Trading with Asymmetric Volatility Spillovers*

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Preliminary Draft, June 2003

* CICYT project BEC2000-1388-C04-04 and the Instituto Valenciano de Investigaciones Económicas (IVIE) provided financial support. We are grateful for the comments and suggestions of G. Llorente and V. Meneu. The usual caveat applies.

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Abstract

This article studies the dynamic relationships between large and small firms by using Volatility Impulse-Response Function of Lin (1997) and its extensions, which takes into account the asymmetric structures on volatility. The study reveals that bad news about large firms can cause volatility in both large-firm returns and small-firm returns. Furthermore, contrary to the previous evidence, bad news about small firms can also cause volatility in both kinds of firms. After measuring spillover effects, different trading rules have been designed. There is evidence that these rules provide very profitable strategies, especially after bad news coming from its own and the "other" market. These results are of special interest for practitioners because of its implications for portfolio management.

Keywords: volatility spillovers, asymmetric volatility and large and small stock exchange indices

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1. Introduction

Unexpected shocks between large and small companies have attracted the attention of both academics and practitioners because of its implications for portfolio management and asset pricing. A great number of papers have shown that large-firm returns can be used to forecast small-firm returns, but not *vice versa*. In this way, Conrad, Gultekin and Kaul (1991) find that volatility surprises are important to the future dynamics of their own returns as well as the returns of smaller firms. However, the converse is not true. This unidirectional causality agrees with the "directional asymmetry" found in McQueen *et al.* (1996). They show that the lead-lag relationship between large and small portfolio returns exists only after unexpected positive shocks in large stock portfolio returns because unexpected negative shocks are updated immediately.

There are several hypotheses that have tried to explain the existing cross-correlation between large and small stock returns. The first one is focused on the non-synchronous trading effect. Boudoukh *et al.* (1994) and Chelley-Steeley and Steely (1995) find that non-synchronous trading can be an important determinant of cross-correlations. In stark controversy, Lo and Mackinlay (1990) and Conrad, Kaul and Nimalendran (1991) indicate that this effect could account only for a small part of the observed portfolio returns serial autocorrelation. The second hypothesis relates the significant cross-correlation to the differential quality of information caused both by large and small firms and to differences in response of them to general economic and firm-specific factors (Yu and Wu, 2001). Finally, the last hypothesis blames the more quantity of information produced from large companies as the most important reason for the existence of the unidirectional lead-lag relationship from large to small stock returns (see Chopra *et al.*, 1992 and Badrinath *et al.*, 1995).

Although relationships between large and small portfolio returns are very well documented in the literature, volatility spillovers between them have not been studied enough. When variances and covariances are applied to study the dynamic relation between large and small firm returns, it is important to differentiate between asymmetric volatility and covariance asymmetry. The first one refers to the empirical evidence that stocks returns are more volatile in bearish than bullish markets while the second one helps to explain the former (see Bekaert and Wu (2000)).

Volatility asymmetry first appeared in the financial literature with Black (1976) and Christie (1982). The explanation they put forward is based on the "leverage effect hypothesis": a negative return increases financial leverage, causing the volatility of the equity's rate of return to rise. However, it seems that the leverage effect is too small to fully account for this phenomenon (Christie (1982) and Schwert (1989)). Another explanation is often referred to as "volatility feedback effect": if the market risk premium is an increasing function of market volatility, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline (Campbell and Hentschel (1992)).

Which of both competing explanations is the main cause of asymmetric volatility has been an open question over years. Kroner and Ng (1998) shed more light on this topic by documenting significant asymmetric effects in both the variances and covariances. In particular, bad news about large firms can cause volatility in both small-firm returns and large-firm returns. Moreover, the conditional covariance between large-firm and small-firm returns tends to be higher following bad news about large firms than good news. Following this line, Bekaert and Wu (2000) provide a general empirical framework to examine volatility by differentiating between the two competing explanations and by examining asymmetric volatility at the firm and at the market level. They find evidence that the volatility feedback effect is particularly strong when the conditional covariance between market and stock returns responds more to negative than to positive markets shocks.

In volatility symmetric structures, it is not necessary to distinguish between positive and negative shocks, but with asymmetric structures the Volatility Impulse-Response Function proposed by Lin (1997) change with the shock sign. Therefore, this methodology can be especially useful for obtaining information on the second moment interaction between related markets.

The main objective of this paper is to go deeply into volatility spillovers between large and small firms by studying the impulse-response function for conditional volatility. It is important to point out that, as far as we know, this is the first time that large-small firm portfolio relationship is studied by using Lin's methodology and its extensions. The study of volatility spillovers taking into account the Volatility Impulse-Response Function can be very helpful in designing trading rules based on the inverse relationship existing between expected volatilities and expected returns. Furthermore, we use stock market indices on large and small liquid stocks instead of portfolios. This fact has two clear advantages for practitioners: they can take signals directly from market indices quotations, so it is not necessary to build portfolios and, the implementation of the trading rules can be notably reduced due to the existence of derivative contracts on the large stocks index.

The rest of the paper is structured as follows. Section 2 introduces econometric framework and formulates our empirical model. Section 3 presents the data and discusses the main empirical results. In section 4, trading rules based on volatility spillovers are designed and computed. The final section summarises the main results.

2. The Econometric Framework

2.1. The Means Model

As this paper mostly addresses modelling volatility rather than returns forecasting, a two-step estimation procedure is followed. First, a model in means is estimated and then the residuals of this model are taken in the second step as an input to estimate the conditional variance. To clean up any autocorrelation behaviour, the following vector error correction model (VECM) is estimated:

$$\begin{aligned} \Delta L_t &= c_1 + \alpha_1 z_{t-1} + \sum_{j=1}^{p} a_{1,j} \Delta L_{t-j} + \sum_{j=1}^{p} b_{1,j} \Delta S_{t-j} + \varepsilon_{1,t} \\ \Delta S_t &= c_2 + \alpha_2 z_{t-1} + \sum_{j=1}^{p} a_{2,j} \Delta L_{t-j} + \sum_{j=1}^{p} b_{2,j} \Delta S_{t-j} + \varepsilon_{2,t} \end{aligned} \tag{1}$$

where L_t and S_t refers to the logarithm of the large and small stock indices respectively, z_{t-1} is the lagged error correction term of the cointegration relationship between L_t and S_t; $c_i, \alpha_i, d_i, a_{ij}$ and b_{ij} for i =1,2 and j=1,…,p, are the parameters to estimate, p is the lag of the VECM. The VECM model is estimated by Ordinary Least Squares applied equation by equation (see Engle and Granger (1987) and Enders (1995)). The residual series of this model, ε_{1t} and ε_{2t}, are saved and they will be used as observable data to estimate the multivariate GARCH model. This two steps procedure (see Engle and Ng, 1993 and Kroner and Ng, 1998) reduces the number of parameters to estimate in the second step, decreases the estimation error and allows a faster convergence in the estimation procedure.

