 and 10 in the series of standardized and squared standardized residuals.

<table>
<thead>
<tr>
<th></th>
<th>ω</th>
<th>α</th>
<th>γ</th>
<th>β</th>
<th>Q(5)</th>
<th>Q(10)</th>
<th>Q(5)^2</th>
<th>Q(10)^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>IBEX</td>
<td>0.0528*</td>
<td>0.0971*</td>
<td>−0.1693*</td>
<td>0.8668*</td>
<td>2.0372</td>
<td>3.0001</td>
<td>6.1129</td>
<td>9.4589</td>
</tr>
<tr>
<td></td>
<td>(0.0146)</td>
<td>(0.0181)</td>
<td>(0.0362)</td>
<td>(0.0229)</td>
<td>(0.8439)</td>
<td>(0.9814)</td>
<td>(0.2953)</td>
<td>(0.4891)</td>
</tr>
</tbody>
</table>

Table 5. The results of the estimation of the conditional variance equation, in parenthesis the standard error, * significant at 5% level of significance, Q(5) and Q(10) are the values of the Ljung-Box test statistic for the presence of correlation at lag 5 and 10 in the series of standardized and squared standardized residuals.

First of all the estimated models are correctly specified as Ljung-Box Q-statistics for standardized and squared standardized residuals at lag 5 and 10 are not statistically significant.

The loglikelihood for the model with break improved comparing to the model for the full sample (-1910.92 versus -1934.54). Schwarz Information Criterion for the model with break is smaller (2.9145 versus 2.9258) even with four additional parameters estimated.

The estimated unconditional volatility for the model for the full sample is 1.4586, whereas for the model before break 0.7252 and after break 2.9647. This goes in line with the observed changed in standard deviation for the pre- and post-break sample (see Table 2).

All the parameters for the models are statistically significant at 5% level of significance.

The persistence in volatility, the clustering effect, defines the speed at which the new shocks die out. Higher persistence, defined for QGARCH model as $\alpha + \beta$, means that the volatility shocks die out slowly and would swing prices more than in the past. For the model with the break we observe the change in the persistence of volatility from 0.8266 to 0.9762. The persistence for the post-break sample (the period of financial crises) is higher from the persistence observed in the model for the full sample (0.9639). It shows a stronger clustering behaviour of the conditional volatility during the period of financial meltdown.

The parameter $\gamma$ that governs the impact of negative shocks on conditional volatility is as expected negative and higher in the post-break period than in the model for the full sample and the pre-break sample. It clearly shows a stronger reaction of conditional volatility to negative shocks in the period of financial crisis.
The before discussed kurtosis of the model is a linear function of the absolute value of the $\gamma$ parameter. The kurtosis in the post-break sample is higher than in the pre-break sample and the full sample (5.43 versus 3.76 and 5.22). This shows that the model correctly captures the higher number of bigger both positive and negative returns in the course of 2007-2009.

The Figure 4 shows the fitted series of volatility for both models. We observe that especially in the post-break sample the model with the break estimates higher level of conditional volatility than the model for whole sample.

As already mentioned the news impact curves are a useful tool to show how new information is incorporated into volatility. We have computed the NIC for the model estimated for the full sample and for the model for each of the subsamples - the pre- and post-break sample and present them in Figure 5.

The impact of news on the conditional volatility in the pre-break sample is much smaller for both smaller and bigger news. This is mainly due to lower unconditional variance in the period 2004-2007. On the other hand we observe first much stronger reaction of conditional volatility to news in the period 2007-2009 (the up-shift of the curve). Also the reaction to big negative news is much stronger in this period than in the pre-break period.

5. FORECASTING AND FORECAST EVALUATION

We have computed the out-of-sample volatility forecasts for one day, one week and one month. To evaluate the forecast we use the 1-minute ticks for the IBEX 35 for May 2009, which we have not used in estimation of the models.

To evaluate the out-of-sample forecasting performance of the models we use (as explained in the section 2.4) the loss functions like $MSE$, $HMSE$, $MAE$, $QLIKE$, $LL_1$, $LL_2$ and $TIC$ which in different ways penalize the prediction errors.

The tables 6 and 7 summarize the results of volatility forecasting. Table 6 presents the results for each loss function and Table 7 shows which model (either Full for full sample or Break for the model with imposed structural break in June 2007) has a lowest value of the loss function.
The results of the out-of-sample forecasting show that the model with break in June 2007 is preferred for each of the forecasting period. For one-day and one-week forecasting horizon the model with break produces better forecasts as indicated by all the loss functions. For the one-month forecasting period the model with break is preferred by the majority of the evaluation indicators.

Assuming that the economic stability will finally be restored in the markets the volatility of the financial variable should return to the normal levels. It will be interesting to redo the exercise to detect another break after which the model inducing lower volatility should be used for forecasting purposes.
6. CONCLUSIONS

This paper investigates the structural break in the volatility of IBEX 35. We investigate the volatility of the index over the period 2004-2009, the period that encompasses the period of strong increases in the index and the period of the one of the most severe crises.

Applying the Quadratic GARCH model and the LLM-test for possible break in the conditional volatility at the end of every month, we detect a structural break test around June 2007, few months after the beginning of financial and economic crisis. We also apply other asymmetric GARCH models to check the robustness of our findings. We observe different behaviour of conditional volatility in the pre- and post-break sample. The post break sample is determined by the higher unconditional volatility and stronger reaction to negative shocks. We check the forecasting power of the models for full sample and the model with the detected break in June 2007. The post-break model shows a better forecasting performance than the full sample model.

REFERENCES


Fornari, F., A. Mele, 1996. Modeling the changing asymmetry of conditional variances, Economics Letters 50,
197-203.


