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Conditional volatility in sustainable and traditional stock exchange indexes: analysis of the Spanish market

Volatilidad condicional en índices bursátiles socialmente responsables: Análisis del mercado de valores español

Volatilidade condicional em índices bolsistas socialmente responsáveis: Análise do mercado de valores espanhol

AUTHORS

Eduardo Ortas[1]
Accounting and Finance Deparment University of Zaragoza, Spain
edortas@unizar.es

José M. Moneva
Accounting and Finance Deparment University of Zaragoza, Spain
jmmoneva@unizar.es

Manuel Salvador
Economics Deparment University of Zaragoza , Spain
salvador@unizar.es

1. Corresponding Author: Accounting and Finance Deparment; University of Zaragoza; Business School; C\ María de Luna, s/n; Campus Rio Ebro, Edificio Lorenzo Normante; 50018-Zaragoza; España.

Most of the world's leading economies felt during 2008 into a recession period, mainly due to the emergence of the global financial downturn. This has lead to an increase in the volatility levels on stock markets. Under this context, there is a growing need to accurately assess the risk to which investment portfolios are exposed, in addition to ensuring that these are well diversified. Thus, the aim of this research is to analyse the risk, in terms of volatility levels, associated with investing in socially responsible assets, such as the Socially Responsible Investment stock exchange indexes in the Spanish Market.

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La mayoría de las economías a nivel mundial entraron a mitad del año 2008 en un periodo de recesión económica, principalmente motivado por la aparición de una fuerte crisis de carácter financiero a nivel global. Este aspecto ha motivado que la volatilidad en los distintos mercados de valores a lo largo de todo el mundo se haya incrementado de forma significativa. Ante este escenario, surge la necesidad de efectuar una medición lo mas precisa posible sobre el riesgo que soportan las diferentes carteras de inversión, estableciendo estrategias que permitan una diversificación eficiente. Así, el objetivo del presente trabajo consiste en analizar los niveles de riesgo, a través de la estimación de los niveles de volatilidad condicional, asociados a las carteras de inversión que toman posiciones en índices bursátiles socialmente responsables en el mercado español. Así mismo, se realizará una comparativa con estrategias de inversión tradicionales.

A maioria das economias a nível mundial entraram, a meio de 2008, num período de recessão económica, principalmente motivada pelo aparecimento de uma forte crise de carácter financeiro a nível global. Este aspecto motivou que a volatilidade nos diferentes mercados de valores ao longo de todo o mundo tenha aumentado de forma significativa. Perante este cenário, surge a necessidade de efectuar uma avaliação tão precisa quanto possível sobre o risco que as diferentes carteiras de investimento suportam, estabelecendo estratégias que permitam uma diversificação eficiente. Assim, o objectivo do presente trabalho consiste em analisar os níveis de risco, através da estimativa dos níveis de volatilidade condicional, associados às carteiras de investimento que têm posições em índices bolsistas socialmente responsáveis no mercado espanhol. Será realizada ainda uma comparação com estratégias de investimentos tradicionais.

1. Introducción

Over recent decades there has been a transition from the solely financial view of a company towards another managerial model which considers the different stakeholders' claims. The idea that the only mission of a company is to maximise the shareholders' value (Friedman, 1970) has hardly been questioned by the recent managerial research (Agle *et al.*, 2008; Wood, 2008; Freeman, 2008). Nowadays, an increasing number of organisations are including social and environmental factors when establishing their strategic management policies. Porter and Kramer (2006) noted that disregarding the different stakeholders' demands may have a negative impact on the companies' competitiveness in the mid-long term. Financial markets have incorporated new investment alternatives according to this new business model. The so-called Socially Responsible Investment (SRI), also known as 'ethical investment' and 'sustainable investment' (Renneboog *et al.*, 2008a), considers factors such as environmental preservation, respect for human rights and other social issues. The SRI assets, funds or equity indices give the investors the opportunity to fit their investment policy with their ethical values (Domini, 2001).

The high development of SRI has awakened the interest of academicians and practitioners. The modern portfolio theory is based on the only objective of the investors, that is to maximise their wealth. Under this approach, SRI will under-perform the traditional investment approach, because SRI portfolios are subsets of the market portfolio (Le Maux and Le Saout, 2004). As indicated by Renneboog et al. (2008a). The believers in the efficient market hypothesis think that is impossible that SRI approach out-perform the conventional one. In addition, modern portfolio theory propose us that diversification reduces risk and maximises long term returns and also indicates, that the SRI screening process reduces the investment universe, which leads to a reduction in the risk-adjusted return. However, the data available shows a worldwide SRI growth (mainly in North-America and Europe), based on the increase of sustainable institutional and individual investors.

This work aims to contribute to the limited literature in this field, which is mainly focused on the measurement of risk-adjusted returns of SRI funds (Fowler and Hope, 2007). Although SRI and traditional investment portfolios risk-adjusted returns are analysed, this work asses the conditional volatility, i.e. risk levels associated with SRI equity indices in the Spanish market (FTSE4Good-IBEX), never explored until now, and to compare them with the conditional volatility, i.e. risk levels experienced by the traditional ones (IBEX35). To this end, univariate and multivariate GARCH models (Bauwens *et al.*, 2006), which are widely used tools in the financial-econometrics literature, but scarce used in this field (Hoti *et al.*, 2005, 2008), are applied,. This research is also interesting because the empirical analysis aims to test if investing in SRI equity indices might reduce the risk - volatility levels-, in a complex financial environment.

The rest of the paper is organised as follows. The next section analyses the previous literature and introduces the main features of the FTSE4Good indexes. The third section focuses on the sample selection and the description of the data. Section four introduces the theoretical econometric models applied and the results are showed in section five. Finally, conclusions and further discussion are developed.

2. Background

SRI has existed in several forms since hundreds of years (Renneboog *et al.*, 2008a; Le Maux and Le Saout, 2004). Although original SRI is based on religious traditions, modern SRI has added other ethical and social convictions. There are some recent evidence of ethical investment from 1960s and 1970s, mainly based on the anti-wars, anti-racism and anti-apartheid campaigns, and showing the society the social consequences of their investments. A decade later, on the 1980s, the Chernobyl and Exxon Valdez disasters expanded the SRI approach to a wide range of investors that consider the negative environmental and social consequences of industrial activities. Thus the SRI has changed from being a niche market to become a core factor for mainstream investors (Le Maux and Le Saout, 2004). During the 21st century the SRI has experienced a high increase. Thus the EUROSIF (2008) report emphasizes that 'the total SRI Assets under Management (AuM) in Europe reached €2,665 trillion in 2007, whereas they rose to €336 trillion in 2002'. Likewise, this report shows that the presence of SRI in the market has grown, with SRI assets representing about 17.6% of the AuM in European industry in 2007. This corresponds to a remarkable growth of 102% since 2005. This significant increase was mainly motivated by the demand from institutional and individual investors, the mainstreaming of environmental, social and governance principles into traditional financial services and by the external pressure from the main NGOs worldwide (EUROSIF, 2008).

Research about SRI performance dates back from the 1970s (Moskowitz, 1972). and has growth significantly during the recent decades. Most of research about SRI performance is linked to measure the performance achieved by SRI funds. Thus, some studies have analysed the differences in risk-adjusted returns between SRI and conventional investment funds (Luther *et al.*, 1992; Hamilton *et al.*, 1993; Luther and Matatko, 1994; White, 1995). These papers use simple regressions of SRI investment funds' return against some market indexes' return in order to show if the SRI funds out or under-performance the traditional benchmarks. In general, these works do not evidence out or under-performance of SRI funds compared with the traditional ones. However, these results should be carefully interpreted because they do not broad consider the transaction costs of investment funds. They also do not take into account the ability of the portfolio managers to produce an outstanding performance (Schröder, 2007), that could interferes with the SRI screening criteria effect.