2.2. The Covariance Model

The number of published papers modelling conditional covariance is quite low compared to the enormous bibliography on time-varying volatility. One consequence of this lack of studies in covariance modelling is that asymmetry receipts in volatility are directly extended to the multivariate setting. Because of the cross effects generated in each multivariate GARCH model, the natural extension in asymmetry modelling from a univariate to a multivariate setting can have unexpected effects among all the elements of the covariance matrix. The consequences of this extension are unclear because there is no evidence enough on how asymmetries behave in the covariance. The most common case of volatility asymmetry in stock markets is the negative one, where unexpected falls in prices increase more the volatility than an unexpected increase in prices of the same amount. Engle and Ng (1993) analyse different asymmetric volatility models; they show that the asymmetry depends not only on the sign but also on the innovation size. That is, the asymmetry, if it exists, is clearer when unexpected shocks in prices are important. These authors propose a battery of tests to verify the importance and sense of the asymmetries. They obtain evidence for the Glosten *et al.* (1993) model where a dummy variable is included in a GARCH(1,1) taking value 1 when the previous innovation is negative.

Multivariate asymmetric GARCH allows for spillover in volatility between large and small firm portfolios. Furthermore, the cross relationships existing in multivariate modelling allows, for example, for the small firm portfolio to be sensitive to the large firm portfolio volatility asymmetry although no asymmetries exist in the small firm portfolio volatility. These kind of cross relationships can have several consequences in the large-small covariance dynamics, especially in periods of high volatility.

Kroner and Ng (1998) study asymmetries following the Glosten *et al.* (1993) approach in a multivariate setting. This is the most common method for introducing asymmetries in multivariate GARCH modelling in finance. Kroner and Ng (1998) adopt a structured approach, similar to Hentschel (1995) nesting the most common covariance models[1]. Under this framework, model selection is made easier by testing restrictions and it will allow choosing the right multivariate time-varying covariance avoiding *ad hoc* selections. After applying the above mentioned specification

[1] The four most widely used models are: (1) the VECH model proposed by Bollerslev *et al*. (1988), (2) the constant correlation model, CCORR, proposed by Bollerslev (1990), (3) the BEKK model of Engle and Kroner (1995) and (4) the factor model proposed by Engle *et al.* (1990).

test, it was picked up the asymmetric extended BEKK model. This model has the following two-dimensional compacted form:

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'\eta_{t-1}\eta'_{t-1}G \qquad (2)$$

where C, A, B and G are 2×2 matrices of parameters, H_t is the 2×2 conditional covariance, ε_t and η_t are 2×1 vectors containing the shocks and the threshold terms series, see below. So, the unfolded covariance model is written as follows:

$$\begin{bmatrix} h_{11t} & h_{12t} \\ . & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11t-1} & h_{12t-1} \\ . & h_{22t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$
$$+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1t-1} & \varepsilon_{1t-1}\varepsilon_{2t-1} \\ . & \varepsilon^2_{2t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} \eta^2_{11t-1} & \eta_{1t-1}\varepsilon_{2t-1} \\ . & \eta^2_{22t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \qquad (3)$$

Where c_{ij}, b_{ij}, a_{ij}, and g_{ij} for all $i,j = 1,2$ are parameters, ε_{1t} and ε_{2t} are the unexpected shock series obtained from equation (1). $\eta_{1t} = \max\ [0, -\varepsilon_{1t}]$ and $\eta_{2t} = \max\ [0, -\varepsilon_{2t}]$ are the Glosten *et al.* (1993) dummy series collecting a negative asymmetry from the shocks and h_{ijt} for all $i,j = 1,2$ are the conditional second moment series.

2.3. Asymmetries Analysis

Covariance asymmetry analysis is carried out in two steps. First, a misspecification test on asymmetries filtering is conducted before and after estimating the asymmetric covariance model. Second a graphical analysis of news impact surfaces[2] and the Asymmetric Volatility Impulse-Response Functions (AVIRF) is displayed.

The robust conditional moment test of Wooldridge (1990) is applied to test how the Glosten *et al.* (1993) modification to the multivariate GARCH models cleans the asymmetries in the conditional

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[2] A "news impact surface" is defined as the relationship between each conditional second moment (or a function of them) and the last period pair of shocks holding past conditional variances and covariances constant at their unconditional sample mean.

covariance matrix. This test enables the identification of possible sources of misspecification in the model, and is robust to distributional assumptions (see also Brenner *et. al* (1996)). The generalized residual is defined as $\upsilon_{ijt} = \varepsilon_{it}\varepsilon_{jt} - h_{ijt}$ for all *i,j* = 1,2, which is the distance between the covariance, or variance, news impact surface and its $\sqrt{T}$-consistent estimator. Using the same misspecification indicators as Kroner and Ng (1998), the Wooldridge (1990) robust conditional moment test is computed. Kroner and Ng (1998) suggest the use of three kinds of indicator variables to detect misspecification of the conditional covariance matrix. These indicators try to detect misspecification caused by shock signs $\left(I(\varepsilon_{1t-1} < 0\right)$ and $I\left(\varepsilon_{2t-1} < 0\right))$, the four quadrants sign combinations $\left(I\left(\varepsilon_{1t-1} > 0; \varepsilon_{2t-1} > 0\right)\right.$, $I\left(\varepsilon_{1t-1} < 0; \varepsilon_{2t-1} > 0\right)$, $I\left(\varepsilon_{1t-1} > 0; \varepsilon_{2t-1} < 0\right)$, $\left.I\left(\varepsilon_{1t-1} < 0; \varepsilon_{2t-1} < 0\right)\right)$ and the misspecification induced because of the cross effect of shock sings and shock sizes $\left(\varepsilon_{1t-1}^2 I\left(\varepsilon_{1t-1} < 0\right)\right.$, $\varepsilon_{1t-1}^2 I\left(\varepsilon_{2t-1} < 0\right)$, $\varepsilon_{2t-1}^2 I\left(\varepsilon_{1t-1} < 0\right)$, $\left.\varepsilon_{2t-1}^2 I\left(\varepsilon_{2t-1} < 0\right)\right)$.

The Volatility Impulse-Response Function (VIRF) is a useful methodology for obtaining information on the second moment interaction between related markets. The impulse-response function for conditional volatility is defined in Lin (1997) as the impact of an unexpected shock on the predicted volatility, that is

$$R_{s,3} = \frac{\partial \text{ vech } E[H_{t+s} \mid \psi_t]}{\partial \text{ dg } (\varepsilon_t \varepsilon_t')} \tag{4}$$

where $R_{s,3}$ is a 3 × 2 matrix, *s=1,2,...* is the lead indicator for the conditioning expectation operator, H_t is the 2 × 2 conditional covariance matrix, $\text{dg}\,(\varepsilon_t \varepsilon_t') = (\varepsilon_{1,t}^2, \varepsilon_{2,t}^2)'$, ψ_{t-1} is the set of conditioning information. The operator 'vech' denotes the operator that transforms a symmetric *N* × *N* matrix into a vector by stacking each column of the matrix underneath the other and eliminating all supradiagonal elements.

In symmetric GARCH structures it is not necessary to distinguish between positive and negative shocks to obtain the VIRF, but with asymmetric GARCH structures the VIRF must change with the shock sign. The VIRF for the asymmetric BEKK model[3] is taken from Meneu and Torro (2003) by applying (4) to (2),

$$R^{+}_{s,n} = \begin{cases} a & s = 1 \\ (a + b + ½\, g) R^{+}_{s-1,n} & s > 1 \end{cases} \tag{5}$$

$$R^{-}_{s,n} = \begin{cases} a + g & s = 1 \\ (a + b + ½\, g) R^{-}_{s-1,n} & s > 1 \end{cases} \tag{6}$$

where $R^{+}_{s,n}$ ($R^{-}_{s,n}$) represents the VIRF for positive (negative) initial shocks and where c is a 3 × 1 parameter vector and *a*, *b* and *g* are 3 × 3 parameter matrices[4]. The AVIRF asymptotic distribution is obtained straight away from VIRF results appearing in Lin (1997).

3. Data and Empirical Results

3.1. Data

The data used in this study has been provided by the *Sociedad de Bolsas*, which manages the most important indexes of the Spanish Stock Exchanges. Specifically, the data used in this study consists of daily closing values of the IBEX-35 index and the IBEX-Complementario from January 2nd of 1990 to June 28th of 2002.

The IBEX-35 index is composed of the most liquid 35 securities quoted on the Spanish Joint Stock Exchange System of the Four Spanish Stock Exchanges (Madrid, Barcelona, Bilbao and Valencia). The IBEX- Complementario index is composed of the securities included in the Sectorial Indexes of

[3] The probability distribution of shock signs is needed to obtain the conditioning information flow at any time. It is assumed that prob ($\varepsilon_t < 0$) = ½ and prob ($\varepsilon_t \geq 0$) = ½ for all *t*. Furthermore, shock sign independence over time and independence between shock signs and squared unexpected shocks is also assumed.

[4] Where $b = D_N^{+}(B' \otimes B')D_N$, $a = D_N^{+}(A' \otimes A')D_N$, $g = D_N^{+}(G' \otimes G')D_N$, $D_N = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ is a duplication matrix,

$D_N^{+} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & ½ & ½ & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ is its Moore-Penrose inverse and ⊗ denotes the Kronecker product between matrices.

the *Sociedad de Bolsas* that do not belong to the IBEX-35.[5] It is important to point out that only the most liquid stock are traded in the Spanish Joint Stock Exchange System. Therefore, this is a guarantee of liquidity. However, in order to overcome possible problems associated with thin trading, weekly frequency is used, taking Wednesday closing values or the previous trading day if the Wednesday is not a trading day. Returns series are obtained by taking first differences in the *log* prices.[6]

3.2. Preliminary Analysis

Figure 1 displays the weekly evolution of the stock indices IBEX-35 and IBEX-Complementario in the studied period and preliminary data analysis is presented in Tables I, II and III. Table I displays returns, volatilities and correlation coefficients, year by year through the sample period for both stock indices, the IBEX-35 (I_t) and the IBEX-Complementario (C_t). Three facts can be highlighted from this table. First, there are 4 years (1994, 1999, 2000 and 2002) in which both indices offer a different sign return but means equality hypothesis can not be rejected. A second appealing fact in Table I is that after 1992 the IBEX-35 volatility is fairly larger than the IBEX-Complementario volatility. Variance equality test rejects the null in years 1999 to 2002. Finally, last column shows that the correlation between both series has decreased as time pass.

Differences in means and variances can be understood as both classes of stocks offering different sensitivities to risk factors. For example, large companies are more internationalised depending on global risk factors and small companies risk factors are localised basically in its own economy. This fact can be seen as a globalisation effect on the Spanish stock market through several global crises (European Monetary System suffered several crises in the early nineties, Asian crisis in October 1997,…), international strategic positions taken by the most important Spanish companies (especially in Latin America) and, simultaneously, these companies have begun to be traded in the most important stock markets in the world.

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[5] During the studied period, the IBEX-35 and IBEX-Complementario represented the 82% and the 6%, respectively, of the overall capitalisation of the Spanish Stock Exchange.

[6] The common tests of unit roots and cointegration (Dickey and Fuller (1981), Phillips and Perron (1988), and Johansen (1988)) offered no doubt about this point.

From Table II, it can be stated that the pair of financial time series used in this paper offers very similar statistics. Both have significant skewness, kurtosis, autocorrelation, heteroskedasticity and a single unit root. Moreover, although equality in means can not be rejected the variances equality test is rejected. This preliminary result points out that more research is necessary in the covariance dynamics between both financial time series.

3.3. Estimating the Model

The model in equations (1) and (3) is estimated in a two-step procedure. To take account of the pre-holiday effect on the Spanish Stock Exchange[7], a dummy variable has been also included in the mean equation. The model for the means is:

$$\begin{aligned} \Delta I_t &= c_1 + \alpha_1 z_{t-1} + d_1 HOL_t + \sum_{j=1}^{p} a_{1,j}\Delta I_{t-j} + \sum_{j=1}^{p} b_{1,j}\Delta C_{t-j} + \varepsilon_{1,t} \\ \Delta C_t &= c_2 + \alpha_2 z_{t-1} + d_2 HOL_t + \sum_{j=1}^{p} a_{2,j}\Delta I_{t-j} + \sum_{j=1}^{p} b_{2,j}\Delta C_{t-j} + \varepsilon_{2,t} \end{aligned} \qquad (7)$$

where HOL_t is a dummy variable that equals to one when the next weekly return contains a pre-holiday.