Recent works mitigates these shortcomings by analysing SRI and conventional funds of similar characteristics applying the 'matching approach' (Mallin *et al.*, 1995; Gregory *et al.*, 1997; Statman, 2000; Stone *et al.*, 2001; Kreander *et al.*, 2002; Bauer *et al.*, 2005). These studies overcome the limitations of the previous studies, but they observe that SRI and conventional funds show a similar performance. There are studies showing a significant out-performance (Derwall *et al.*, 2005) and under-performance (Geczy *et al.,* 2005) of SRI funds. Other studies have focused on portfolio risk reduction by investing in SRI funds (Hickman *et al.*, 1999).

Sustainability stock exchange indexes constitute a tool to enable responsible investors to identify companies that meet globally-recognised CSR principles. Although there are several socially responsible stock exchange indexes, the Dow Jones Sustainability Indexes (DJSI) and the FTSE4Good families are the most important. There are very few papers that

analyse the risk associated directly with SRI stock indexes (Kurtz and DiBartolomeo, 1996; Sauer, 1997; DiBartolomeo and Kurtz, 1999; Statman, 2000; Garz *et al.*, 2002). These studies, mainly focused on Domini 400 Social index and DJSI, conclude that SRI equity indices show similar risk-adjusted returns to their benchmarks. A recent study of Schröder (2007), which analyses 29 SRI equity indices around the world, confirms the results obtained in previous research, and indicates that investing in SRI stock exchange indexes does not impose additional costs in terms of lower returns to the investors. In the Spanish market, the appearance of the FTSE4Good-IBEX in April 2008 enabled the market to invest in Spanish best-in-class sustainability companies for the first time. The launch of the FTSE4Good-IBEX took place during the financial crisis which is currently affecting the international markets. Confidence in the stock markets has fallen and the volatility levels of the main stock exchange indexes has risen, a common effect in periods of economic downturn and financial crisis (Schwert, 1989). In these periods of uncertainty in stock markets, it is desirable for investors to be able to identify, as precisely as possible, their portfolio risk levels.

2.1. Sustainable stock exchange indexes: FTSE4Good family

The DJSI and FTSE4Good indexes are the main families of stock exchange indexes that apply social and environmental screening criteria worldwide. The DJSI, created in 1999, were the first global indexes to track the financial performance of leading sustainability-driven companies around the globe. Later, in 2001, as a result of the growing interest in SRI, the FTSE launched a family of tradable indexes (see Table I). The FTSE4Good indexes seek to measure the performance of companies that meet globally-recognised corporate responsibility standards and to facilitate investment in socially responsible companies.

Table I. Main FTSE4Good Indexes

Benchmark Index	Tradable Index
FTSE4Good Global Index	FTSE4Good Global 100 Index
FTSE4Good USA Index	FTSE4Good USA 100 Index
FTSE4Good Europe Index	FTSE4Good Europe 50 Index
FTSE4Good UK Index	FTSE4Good UK 50 Index
FTSE4Good Japan Index	Not available

In addition, the FTSE4Good Index series incorporates the following indexes: FTSE4Good Australia 30 Index, FTSE4Good Environmental Leaders Europe 40 Index, FTSE Environmental Market Index, FTSE KLD Index and FTSE4Good-IBEX.

The FTSE4Good-IBEX was launched in cooperation with Bolsas y Mercados Españoles[1] (BME). Its screening criteria are developed using a thorough market consultation process and are shaped by a broad range of stakeholders including NGOs, government bodies, consultants, academics, the investment community and the corporate sector. Corporate responsibility data used to assess the constituents of the FTSE4Good-IBEX are provided by the Ethical Investment Research Service[2] (EIRIS) and its network of international partners, which includes the Fundación Ecología y Desarrollo[3] (ECODES) in Spain (FTSE, 2008). The selection of companies is based on a three-step procedure and covers three key areas (environment, social and human rights):

a) The eligible universe is based on constituents of the IBEX35 and FTSE Spain All Cap Index.

b) Companies with business interests in tobacco and weapons systems, companies manufacturing either whole, strategic parts, or platforms for nuclear weapons systems, and owners or operators of nuclear power stations are excluded.

c) The inclusion criteria are based on environmental issues (environmental management, climate change) and social concerns (human and labour rights, supply chain labour standards and countering bribery).

The FTSE4Good-IBEX is not a static index because it is reviewed twice a year in order to add or remove companies, depending on their economic, social and environmental performance[4].

3. Sample Selection and Data Description

The empirical analysis was carried out on the IBEX35 and FTSE4Good-IBEX indexes. Information about historical closing prices and other interesting data for both indexes is freely available at http://www.bolsamadrid.es. The initial data obtained refers to the daily closing prices (in Euro currency) for both indexes, adjusted by dividends and capital increases for the period from 9 April 2008 to 5 February 2010 inclusive. 465 daily closing prices were obtained that cover all the information available to date (referring to the FTSE4Good-IBEX). Table II shows the main descriptive statistics of the log-differences series (return series) of both indexes during the period analysed.

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1. Visit http://www.bolsasymercados.es/ for more details about BME.

2. More information about EIRIS research and publications can be obtained at http://www.eiris.org/

3. Additional information about ECODES work can be obtained at http://www.ecodes.org/

4. Further information about the screening criteria and the FTSE4Good indexes' rules can be obtained at http://www.ftse.com/Indices/ FTSE4Good_Index_Series/index.jsp and specifically for the FTSE4Good-IBEX at http://www.ftse.com/Indices/FTSE4Good_IBEX_ Index/index.jsp

Table II. Descriptive statistics of IBEX35 and FTSE4Good-IBEX return series

	IBEX35	FTSE4Good-IBEX
Mean	-0.0640%	-0.0703%
Median	0.0984%	0.0706%
Maximum	10.1176%	9.5260%
Minimum	-9.5858%	-7.9996%
Std. Dev.	2.0895	1.9495
Skewness	0.0659	0.0763
Kurtosis	6.8234***	6.3996***
Jarque-Bera	282.9587***	223.8975***

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

Over the period analysed, the IBEX35 mean daily return is -0.064%, while mean daily return for the FTSE4Good-IBEX were slightly lower -0.0703%. The main daily return of both series presented non-significant differences, given that t-test estimate of equality of means was 0.0473 (p-value: 0.9623, df: 926). However, the standard deviation of the daily returns of the FTSE4Good-IBEX is lower than that of the IBEX35, which shows a smaller overall variability in the FTSE4Good-IBEX daily returns. The Jensen's alpha was also calculated in order to test if the FTSE4Good-IBEX out or under-performance the IBEX35 during the period analysed (Jensen, 1968). It has been computed by the excess returns of the benchmark index ($r_t^{Ibex.35}$) on the excess returns of the SRI equity index ($r_t^{Ftse4Good-Ibex}$). Although other works, mainly focused on SRI funds performance, compute monthly excess returns in order to obtain the Jensen's Alpha (Luther *et al.*, 1992; Hamilton *et al.*, 1993; Luther and Matatko, 1994; White, 1995, Gregory *et al.*, 1997; Carhart, 1997; Schöder, 2004; Kreander *et al.*, 2005; Schröder, 2007; Renneboog *et al.*, 2008b), in this research r_t^{Ibex35} and $r_t^{Ftse4Good-Ibex}$ refers to daily excess returns of both indexes (IBEX35 and FTSE4Good-IBEX). Daily excess returns of both indexes have been computed by the difference between their daily returns and a risk-free interest rate (one-day Spanish Treasury bill repo rates have been used as a proxy of the return on the risk-free asset).

$$r_t^{FtseGood-Ibex} = \alpha + \beta r_t^{Ibex35} + \varepsilon_t \quad (1)$$

Equation (1) represents the relative performance of the introduced equity indices. As noted by Schröder (2007), it is not necessary to include additional factors into the equation, like when analysing investment funds relative performance. This is because FTSE4Good-IBEX is only restructured twice per year, there is no active portfolio management and the investment

universe can be approximated very well by its benchmark (IBEX35). So, market timing (Admati and Ross, 1985), public available information of portfolio management stile (Ferson and Schadt, 1996) and including other benchmarks into the equation are factors that should not been considered in the present analysis. Table III shows the estimates of the Equation (1) (estimated by ordinary least squares algorithm).