First, the VECM model in equation (7) is estimated by Ordinary Least Squares applied equation by equation (see Engle and Granger (1987)). The VECM lag was chosen by maximising AIC criterion. Table III shows that series are cointegrated being 3 the optimum lag length. Panel (A) in Table IV displays the estimated coefficients and the residual analysis.

Examination of the speed of adjustment coefficients (α_1 and α_2) provides insight into the adjustment process of stock indices towards the long-run equilibrium. For the stock indices to adjust to the long-run relationship it is necessary that $\alpha_1 > 0$ and $\alpha_2 < 0$ (assuming IBEX-35 to be weak

[7] See Meneu and Pardo (2003).

exogenous and IBEX-Complementario endogenous) [8]. The estimated coefficients have the expected sign in the IBEX-Complementario (α_2) equation but it has the opposite sign in the IBEX equation (α_1). It can be conclude that the IBEX-35 leads the IBEX-Complementario in the long run.

From Table IV, it can be seen that the pre-holiday dummy coefficients are significant in both equations. This variable has already been studied in Meneu and Pardo (2003) with daily series, but it is the first time that it is found significant in weekly series. So it can be inferred that it is a very important anomaly and it should not be omitted.

The residual analysis in Table IV shows that with the estimated model autocorrelation disappears but heteroskedasticity remains. Furthermore, in Panel (B) Granger causality tests reject the null hypothesis. Therefore, there is no causality in any sense in the short run.
Table V and VI display the estimated conditional covariance model and its standardised residual analysis, respectively. Table V estimates have been computed assuming a conditional normal distribution for the innovation vector $(\varepsilon_{1t}, \varepsilon_{2t})'$. The standard errors and their associated critical significance levels are calculated using the quasi-maximum likelihood method of Bollerslev and Wooldridge (1992) which are robust to the non-normality assumption. Panel (A) displays the estimates. The low critical significance level obtained for 13 out of 15 parameter estimates reveals that this model fit very well with the data.[9] Restrictions on cross-variance effects and asymmetric covariance are clearly rejected (see Panel (B)). As a consequence, cross relationships across all conditional moments and their shocks (symmetric and non-symmetric) cannot be skipped. Moreover, asymmetries but it self are also significant. Panel (C) shows the estimated persistence to any shock in the estimated conditional covariance model. The conditional variance for the IBEX-35 has a very high persistence to its own shock. But volatility persistence is a quite common feature in financial time series.

Table VI displays standardised residual analysis. From this table it can be concluded that autocorrelation and heteroskedasticity problems have been successfully amended. Finally, Figure 2 displays the conditional second moments evolution overall the estimation period. Both volatility

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[8] From the cointegration relationship, the error correction term can be written as $z_t = C_t - \beta_1 I_t - \beta_{2_t}$. For the existence of a long-run equilibrium relationship, it is necessary that $\alpha_1 z_{t-1} > 0$ and $\alpha_2 z_{t-1} < 0$. See Johansen (1995), chapter 8 for more details.

[9] The maximum log-likelihood function value obtained in the estimation process was 4460.

series have similar patterns but Ibex-35 volatility is almost ever above of the Ibex-Complementario volatility, especially after 1997 when the globalisation effect on the biggest companies in the IBEX-35 is particularly important.

3.4. Filtering Covariance Asymmetries

Table VII contains the results of the robust conditional moment of Wooldridge (1990) to test how the Asymmetric BEKK-GARCH model cleans up the asymmetries in the conditional covariance matrix. Panel (A) displays the test result when unconditional covariance estimate is used. It can be seen than asymmetries are very important, especially in the covariance between both series and beta coefficients. Panel (B) offers the test results once asymmetries are included in the covariance specification. After this, only one asymmetric pattern seems to remain in the conditional covariance specification. This is an important result because it means that the GARCH specification is gathering almost all the possible asymmetries in the conditional covariance matrix: direct and crossed asymmetries and asymmetries of sign and size in the unexpected shocks. This result is also a guarantee that the analysis of the asymmetric volatility impulse response function carried out later is reliable. That is, it will be able to answer the following questions: Are spillovers of volatility important in the large-small firm system? Are the unexpected negative shocks of large stocks conditional variance important in the small stocks conditional covariance? And the reverse? Which market leads the volatility system?

The effect of asymmetric behaviour in conditional beta coefficients is also investigated. Last column in Table VII contains its robust conditional moment test[10]. The presence of any asymmetric effect is clearly rejected in Panel (B). This result shows that conditional beta estimates are insensitive to volatility asymmetries. This appealing result comes from the fact that a ratio between two second moments tends to compensate the asymmetric effect if a stable proportion is maintained between both conditional second moments. This lack of sensitivity is important for portfolio management based on beta estimates, as it seems unnecessary to consider asymmetries[11], therefore simpler models can be used. It is also important because beta coefficients are a market risk

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[10] Following Wooldridge (1990), a consistent estimator of the minimum variance hedge ratio is built using the continuous function property on consistent estimators (see Hamilton (1994), p. 182).

[11] Results on symmetric BEKK model show that conditional beta estimates are insensitive to any asymmetry in the conditional covariance matrix. Results are omitted to conserve space.

sensitivity measure and it is shown that conditional beta estimates are insensitive to sign and size shocks. Furthermore, this result is comparable to the Braun *et al.* (1995) and Bekaert and Wu (2000) empirical findings on beta coefficients: while asymmetries are very strong in the conditional second moments they appear to be entirely absent in conditional betas.

Figures 3-a and 3-b display the unconditional and conditional correlation and beta coefficients, respectively. It can be appreciated that conditional correlation is quite stable around is unconditional estimate with a smooth decreasing trend. The conditional beta coefficient has a similar but more acute pattern. Recovering Figure 2, where IBEX-35 conditional volatility has increased in level after 1998, it can be inferred that both markets have a weaker relationship than before 1998. So, diversification strategies are getting an important role in portfolio management.

Figure 4 collects the news impact surfaces for the conditional second moments and the conditional beta obtained from the asymmetric bivariate GARCH specification.[12] It can be appreciated that the IBEX-35 variance surface shows a clear size asymmetry when opposite signs are registered in both markets. The IBEX-Complementario variance surface shows a clear sensitivity to its own negative shocks when positive shocks on the IBEX-35 comes together. Moreover, covariance surface is quite plane, increasing smoothly as negative shocks in the IBEX-Complementario takes larger values. Finally, it can be seen that when large and small stock shocks are perfectly correlated, the beta coefficient is quite stable on its unconditional value (0.67) and it is insensitive to shock size. But when large cross-signed shocks are allowed (quite possible in this financial system) conditional betas fall to small values, a very wise result.

3.5. Measuring Volatility Spillovers

Cheung and Ng (1996) propose a no causality in variance test based on the residual cross-correlation function and robust to distributional assumptions. Causality in variance is of interest to both academics and practitioners because of its economic and statistical significance. First, changes in variance are said to reflect the arrival of information and the extent to which the market evaluates and assimilates new information. As Ross (1989) shows, conditional variance changes are related to

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[12] Following Engle and Ng (1993) and Kroner and Ng (1998), each surface is represented in the region $\varepsilon_{it} = [-5,5]$ for i = 1,2.

the rate of flow information. So, one way to study how information flow is transmitted between large and small companies is studying its volatility relationships. Second, the causation pattern in variance provides an insight concerning the characteristics and dynamics of economic and financial prices, and such information can be used to construct better econometric models describing the temporal dynamics of the time series.

Cheung and Ng (1996) no causality in variance test can be viewed as a natural extension of the well-known Granger causality in mean[13]. This test is based on the asymptotic distribution of the cross-correlation function trying to detect causal relations and identify patterns of causation in the second moment. Panel (A) in Table VIII displays the cross-correlation test for the standardised residuals obtained from Equation (7). The model is cleaned up of level correlation but there remains cross-correlation in both senses across squared standardised residuals. After estimating the covariance model in Equation (3), significant cross-lagged-correlation between standardised residuals and squared standardised residuals disappears. It is important to stress that cross-lagged-correlation in both senses exists in squared standardised residuals (Panel A) but they disappear after introducing the GARCH model (Panel B). So, the AVIRF analysis must be able to exhibit volatility spillovers across markets.

Figures 5 and 6 present the asymmetric volatility impulse-response functions (AVIRF) computed following Lin (1997) and Meneu and Torro (2003). Now, it is possible to split the volatility spillover effect depending on the unexpected shock sign. When unexpected shocks are positive —Figure 5—, graphical analysis shows that there exist a relatively low volatility spillover from the small to the large stock index (about 5% of the shock —Figure 5-A), but not the reverse—Figure 5-F,. If unexpected shocks are negative —Figure 6—, graphical analysis shows that there exist bi-directional volatility spillovers between both markets. It can be observed that negative shocks in the IBEX-Complementario have an important effect on its own volatility that takes about 10 weeks to be absorbed —Figure 6-C, and it is spilled to the IBEX-35 volatility but with a small impact level (about 7% of the shock —Figure 6-A). On the other hand, about a 5% of a negative shock in the IBEX-35 volatility is spilled to the IBEX-Complementario volatility —Figure 6-F. By comparing Figures 5 and 6, we can observe that good and bad news coming from the IBEX-35 have a similar

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[13] Whether the causality in mean has any potential effect on the test for causality in variance –or *vice versa*– depends on the model specification. In a GARCH-M the causality in variance is likely to have a potential large impact on the causality in mean. As this test can be also used to test no causality in mean both test can be used simultaneously to improve model specification highlighting the causal relationships both in mean and variance.

impact on its own volatility, taking a very long time to die out due to its persistence —Figures 5-D and 6-D. Finally, the only kind of news items affecting to the IBEX-Complementario volatility are the negative ones, specially its own negative shocks, taking about 10 weeks to be absorbed—Figure 6-C.

These figures are according to the coefficient estimates of matrix *G*. First, g_{11} (−0.0794) and g_{22} (0.5752) are the coefficients collecting the impact of a negative shock on the IBEX-35 and the IBEX-Complementario on their own conditional variance, respectively. It is quite clear than only in the case of the small firm index, the negative volatility asymmetry is relatively important on its dynamics. Second, g_{12} (−0.1978) and g_{21} (0.1895) coefficients reveal than negative asymmetries spillovers between both markets have a very similar size.[14]

The empirical results presented here will add evidence against the hypothesis of unidirectional variance causality from large to small stock portfolios. So the common conclusion of volatility spillover from large to small stock portfolios (see Kroner and Ng, 1998) may be due to model misspecification. The AVIRF analysis uncover that any volatility shock coming from small stock market is important to large stock market but the reverse is only true for bad pieces of news coming from large stock markets. That is, good news in the large stock markets are not signals for small stock traders but bad items of news are. Therefore, it can be said that main source of information comes with bad news coming from any market and it spreads into the 'other' stock market.

4. Trading strategies

In order to explore possible consequences to portfolio managers of the uncovered volatility spillovers across sized portfolios some trading strategies are designed based on them. There are two competing hypotheses about covariance asymmetries in stock market known as 'leverage effect' and 'feedback effect'. The second one has the empirical evidence and it is based on the existence of a negative relationship between expected returns and expected volatility.

We have designed a trading rule in order to exploit the inverse relationship between expected returns and expected volatility once conditional volatility is forecasted. The trading rule consists of

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[14] Coefficient g_{12} (g_{21}) measures the impact of a negative shock in the IBEX-35 (IBEX-Complementario) in the "other" market.

selling assets when conditional variance is forecasted to increase and buying assets in the opposite case. Furthermore, it is possible to exploit volatility spillovers across markets taking signals from a related market. That is, if an increasing volatility spillover is forecasted then you must sell stocks in the spilled market. If a decreasing volatility spillover is forecasted then you must buy stocks in the spilled market. The above section has highlighted a different volatility response depending on the unexpected shock sign so it is necessary to know the sign of the last item of news in order to improve volatility forecasting ability.