Table III. FTSE4Good-IBEX versus IBEX35 performance

Index	Adjusted R^2	α	β	Spanning test (α=0 & β=1)
Parameter (Standard deviation)	0.9999	-0.0071*** (0.0004)	1.0003*** (0.0002)	152.7715***

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

The estimate of the Jensen's alpha is significant but its impact is very low. This shows that there are significant differences between the relative risk-adjusted return of the FTSE4Good-IBEX compared to the IBEX35. However, the Jensen's Alpha coefficient is very low, indicating that the performance of the SRI equity index do not much deviate from its benchmark (IBEX35). The estimate of the β coefficient is significant but close to one, showing that the relative risk of the FTSE4Good-IBEX is similar from its benchmark. The FTSE4Good-IBEX seems not to be spanned by its benchmark. This indicates that the risk and return levels of the two stock exchange indexes are significantly different. However these differences are very low, and are agree with the results obtained by previous research in this field (Schröder, 2007).

Additionally, Figures 1 and 2 show the evolution of the daily closing prices (left axis contains their box plot) and the return series (left axis contains their histogram) of the two indexes. The return series displays are non-normally distributed, due to the presence of high levels of leptokurtosis, a common effect in high frequency-observed financial series. The Pearson[5] correlation between daily returns for both series was 0.983*** (p-value: 0.000), which shows similar levels of returns in the two indexes analysed. This effect seems to be due to the high percentage of companies belonging to the IBEX35 that are included in the FTSE4Good-IBEX.

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5. *** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

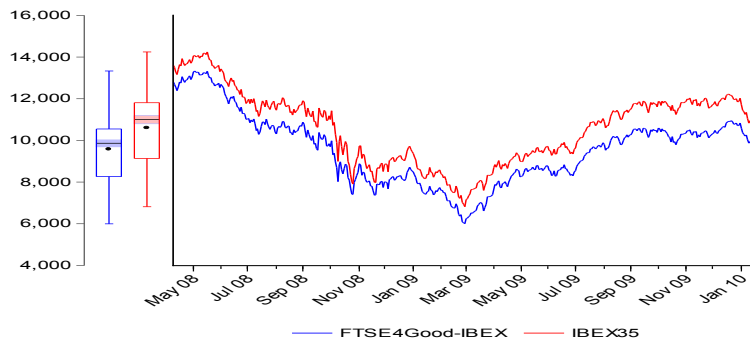Figure 1: FTSE4Good-IBEX and IBEX35 daily closing prices

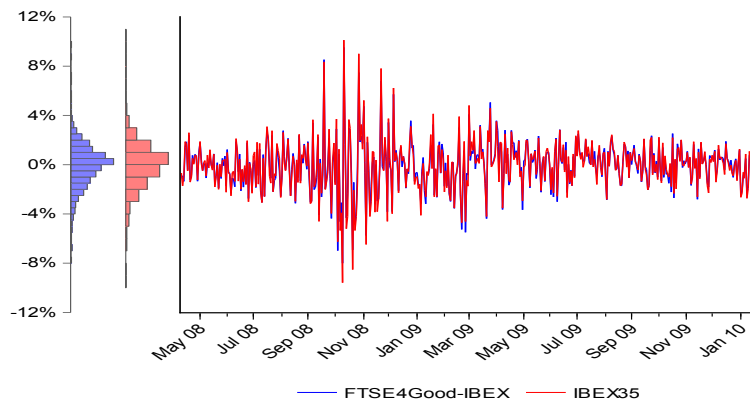Figure 2: FTSE4Good-IBEX and IBEX35 daily returns

Figure 1 shows that the closing prices series are non-stationary. On the other hand, return series (Figure 2) seem to be stationary on their first moment, but they are highly heteroskedastic, with the higher volatility levels running from September 2008 to December 2008, a point that will be analysed later in this paper. Furthermore, the volatility clustering effect is present, in which large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes in all cases. In order to confirm these aspects parametrically, Table IV shows the results obtained after applying the Dickey–Fuller (DF) and Phillips–Perron (PP) stationarity tests and ARCH (five lags) and Ljung–Box (LB) (five lags) tests on squared returns to test the heteroskedasticity and autocorrelation of the residuals. Furthermore, Figures 3 to 6 show the residuals and squared residuals correlograms of a random walk with intercept model on the return series for both indexes.

Table IV. Stationarity and Heteroskedasticity tests of IBEX35 and FTSE4Good-IBEX return series

Test / Index	IBEX35	FTSE4Good-IBEX
DF	-21.49***	-21.14***
PP	-21.58***	-21.14***
ARCH$_{(5)}$	18.84***	13.02***
LB$_{(5)}$	18.23***	12.47**

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level. Critical values for Dickey-Fuller and Phillips-Perron unit root tests: 1% level = -2.574, 5% level = -1.942, 10% level = -1.616. ARCH and LB tests are based on residuals of a random walk with an intercept model of return series of both stock exchange indexes

As can be seen in Figures 3 and 4, there are no residual stationarity or autocorrelation problems for either model so the econometric models introduced in the next section will be based on this process.
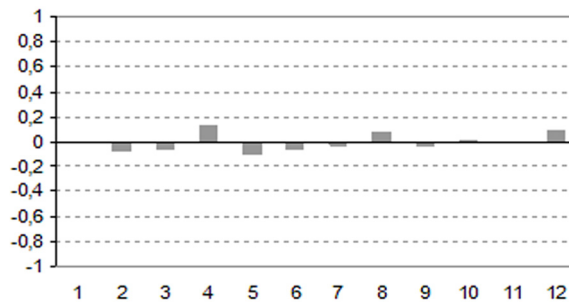
Figure 3: IBEX35 residuals correlogram

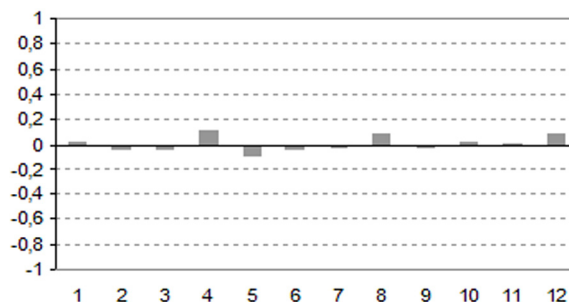Figure 4: FTSE4Good-IBEX residuals correlogram

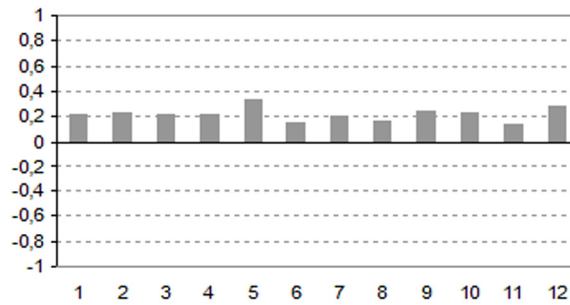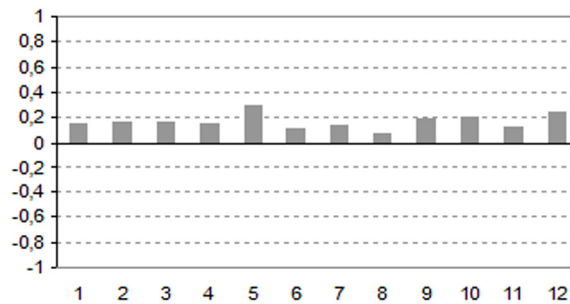Figure 5: IBEX35 squared residuals correlogram

Figure 6: FTSE4Good-IBEX squared residuals correlogram

Furthermore, Arch test and Figures 5 and 6 shows that the residuals are heteroskedastic and prove the suitability of univariate and multivariate GARCH parameterisation for the conditional volatility modelling of both return series.

4. Econometric models

Over the last few years, univariate GARCH modelling, which considers the volatility of each asset separately, is a commonly used technique in financial-econometrics literature (Andersen *et al.*, 2006 a, b; Bauwens *et al.*, 2006). However, volatility moves together over time across assets and markets (Bauwens *et al.*, 2006), so, it seems reasonable to model conditional volatility considering this co-dependent relationship. To this end, multivariate GARCH

models provide powerful tools to analyse the evolution of the conditional variance-covariance matrix for a group of assets or other financial series. Multivariate conditional volatility modelling involves an increase in the number of parameters to be estimated if a large number of series is analysed. In consequence, the accuracy of the inference methods decreases and, therefore, the estimates obtained are less robust. In any case, given the small number of series to be analysed (two in this case) and the parsimony of the multivariate GARCH models chosen, it is not thought that the robustness of the estimates will be affected.

4.1. Univariate volatility modelling

Three univariate GARCH models were selected to estimate the conditional volatility of the historical return series of both indexes (IBEX35, FTSE4Good-IBEX). The first is the GARCH model proposed by Bollerslev (1986) and specified as GARCH(1,1).

P_t is the index closing price in period t, $y_t = 100 \log \left(\dfrac{P_t}{P_{t-1}} \right)$ is the daily continuous return of

the index and Ω_t denotes the information set available in period t. Thus, the GARCH(1,1) process can be represented by the following equations:

$$y_t = \mu + \varepsilon_t \qquad (2)$$

$$\varepsilon_t = \eta_t \sigma_t \text{ with } \eta_t \text{ i.i.d.; } E\left[\eta_t\right] = 0 \text{ , } Var\left[\eta_t\right] = 1 \quad (3)$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \text{ ; } \omega > 0, \ \alpha, \ \beta \geq 0 \quad (4)$$

It is verified that $\mu = E\left[y_t | \Omega_{t-1}\right]$ is the mean expected return and $\sigma_t^2 = \text{Var}\left(\varepsilon_t | \Omega_{t-1}\right) = \text{Var}\left(y_t | \Omega_{t-1}\right)$ is the daily conditional volatility of the return y_t in period t, which reflects the short-run persistence of shocks (ARCH effect - α) and the contribution of shocks to long-run persistence (GARCH effect - β). Parameter $\alpha + \beta$ measures the persistence in volatility, so that the greater the value, the more pronounced the volatility clustering effect appears. Under a GARCH(1,1) model, if $\alpha + \beta < 1$, the process is second-order stationary in volatility, in which case, $\sigma^2 = Var(y_t) = Var(\varepsilon) = \dfrac{\omega}{1 - \alpha - \beta}$ shows the unconditional volatility of the return series.

This approach supposes that the impact of return shocks (ε_t) on the volatility is symmetrical. However, there is empirical evidence that, in most financial series, these shocks are asymmetric, and the impact of a negative shock on volatility is greater than a positive one, showing the so-called leverage effect. In order to capture this effect, additional parameters have to be added to the model. The most commonly used models are the GJR and EGARCH proposed by Glosten *et al.* (1993) and Nelson (1991), respectively.

Under the GJR(1,1) model, the volatility of the return series is given by:

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma I\left(\varepsilon_{t-1} < 0\right)\varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \text{ ; } \omega > 0, \ \alpha, \ \beta \geq 0, \ \gamma \in \Re \qquad (5)$$

where $I(\varepsilon_t < 0) = 1$ when $\varepsilon_t < 0$ and 0 otherwise. Coefficient γ shows the asymmetry of the impact of the return shocks (ε_t) on the volatility of the indexes. A leverage effect is displayed when coefficient γ is positive and significant. Additionally, if the conditional distribution of the error term η_t is symmetrical, persistence on volatility is given by $\alpha + \beta + \frac{\gamma}{2}$.

Another approach to analysing the asymmetrical effect of return shocks on volatility, which also does not impose restrictions of non-negativity on the volatility equation parameters, is the EGARCH model, proposed by Nelson (1991). Under the EGARCH(1,1) specification, conditional variance is determined by the following expression:

$$\log(\sigma_t^2) = \omega + \alpha \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \log(\sigma_{t-1}^2) \qquad (6)$$

In this case, γ refers to the asymmetry in the link between the return shocks (ε_t) and the volatility of the series, there being a leverage effect if the parameter is negative and significant.

4.2. Multivariate volatility modelling

In recent years, several multivariate conditional volatility models have been developed (Bauwens *et al.*, 2006). Furthermore, there has been recent empirical work applying these methods (Smyth and Nandha, 2003; Lee, 2004; Antell and Vaihekoski, 2007; Chuang *et al.*, 2007; León *et al.*, 2007; Hsu, 2008; Saleem, 2008; Tai, 2008; Savva, 2009). In this study, three multivariate GARCH models have been selected and are described below.

Given $y_t = (y_{1,t} \dots, y_{N,t})'$ as the vector of continuous returns of the indexes in period t (in this case, N=2), the multivariate GARCH(1,1) is expressed by the following equations:

$$y_t = \mu + \varepsilon_t \text{ with } \mu \in R^N \text{ and } \varepsilon_t = (\varepsilon_{1,t} \dots, \varepsilon_{N,t})' \qquad (7)$$

$$\varepsilon_t = \Sigma_t^{1/2} \eta_t \text{ with } \eta_t \ (Nx1) \text{ i.i.d. } E[\eta_t] = 0 \text{ and } Cov(\eta_t) = I_N \qquad (8)$$

and Σ_t is a positive semi-definite matrix (NxN), so that:

$$vech(\Sigma_t) = vech(C) + Bvec(\Sigma_{t-1}) + Avech(\varepsilon_t \varepsilon_t') + Dvech((\varepsilon_t \circ I(\varepsilon_t < 0))(\varepsilon_t \circ I(\varepsilon_t < 0))') \qquad (9)$$

where the vech ('vector half') operator converts the unique upper triangular elements of a symmetric matrix into a $\frac{N(N+1)}{2}$ x1 column vector; **A, B, C** and **D** are $\frac{N(N+1)}{2}$ x $\frac{N(N+1)}{2}$ matrices with **C** symmetric; $\circ$ denotes the Hadamard product; and $I(\varepsilon_t < 0)$ is the Nx1 vector such that the i-th component is equal to 1 if $\varepsilon_{i,t} < 0$ and 0 otherwise. This verifies that $E[y_t|\Omega_{t-1}] = \mu$, $Cov(y_t|\Omega_{t-1}) = Cov(\varepsilon_t|\Omega_{t-1}) = \Sigma_t$.