Table IX displays trading rules designing and its results based on *ex post* and *ex ante* volatility changes are presented in Table X and Table XI, respectively. The period taken to test the profitability of these strategies is January 2nd, 2001 to June 30th, 2002 with 78 weekly observations. During this period of time, the IBEX-35 had a clear decreasing trend and the IBEX-Complementario was quite stable on its initial level. Table IX presents all the strategies designed. Panels (A) and (B) show how to take positions in the stock market when last item of news is negative and positive, respectively. In each panel, overall strategies are classified into 'Direct' and 'Crossed', depending on the market from which signal arises. Finally, if conditional variance is forecasted to increase a short position must be taken and a long position must be taken in the opposite case. Strategies $1A$ to $8A$ are those taking short positions in the stock indices when a volatility increase is forecasted in its own or in the spilling market. Strategies $1B$ to $8B$ are those taking long positions in the stock indices when a decrease in its own or in the spilling market volatility is forecasted. In Table X *ex post* results are obtained with the estimated model appearing in Table V and using estimated volatilities for the studied period. In Table XI *ex ante* results are obtained by estimating the model each time new weekly returns are known, and forecasting volatility for the next week, taking stock positions depending on the volatility forecast.

Panels (C) in Tables X and XI display the buy and hold strategies return for stock indices and for the risk-free investment[15]. In this period, returns were −30.63% for the IBEX-35, 0.54% for the IBEX-Complementario and 5.95% for the accumulated risk-free investment. The number of weeks with positive and negative return is also computed. During this period of time there were 35 (47) weeks with positive return and 43 (31) weeks with negative return in the IBEX-35 (IBEX-Complementario).

[15] The accumulated weekly Spanish Treasury bill repo rate is taken as the risk-free investment.

Before considering profitable a trading rule, transaction cost must be considered. Approximately, institutional investors trading on the IBEX-35 will require no more than a 0.5% expenses in transactions costs (commissions, spreads, …). The IBEX-Complementario will require no more than 1%. Finally, if the futures contract on the IBEX-35 is used instead of the spot index, no more than 0.1% expenses will be required. Results on the futures contract are not displayed but are virtually identical to the spot index using the first to delivery contract. So the viable strategies are those than have a positive return after considering transaction costs of 0.1% in the IBEX-35 based strategies and 1% in the IBEX-Complementario case.

Tables X and XI show similar results. There only exists one strategy that is profitable *ex post* but it is no profitable in the *ex ante* case, the strategy $8A$. All the remaining strategies identified as profitable or non-profitable agree in both tables[16]. Hence, the following comments refer to both tables but after excluding this strategy. Profitable strategies are marked with an asterisk in the case of positions taken in the IBEX-35 and with two asterisks in the case of the IBEX-Complementario positions. The profitable strategies are the following: $1A$, $2A$, $3A$, $4A$, $5A$, $1B$, $7B$ and $8B$. From net returns it is easy to see that the four strategies involving short positions after bad news ($1A$, $2A$, $3A$ and $4A$) have the better performance. So one can conclude that when an increase in volatility is forecasted after bad news, then a short position must be taken in the stock market. It is important to stress that strategies based on signals coming from the neighbour market ($2A$ and $4A$) are very profitable. It is important to point out that this is a decreasing period for the IBEX-35 and selling rules will tend to have positive returns. However, this is not true for the IBEX-Complementario (see Figure 1). It should be remembered that there are 43 out of 78 weeks with negative return in the IBEX-35, but there are only 31 in the IBEX-Complementario. Therefore, this is not a hazardous result.

The four strategies with better performance ($1A$, $2A$, $3A$ and $4A$) involve taking short positions in the stock market. For large financial institutions is possible to take short positions in both the small and large stock index. In concrete, taking short positions in the IBEX-35 is very easy to any investor by joining its futures market. So one can conclude that profitable strategies have existed in the studied period of time.

[16] If a risk-free investment position were taken each non-trading week, it should be added at least a 3% of extra return.

5. Summary and conclusions

In this article we study the dynamic relationships between large and small firms taking into account asymmetric volatility and covariance asymmetry. When these types of structures appear, it is necessary to distinguish between positive and negative shocks. The Volatility Impulse-Response Functions proposed by Lin (1997) and extended by Meneu and Torró (2003) become especially useful in this case, since they give information on the second moment interaction between related markets, and they allow practitioners to design trading rules based on the inverse relationship existing between expected volatilities and expected returns.

The main result is that there exist volatility spillovers across sized portfolios in both senses after bad pieces of news. Therefore, bad news about large firms can cause volatility in both large-firm returns and small-firm returns but bad news about small firms can also cause volatility in both kind of firms. Ross (1989) demonstrated that variance changes are related to the rate of information flow. Our results indicate that only bad piece of news contains information, no matter the size of the firm.

After measuring spillover effects, different trading rules have been designed. Specifically, a trading rule taking advantage of this empirical supported feature is selling assets when conditional variance is forecasted to increase and buying assets in the opposite case. Furthermore, it is possible to exploit volatility spillovers across markets taking signals from a related market. Results show that very profitable strategies exist, especially after bad news coming from its own and the 'other' market. Whether this result is against rational market hypothesis or it can be explained by time-varying risk-premiums overcomes the objectives of this paper and it is left for further research.

6. Tables

Table I
Returns, volatilities and correlations

	Annualised Returns (%)			Annualised Volatilities (%)			Correlation (3)
Year	IBEX-35 (1)	IBEX-Compl. (1)	KW Test (5)	IBEX-35 (2)	IBEX-Compl.(2)	Levene Test (6)	
1990	-30.40	-41.69	0.00	24.74	28.97	0.04	0.91
1991	13.96	12.55	0.29	15.90	20.40	2.25	0.91
1992	-10.12	-14.89	0.00	20.73	17.41	0.93	0.82
1993	40.08	30.19	0.41	17.19	15.82	0.48	0.83
1994	-13.30	4.38	0.12	21.90	20.64	1.22	0.89
1995	14.00	2.51	0.32	15.45	15.21	0.01	0.88
1996	36.95	30.10	0.39	14.18	10.80	2.89	0.79
1997	34.18	25.95	0.76	20.41	15.57	3.07	0.88
1998	30.44	32.58	0.00	27.70	21.85	2.01	0.76
1999	16.33	-20.68	3.63	24.89	12.54	8.95*	0.74
2000	-24.35	12.18	0.00	25.69	15.58	10.38*	0.64
2001	-7.89	-8.58	0.00	24.92	18.96	5.92*	0.77
002(4)	-46.98	19.31	2.82	21.68	12.15	9.24*	0.68

(1) This column displays the annualised return of the heading index computed from its weekly mean return in that year as the mean return multiplied by 52.
(2) This column displays the annualised volatility of the heading index computed from its weekly returns in that year as a sample standard deviation multiplied by $(52)^{0.5}$.
(3) This column displays the annual correlation between both indices computed from their weekly returns in that year.
(4) This row displays the results for the period January 2nd to June 28th in 2002.
(5) This column displays the means equality test between weekly means known as Kruskal-Wallis.
(6) This column displays the variances equality test between weekly variances known as Levene.
Significant coefficients at 95% of confidence level are highlighted with one (*) asterisk.