An asymmetric effect will also be present if the **D** matrix is significantly different from 0.

The number of parameters in the model is equal to $N + \frac{N(N+1)}{2} + 3x \frac{N^2(N+1)^2}{4}$, which, in this case, is 32.

In this research, the diagonal GARCH (DVEC) model proposed by Bollerslev et al. (1988), the diagonal BEKK (DBEKK) model introduced by Engle and Kroner (1995) and the Constant Conditional Correlation GARCH model (CCC) proposed by Bollerslev (1990) have been applied. The choice of these models is based on the criterion of parsimony, so that fewer parameters are estimated (Andersen *et al.*, 2006a).

The DVEC(1,1) specification of conditional variance supposes that matrices **A, B** and **D** are diagonal. Due to this requirement, the number of parameters is reduced to $N + 4x \dfrac{N(N+1)}{2}$,

which, in this case, is 14. In practice, situations may arise in which it is difficult to ensure that the Σ_t matrix is positive without imposing extra restrictions to the ones already mentioned. In order to overcome this limitation, the DBEKK(1,1,1) model has also been estimated. With this approach, the conditional variance matrix can be expressed as:

$$\Sigma_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + D\left(\varepsilon_{t-1} \circ I\left(\varepsilon_{t-1} < 0\right)\right)\left(\varepsilon_{t-1} \circ I\left(\varepsilon_{t-1} < 0\right)\right)D' + B\Sigma_{t-1}B' \qquad (10)$$

where **C, A, D** and **B** are N x N matrices; with C being upper triangular; and **A, B** and **D** are diagonal matrices which represent the ARCH (matrix **A**), asymmetrical (matrix **D**) and GARCH (matrix **B**) effects. This ensures that Σ_t is a positive definite matrix. The number of parameters in the model is 4N+1, which, here, equals nine, making it a more parsimonious model than the DVEC(1,1) introduced above. Finally, the CCC(1,1) model was considered, it being the most parsimonious of the three applied in this research. Unlike the DVEC and BEKK models, it supposes that the correlation matrix for the series comprising **y**$_t$ is constant in time, so that:

$$\Sigma_t = D_t R D_t \qquad (11)$$

where $D_t = \mathrm{diag}(\sigma_{1t}, \ldots, \sigma_{Nt})$ with $\sigma_{i,t}^2 = Var\left(y_{i,t} \mid \Omega_{t-1}\right)$; i=1,…, N the volatilities of the series comprising $y_{i,t}$ which are modelled by a GARCH(1,1) univariate specification; and $R = (\rho_{ij})$ is the correlation matrix for the series (with $\rho_{ij} = Corr(y_{i,t}, y_{j,t} \mid \Omega_{t-1})$) 1≤i<j≤N). Thus,

the number of parameters is reduced to 3N+ $\dfrac{N(N-1)}{2}$, which, in this case, is six (6).

5. Results and Discussion

5.1. Univariate results

Table V shows the parameters estimated by the three univariate GARCH models by means of a maximum likelihood algorithm, and under normal error distribution η_t . GARCH estimates indicate the presence of a positive average return in the two series analysed, meanwhile the asymmetric models (GJR and EGARCH) place it lower than zero. However, the estimated mean average return for all models are non significant.

Moreover, the estimates of the variance equation show a high level of persistence in volatility for both series. Furthermore, a significant leverage effect was captured by the GJR(1,1) and EGARCH(1,1) models, this being higher for the IBEX35. This seems to show that the negative return shocks had a greater impact on the IBEX35 volatility than on the FTSE4Good-IBEX. Additionally, all the models estimated present a suitable goodness of fit, the residuals being normal, non-autocorrelated and homocedastic both in the mean and in the variance equations. The presence of non-normality in the residuals of the model adjusted to the series of FTSE4Good-IBEX is appreciated. However, this effect is weakly significant and it is not appreciated in the multivariate analysis carried out in section 5.2.

Table V. Univariate conditional volatility modelling of IBEX35 and FTSE4Good-IBEX return series

IBEX35	GARCH		GJR		EGARCH	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Mean equation						
μ	0.0179	0.0750	-0.0680	0.0732	-0.0678	-0.0736
Variance equation						
ω	0.0619	0.0407	0.0641**	0.0315	-0.0725**	0.0365
α	0.1135***	0.0292	-0.0197	0.0224	0.1265***	0.0447
β	0.8765***	0.0311	0.9049***	0.0267	0.9786***	0.0087
γ			0.2081***	0.0449	-0.1343***	0.0241
Jarque Bera	2.5349		3.2419		2.2959	
ARCH$_{(5)}$	4.1318		7.6122		8.2887	
LB$_{(5)}$	2.8324		2.2073		2.6292	
Log-Likelihood	-926.4310		-914.7262		-915.6051	

FTSE4Good-IBEX	GARCH		GJR		EGARCH	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Mean equation						
μ	0.0018	0.0750	-0.0727	0.726	-0.0763	0.0733
Variance equation						
ω	0.0536	0.0339	0.0480**	0.0229	-0.0721**	0.0346
α	0.1035***	0.0262	-0.0167	0.0197	0.1190***	0.0427
β	0.8877***	0.0275	0.9210***	0.0224	0.9832***	0.0073
γ			0.1712***	0.0327	-0.1064***	0.0189
Jarque-Bera	9.0817**		7.0915**		5.4782*	
ARCH$_{(5)}$	2.4555		6.8055		6.2606	
LB$_{(5)}$	2.4628		2.1803		2.5856	
Log-Likelihood	-909.9745		-899.0836		-899.4889	

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level

The evolution of the estimated volatility for each of the three models is shown in Figures 7 to 9 (left axis contains their kernel density plot). These figures show that the conditional volatility is lower in the case of the FTSE4Good-IBEX than in the IBEX during the period analysed. All three univariate models (GARCH, GJR and EGARCH) show a similar behaviour of conditional volatility for both indexes. This ensures the results are more robust.
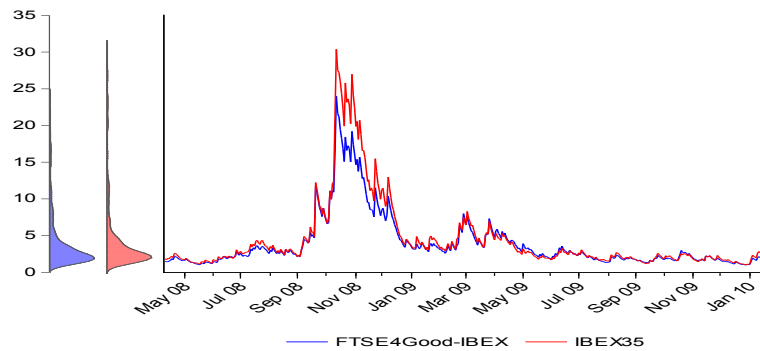
Figure 7: Conditional Volatility under GARCH
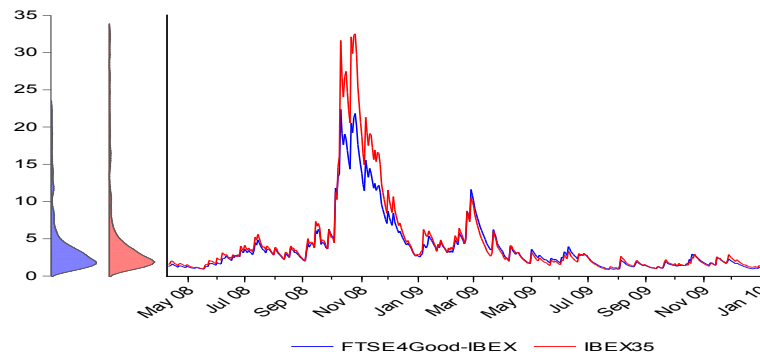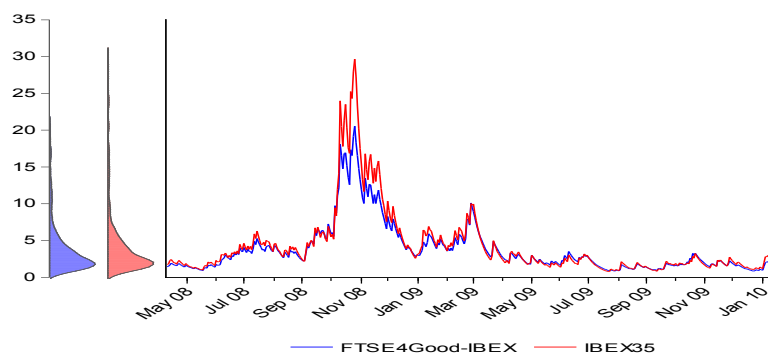

Figure 8: Conditional Volatility under GJR

Figure 9: Conditional Volatility under EGARCH

5.1.1. Comparing the Models

Table VI shows the results of a comparative study of the estimated univariate models analysing their one-step-ahead predictive behaviour (both on average and at prediction intervals). The model's goodness of fit is also displayed (computed by means of penalised likelihood criteria). More specifically, Table VI shows the values of the Root Mean Squared Error (RMSE), as well as the Mean Absolute Deviation (MAD) for the return series. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan–Quinn criteria (HQ) were also computed. In addition, the empirical one-step-ahead coverage (COV) of the prediction intervals is shown at 95 and 99% confidence levels. Independence Comparisons (INC), Conditional Coverage (CC) and Unconditional Coverage (UC), as described by Christoffersen (1998), are shown.

Finally, the mean WIDTH is given as WIDTH $= \frac{1}{T}\sum_{t=1}^{T}\left(y_{sup,t} - y_{inf,t}\right)$, and the score function, recently proposed by Gneiting and Raftery (2007), is expressed by:

$$\text{LOSS} = \sum_{t=1}^{T}\left(y_{sup,t} - y_{inf,t}\right) + \frac{2}{\alpha}\left(\sum_{t=1}^{T}I\left(y_t < y_{inf,t}\right)\left(y_{inf,t} - y_t\right) + \sum_{t=1}^{T}I\left(y_t > y_{sup,t}\right)\left(y_t - y_{sup,t}\right)\right) \quad (12)$$

where I(A) denotes the indicator function of set A. Additionally, $y_{inf,t} = \hat{\mu} - z_{\frac{\alpha}{2}}\hat{\sigma}_t$ and

$y_{sup,t} = \hat{\mu} + z_{\frac{\alpha}{2}}\hat{\sigma}_t$ are the upper and lower limits of the one-step-ahead prediction interval for

a 100(1- α)% confidence level. $\hat{\mu}$ and $\hat{\sigma}_t^2$ are the return and volatility estimates for each model, and z_α denotes the (1- α) quantile of a standard normal distribution.

As demonstrated by Gneiting and Raftery (2007), this function provides a proper score rule to evaluate the predictive behaviour of a model at a given confidence level (100(1- α)%), using on one hand, the WIDTH of the one-step-ahead prediction intervals, {($y_{inf,t}$,$y_{sup,t}$); t=1,…, T} and, on the other, the size of deviation from the lack of intervals coverage, both at the lower end $\sum_{t=1}^{T}I\left(y_t < y_{inf,t}\right)\left(y_{inf,t} - y_t\right)$ and the upper end $\sum_{t=1}^{T}I\left(y_t > y_{sup,t}\right)\left(y_t - y_{sup,t}\right)$, which is highly relevant information for assessing the risk associated with the estimated risk value for each model.

The results show non-significant differences in the mean returns (RMSE, MAD) of the two series for each model, with the GARCH model performing better in the MAD criterion and the GJR model better in the RMSE criterion. The levels of goodness of fit (AIC, BIC, HQ) of the three models are also similar, although models that include the asymmetric effect obtain the better levels. Furthermore, the coverage of the three models is adequate, both at the 95 and 99% confidence levels, without rejecting the hypothesis of conditional coverage and independence in any of the models. The most significant differences are found in the prediction intervals WIDTH and LOSS, where it is seen that models including the asymmetric effect have the least losses.

Table VI. Comparative predictive study of the univariate models estimated for IBEX35 and FTSE4Good-IBEX

Series	Criteria	IBEX35			FTSEGood-IBEX		
		GARCH	GJR	EGARCH	GARCH	GJR	EGARCH
y_t	RMSE	2.0889	2.0873	2.0873	1.9488	1.9475	1.9475
	MAD	1.4901	1.4947	1.4947	1.3991	1.4041	1.4044
	AIC	4.0105	3.9643	3.9681	3.9395	3.8969	3.8987
	BIC	4.0462	4.0089	4.0127	3.9752	3.9415	3.9433
	HQ	4.0245	3.9819	3.9857	3.9536	3.9145	3.9162
	COV95	95.03	95.46	95.46	95.68	95.46	96.11
	PVALUECC95	0.9453	0.3307	0.8525	0.7409	0.8525	0.4622
	PVALUEUC95	0.9745	0.6416	0.6416	0.4921	0.6416	0.2539
	PVALUEIND95	0.7385	0.1577	0.7487	0.7208	0.7487	0.6228
	WIDTH95	7.5313	7.4211	7.3960	7.1903	7.0791	7.0654
	LOSS95	7717.60	7487.68	7504.94	7458.49	7235.24	7274.96
	COV99	99.35	99.35	99.35	99.14	98.92	98.92
	PVALUECC99	0.7042	0.7042	0.7042	0.9229	0.9332	0.9332
	PVALUEUC99	0.4158	0.4158	0.4158	0.7632	0.8645	0.8645
	PVALUEIND99	0.8432	0.8432	0.8432	0.7917	0.7411	0.7411
	WIDTH99	9.9136	9.7686	9.7356	9.4649	9.3184	9.3003
	LOSS99	10184.69	9751.93	9653.86	9877.30	9769.18	9595.28

5.2. Multivariate results

In this section, an analysis is carried out of the joint evolution of the conditional volatility of both the FTSE4Good-IBEX and IBEX35, in order to capture any inter-relationships. Bearing in mind the results obtained from the univariate analysis, in which a significant asymmetric effect was observed, it was decided to compute a multivariate GARCH(1,1) model, with normal errors and an asymmetric effect, whose equations are:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \text{ with } \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} | \Omega_{t-1} \sim N_2 \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{12,t} & \sigma_{22,t} \end{pmatrix} \right) \quad (13)$$

$$\sigma_{11,t}^2 = \omega_{11} + \alpha_{11}\varepsilon_{1,t-1}^2 + \gamma_{11}\varepsilon_{1,t-1}^2 I\left(\varepsilon_{1,t-1} < 0\right) + \beta_{11}\sigma_{11,t-1}^2 \quad (14)$$

$$\sigma_{12,t} = \omega_2 + \alpha_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + \gamma_{12}\varepsilon_{1,t-1}\varepsilon_{2,t-1} I\left(\varepsilon_{1,t-1} < 0\right) I\left(\varepsilon_{2,t-1} < 0\right) + \beta_{12}\sigma_{12,t-1} \quad (15)$$

$$\sigma^2_{22,t} = \omega_{22} + \alpha_{22}\varepsilon^2_{2,t-1} + \gamma_{22}\varepsilon^2_{2,t-1}I\left(\varepsilon_{2,t-1} < 0\right) + \beta_{22}\sigma^2_{22,t-1} \qquad (16)$$

and under the restrictions imposed by the DVEC, DBEKK and CCC models described in Section 4. Under the CCC model, $\sigma_{12,t} = \rho_{12}\sigma_{11,t}\sigma_{22,t}$ is verified, where $Corr(y_{1t}, y_{2t}|\Omega_{t-1})$.