Table II
Summary statistics for the data

	ΔI_t		ΔC_t	
Mean	0.0012		0.0011	
Kruskal-Wallis Test	0.4914	[0.4833]		
Variance	0.0009		0.0006	
Levene Test	20.6246	[0.0000]		
Skewness	-0.4953	[0.0000]	-0.4480	[0.0000]
Kurtosis	1.1941	[0.0000]	3.1056	[0.0000]
Normality	65.2923	[0.0000]	283.41	[0.0000]
Q(20)	33.4216	[0.0303]	56.9280	[0.0000]
$Q^2(20)$	85.0268	[0.0000]	85.0268	[0.0000]
A(20)	54.55	[0.0000]	54.55	[0.0000]
ADF(4)	-0.9852	⟨-2.5693⟩	-0.7918	⟨-2.5693⟩
PP(6)	-0.8443	⟨-2.5693⟩	-0.5974	⟨-2.5693⟩

Notes: Kruskal-Wallis statisitic tests the means equality and its *p*-value appears in brackets. Levene statistic tests the variances equality and its *p*-value appears in brackets. *Skewness* means the skewness coefficient and has the asymptotic distribution N(0,6/T), where T is the sample size. The null hypothesis tested is the skewness coefficient is equal to zero. *Kurtosis* means the excess kurtosis coefficient and it has an asymptotic distribution of N(0,24/T). The hypothesis tested is kurtosis coefficient is equal to zero. *Normality* means the Bera-Jarque statistic test for the normal distribution hypothesis. The Bera-Jarque statistic is calculated $T[Skewness^2/6+(Kurtosis-3)^2/24]$. The Bera-Jarque statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. *Q(20)* and $Q^2(20)$ are Ljung Box tests for twentieth order serial correlation in $\varepsilon_{C,t}$, $\varepsilon_{I,t}$ and $\varepsilon^2_{C,t}$, $\varepsilon^2_{I,t}$ respectively and *A(20)* is Engle (1982) test for twentieth order ARCH; all these tests are distributed as $\chi^2(20)$. The *ADF (number of lags)* and *PP (truncation lag)* refers to the Augmented Dickey and Fuller (1981) and Phillips and Perron (1988) unit root tests. Critical values at 10% of significance level of Mackinnon (1991) for the *ADF* and *PP* test (corresponding to the process with intercept but without trend) are displayed as ⟨.⟩ and marginal significance levels are displayed as [.] in the remaining tests.

Table III
Johansen (1988) tests for cointegration

Lags	**Null**	$\lambda_{trace}(r)$	$\lambda_{max}(r)$	**Cointegration Vector** $\beta'=(1, \beta_1, \beta_2)$
3	r = 0	17.79	15.26	1, –0.775, –1.671
	r = 1	2.53	2.53	
95% c. v.	r = 0	15.41	14.07	
	r = 1	3.76	3.76	

Notes: Lags is the lag length of the VECM model in equation (7); the lag length is determined using the AIC. $\lambda_{trace}(r)$ tests the null hypothesis that there are at most 'r' cointegrating relationships against the alternative that the number of cointegration vectors is greater than 'r'. $\lambda_{max}(r)$ tests the null hypothesis that there are 'r' cointegrating relationships against the alternative that the number of cointegration vectors is 'r+1'. Crítical values are from Osterwald-Lenum (1992, Table 1). $\beta'=(1, \beta_1, \beta_2)$ are the coefficient estimates of the cointegrating vector where the coefficient of C_t is normalised to be unity, β_1 is the coefficient of I_t and β_2 is the intercept term.

Table IV
OLS Estimates of the Error Correction Model and Granger Causality Tests

$$\Delta I_t = c_1 + \alpha_1 z_{t-1} + d_1 HOL_t + \sum_{j=1}^{3} a_{1,j} \Delta I_{t-j} + \sum_{j=1}^{3} b_{1,j} \Delta C_{t-j} + \varepsilon_{1,t}$$

$$\Delta C_t = c_2 + \alpha_2 z_{t-1} + d_2 HOL_t + \sum_{j=1}^{3} a_{2,j} \Delta I_{t-j} + \sum_{j=1}^{3} b_{2,j} \Delta C_{t-j} + \varepsilon_{2,t}$$

PANEL A: OLS Model Estimates

Explanatory variable	Depenent Variable			
	ΔI_t		ΔC_t	
z_{t-1}	-0.0434	(-3.16)	-0.0421	(-3.65)
HOL_t	0.0088	(2.84)	0.0053	(2.08)
ΔI_{t-1}	-0.0597	(-0.91)	0.0582	(1.07)
ΔI_{t-2}	0.0936	(1.42)	0.0163	(0.30)
ΔI_{t-3}	0.0209	(0.32)	-0.0744	(-1.38)
ΔC_{t-1}	0.0159	(0.20)	0.0300	(0.46)
ΔC_{t-2}	0.0127	(0.16)	0.1141	(1.78)
ΔC_{t-3}	-0.0255	(-0.34)	0.1812	(2.88)

Residual Analysis

$\overline{R}^2$	0.0453		0.076	
Log-likelihood		3183.809		
AIC		3183.868		
Q(20)	16.69	[0.6728]	24.36	[0.2267]
Q^2(20)	74.83	[0.0000]	129.27	[0.0000]
A(20)	50.66	[0.0002]	76.99	[0.0000]

PANEL B: Granger Causality Tests

$H_0 : b_{1,1} = b_{1,2} = b_{1,3} = 0$	0.0548	[0.98]		
$H_0 : a_{2,1} = a_{2,2} = a_{2,3} = 0$			0.9907	[0.40]

Notes: t-Student values are displayed as (.) and marginal significance levels are displayed as [.]. *Q(20)* and *Q^2(20)* are Ljung Box tests for twentieth order serial correlation in $\varepsilon_{1,t}, \varepsilon_{2,t}$ and $\varepsilon_{1,t}^2, \varepsilon_{2,t}^2$ respectively and *A(20)* is Engle (1982) test for twentieth order ARCH; all these tests are distributed as χ^2 (20). $\overline{R}^2$ represents the adjusted determination coefficient. *Log-likelihood* is the maximun value of the log-likelihood function of the system. The Akaike Information Criterium of the system appears as AIC. The Granger Causality Test statistic has a F(3,639) distribuition under the null hypothesis.