Table VII shows the estimates of the multivariate models where series 1 refers to the IBEX35 daily returns and series 2 to those from the FTSE4Good-IBEX.

Table VII. Multivariate conditional volatility modelling of IBEX35 and FTSE4Good-IBEX return series

	DVEC		DBEKK		CCC	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Mean equation						
μ_1	-0.0305	0.0727	-0.0354	0.0710	-0.0471	0.0738
μ_2	-0.0355	0.0720	-0.0395	0.0703	-0.0536	0.0732
Variance equation						
ω_{11}	0.1147***	0.0363	0.1215***	0.0351	0.0768***	0.0226
ω_{12}	0.1057***	0.0331	0.1115***	0.0317		
ω_{22}	0.1009***	0.0315	0.1046***	0.0301	0.0629***	0.0198
α_{11}	0.0109	0.0168	-0.0288	0.0704	0.0038	0.0161
α_{12}	0.0108	0.0166				
α_{22}	0.0131	0.0170	-0.0702	0.0697	0.0079	0.0146
γ_{11}	0.1289***	0.0309	0.3772***	0.0338	0.1119***	0.0249
γ_{12}	0.1227***	0.0283				
γ_{22}	0.1168***	0.0266	0.3561***	0.0322	0.0895***	0.0192
β_{11}	0.8861***	0.0222	0.9420***	0.0100	0.9166***	0.0164
β_{12}	0.8896***	0.0223				
β_{22}	0.8918***	0.0227	0.9453***	0.0105	0.9262***	0.0161
ρ_{12}					0.9778***	0.0021
Portmanteau	34.1209**		34.3934**		32.3066**	
Jarque-Bera conjunto	5.3981		5.4719		5.3295	
Log-Likelihood	-1093.048		-1093.570		-1092.866	
AIC	4.7674		4.7610		4.7580	
BIC	4.8834		4.8592		4.8561	
HQ	4.8131		4.7997		4.7966	

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level Coefficients regarding IBEX35 are shown by $\phi_{1,j}$ and for the FTSE4Good-IBEX by $\phi_{j,2}$ where $\phi = [\omega, \alpha, \gamma, \beta, \rho]$. Jarque-Bera test for multivariate normality was tested by means of Cholesky of covariance (Lutkepohl)

The estimates obtained from the three multivariate models are similar to each other and to those from the univariate GJR model estimated, both for the mean and variance equations, although with a smaller asymmetrical effect due to the joint-evolution dependence of the two series. In both cases, the leverage effect is significant and highlights the greater impact of negative return shocks on the volatility of each series. The AIC, BIC and HQ criteria indicate that the CCC model shows the best levels of goodness of fit; this is the most parsimonious of the three models estimated. Additionally, Figures 10 to 12 show the estimated volatility of each multivariate model (left axis contains their kernel density plot).

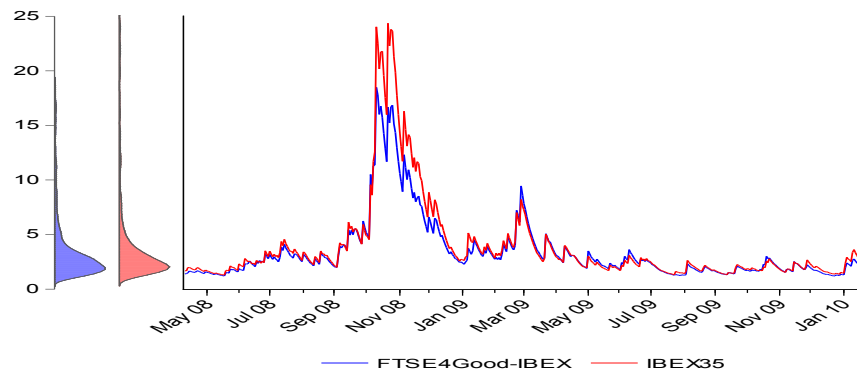Figure 10: Conditional Volatility under DVEC

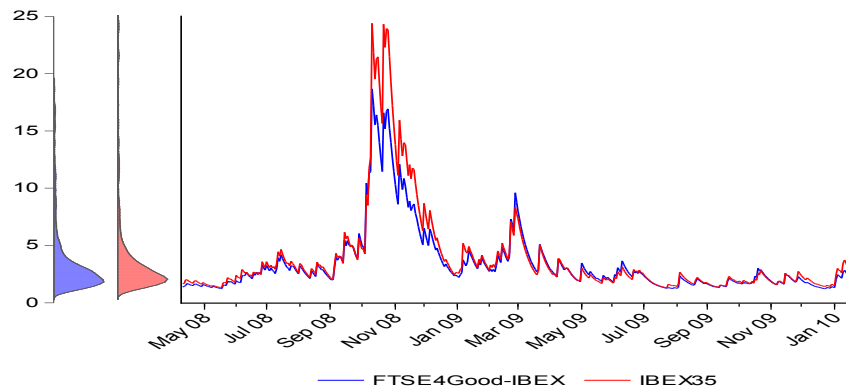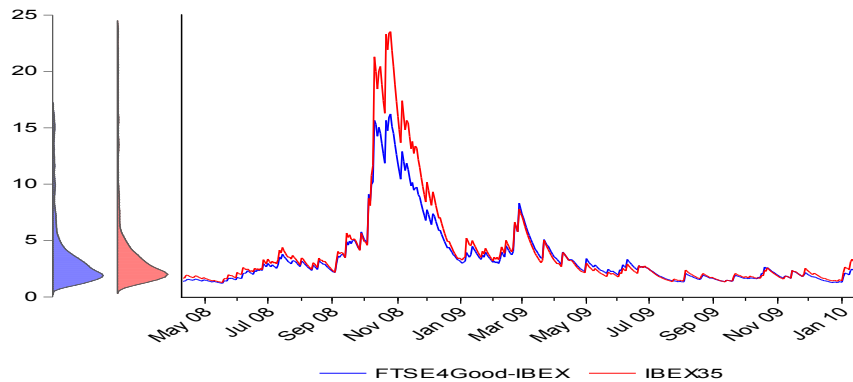Figure 11: Conditional Volatility under DBEKK

Figure 12: Conditional Volatility under CCC

Figures 10 to 12 show that the volatility estimated by the three multivariate models is once again observed to be lower for the FTSE4Good-IBEX with regard to its benchmark (IBEX35), which confirms the results obtained from the univariate analysis. Thus, it seems that portfolios which replicated the sustainable index obtained lower volatility, i.e. risk levels, with this effect being particularly noticeable during periods of maximum volatility, when the FTSE4Good-IBEX risk level was about 10–15% lower than that of the IBEX35. This period of maximum uncertainty started in about the second week of October 2008 and ran to January 2009. It seems to have been caused by a growing lack of confidence in stock market agents under the shadow cast by the announcement of the International Monetary Fund (IMF) that the Spanish economy would fall into an economic recession in January 2009; not even the interest rate reduction effectuated by the European Central Bank (ECB) or the decision of the main European governments to guarantee bank deposits up to € 100,000 could avoid this scenario. Moreover, the main banks throughout the world had been in serious financial difficulties during the first half of 2008 (Northern Rock Bank, Bear Stearns Bank, IndyMac Bank, Fannie Mae, Freddie Mac, Lehman Brothers Bank and Merrill Lynch Bank i.a.). From the beginning of this period of maximum volatility in the indexes analysed, the IBEX35 suffered record losses[6], higher than 5% and up to 9%, for several days in October 2008, accompanied by high trading volumes[7].

Apart from such considerations, it is remarkable that the evolution of returns estimated by the multivariate models for both indexes are strongly correlated (see Figure 13) to an estimated value of 0.98. This reinforces the results obtained in Section 3, showing significant but low differences in daily returns.

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6. As an example, the IBEX35 lost 20%, falling to under 9000 points during the second week of October 2008.

7. During trading on 10 October 2008, the IBEX35 lost more than 9% and experienced the second largest trading volume in its history.

Figure 13: Correlation between FTSE4Good-IBEX and IBEX35 daily returns estimated by the multivariate models
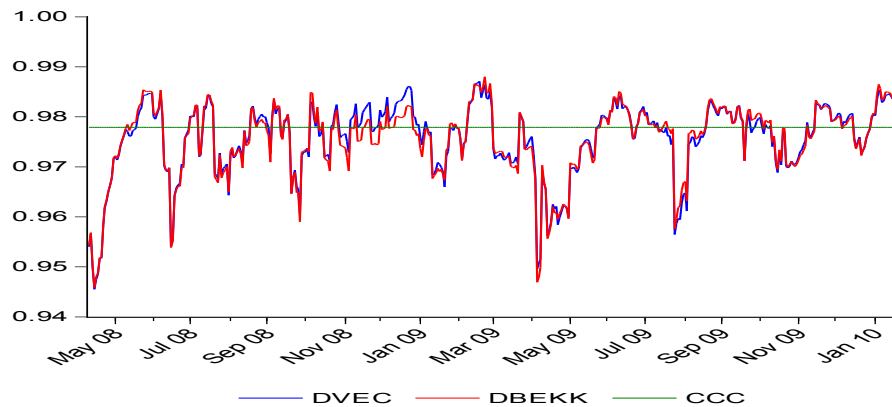

Figure 14 shows the ratio between the estimated volatilities of the multivariate models for the FTSE4Good-IBEX and the IBEX35. It indicates that is during the period of maximum uncertainty (October 2008–January 2009) when the greatest volatility differential, i.e. risk differential was experienced by both indexes.

Figure 14: Evolution of the ratio between the conditional volatility of the FTSE4Good-IBEX and the IBEX35 ($\sigma_{22,t}$ / $\sigma_{11,t}$) estimated by the multivariate models (in %)
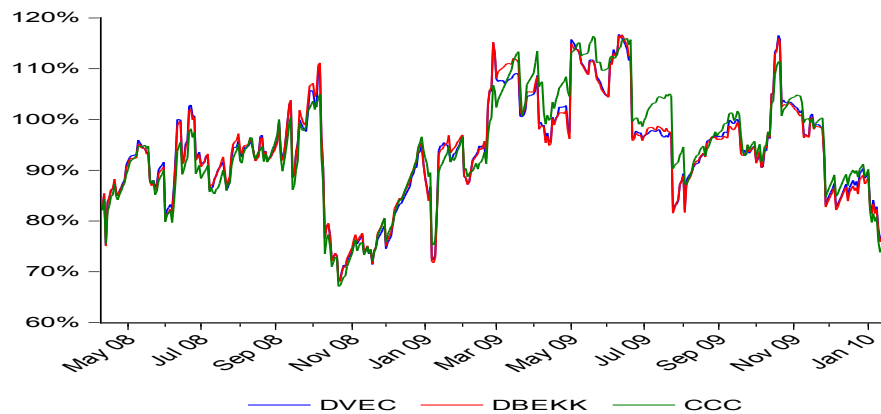
In periods of maximum instability of risk levels, the FTSE4Good-IBEX may be a satisfactory investment choice since, for a similar return, the risk levels are significantly lower.

6. Conclusions

The modern portfolio theory asserts that SRI reduces the possibility of portfolio diversification because SRI screening process reduces the investment universe. Furthermore, this theory support the under-performance of SRI compared with the traditional investment policy. This ideas match with supporters of the efficient market hypothesis, arguing that it is very difficult that SRI outperform the traditional investment approach. The present research aims to test empirically if, in the Spanish market, the principles established by the modern portfolio theory are satisfied. This work aims to contribute to the literature in this field, which is mainly focused on assessing the risk-adjusted returns of SRI mutual and pension funds. To this end, this research aims to asses the conditional volatility, i.e. risk levels linked to investment in leading Spanish sustainability-driven companies (FTSE4Good-IBEX) and its main benchmark (IBEX35) in order to test if ethical investment (FTSE4Good-IBEX) shows lower risk levels than the traditional investment approach. Although the main objective of this research is not to asses the relative risk-adjusted return of the SRI equity index analysed, the estimate of the Jensen's Alpha indicates that there are significant differences in the risk-adjusted returns achieved by the two equity indexes analysed, the FTSE4Good-IBEX under-performing its benchmark (IBEX35). However, this effect is observed very low and could be due to that stock markets misprice information on CSR in the short run. This result matches the results obtained by Le Maux and Le Saout (2004) and Schöder (2004, 2007).

One of the contributions of this work is the use of univariate and multivariate GARCH models to estimate conditional volatility levels for both indexes, as well as to analyse their joint evolution. It seems, that, during the period analysed, the risk levels experienced by the FTSE4Good-IBEX were far lower than that of the IBEX35. This is of relevant interest because it is observed that investing in SRI equity indices might reduce the volatility, i.e. risk of investment portfolios. This could be due to that, social and environmental screening reduces the possibility of incurring high costs during corporate social crises, which financial markets tend to undervalue (Renneboog *et al.*, 2008a). In addition, a very interesting contribution of this study is the observation that, especially during periods of maximum market instability, the risk levels differences between the two indexes was the greatest. These results indicate that, in Spanish market, the SRI equity index better withstand the negative effects of a market crash, like the initiated in mid 2008.

Traditionally, it was considered that investors were primarily attracted to SRI vehicles out of a desire to match their investment policies with their values (Domini, 2001). The results obtained from this study extend this proposition by indicating that investors can replicate Spanish SRI equity indices, satisfying their ethical values, simultaneously obtaining lower risk levels in their portfolios, i.e. investors may do well while doing good (Hamilton *et al.*, 1993). The main findings show that SRI can be a good investment choice in Spain, as it presents a novel focus via which both individual and institutional investors can diversify the risk from different portfolios through other types of unconventional financial assets, such as SRI equity indices.

Given the lack of research that analyses the risk levels associated with socially responsible equity indices (Fowler and Hope, 2007; Schröder, 2007), it would be interesting to extend this analysis to other SRI stock exchange indexes worldwide and, furthermore, to analyse the evolution of all of these together in order to capture any volatility spillover effects.

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