Table V
Multivariate GARCH model estimates and restrictions tests

Panel (A). Multivariate GARCH model estimates

$$H_t = C'C + B'H_{t-1}B + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'\eta_{t-1}\eta'_{t-1}G$$

$$C = \begin{bmatrix} 0.0076 & 0.0120 \\ (0.00) & (0.00) \\ & -3.8\times10^{-8} \\ & (0.99) \end{bmatrix} \quad A = \begin{bmatrix} 0.3527 & 0.1348 \\ (0.00) & (0.00) \\ -0.2110 & 0.0198 \\ (0.00) & (0.25) \end{bmatrix}$$

$$B = \begin{bmatrix} 0.9287 & 0.0168 \\ (0.00) & (0.00) \\ -0.0138 & 0.7788 \\ (0.00) & (0.00) \end{bmatrix} \quad G = \begin{bmatrix} -0.0794 & -0.1978 \\ (0.00) & (0.00) \\ 0.1895 & 0.5752 \\ (0.00) & (0.00) \end{bmatrix}$$

Panel (B). Testing restrictions on the model

sting cross-variance effects significance (H_0: $a_{12}=a_{21}=b_{12}=b_{21}=d_{12}=d_{21}$).	1.61 10^6 (0.00)
sting asymmetric variance significance (H_0: $d_{11}=d_{12}=d_{21}=d_{22}$).	1.09 10^3 (0.00)

Panel (C). Estimated persistence shocks

Half life	h_{11}	h_{22}	h_{12}
$\varepsilon_{1,t}$	$a_{11}^2 + b_{11}^2 + ½g_{11}^2$ 69.20	$a_{12}^2 + b_{12}^2 + ½g_{12}^2$ 0.21	$a_{12}a_{11} + b_{12}b_{11} + ¼g_{12}g_{11}$ 0.43
$\varepsilon_{2,t}$	$a_{21}^2 + b_{21}^2 + ½g_{21}^2$ 0.25	$a_{22}^2 + b_{22}^2 + ½g_{22}^2$ 2.68	$a_{21}a_{22} + b_{21}b_{22} + ¼g_{21}g_{22}$ 0.16

Panel (A) of this table displays the quasi maximum likelihood estimates of the BEKK assuming a conditional normal distribution for the innovation vector $(\varepsilon_{1\tau}.\varepsilon_{2\tau})$'. Critical significance levels appear in brackets.
Panel (B) displays Wald test restrictions on the covariance model. Critical significance levels appear in brackets.
Panel (C) displays the Half-life as a measure of persistence of any squared shock in each element of the conditional covariance matrix, approximated with the following formula: $Half-life = \frac{ln(0.5)}{ln(a^2+b^2+½g^2)}$, using the right coefficients appearing above.

Table VI
Summary statistics for the Standardised residuals from the VECM-Asymmetric BEKK Model

	Dependent Variable			
	$\varepsilon_{1t} / \sqrt{h_{11,t}}$		$\varepsilon_{2t} / \sqrt{h_{22,t}}$	
Mean	-0074		-0.011	
Variance	1.029		0.998	
Skewness	-0.5252	[0.0000]	-0.4652	[0.0000]
Kurtosis	0.9492	[0.0000]	1.7382	[0.0000]
Normality	54.1220	[0.0000]	104.9578	[0.0000]
Q(20)	17.77620	[0.6021]	21.7987	[0.3515]
Q^2(20)	22.1983	[0.3298]	17.2743	[0.6351]
A(20)	17.6605	[0.6097]	17.0650	[0.6487]

Notes: *Skewness* means the skewness coefficient and has the asymptotic distribution N(0;6/T), where T is the sample size. The null hypothesis tested is the skewness coefficient is equal to zero. *Kurtosis* means the excess kurtosis coefficient and it has an asymptotic distribution of N(0,24/T). The hypothesis tested is kurtosis coefficient is equal to zero. *Normality* means the Bera-Jarque statistic test for the normal distribution hypothesis. The Bera-Jarque statistic is calculated T[*Skewness*^{2}/6+(*Kurtosis*-3)^2/24]. The Bera-Jarque statistic has an asymptotic χ^2 (2) distribution under the normal distribution hypothesis. *Q(20)* and *Q^2(20)* are Ljung Box tests for twentieth order serial correlation in $\varepsilon_{1,t}, \varepsilon_{2,t}$ and $\varepsilon_{1,t}^2, \varepsilon_{2,t}^2$ respectively and *A(20)* is Engle (1982) test for twentieth order ARCH; all these tests are distributed as χ^2 (20). Marginal significance levels are displayed as [.] overall the tests.

Table VII
Robust conditional moment tests

Panel (A). VECM Model.

Generalised residual tests

	$\upsilon_{12t}=\varepsilon_{1t}\varepsilon_{2t}-h_{12}$	$\upsilon_{11t}=\varepsilon_{1t}^2-h_{11}$	$\upsilon_{22t}=\varepsilon_{2t}^2-h_{22}$	$\upsilon_{beta\ t}=\varepsilon_{1t}\varepsilon_{2t}/\varepsilon_{1t}^2-h_{12}/h_{11}$
$I(\varepsilon_{1t-1}<0;\varepsilon_{2t-1}<0)$	41.1666***	0.1726	0.8747	305.9997***
$I(\varepsilon_{1t-1}<0;\varepsilon_{2t-1}>0)$	50.0959***	0.0095	0.2497	311.9997***
$I(\varepsilon_{1t-1}>0;\varepsilon_{2t-1}<0)$	30.6636***	0.0633	0.5989	249.9997***
$I(\varepsilon_{1t-1}>0;\varepsilon_{2t-1}>0)$	13.3555***	0.3289	0.5083	55.9999***
$I(\varepsilon_{1t-1}<0)$	28.5992***	1.0480	1.0416	61.9999***
$I(\varepsilon_{2t-1}<0)$	72.3229***	0.0069	1.7949	278.9998***
$\varepsilon_{1t-1}^2 I(\varepsilon_{1t-1}<0)$	0.4273	2.1365	2.6833	67.4989***
$\varepsilon_{1t-1}^2 I(\varepsilon_{2t-1}<0)$	0.2633	2.3276	2.8508	66.5590***
$\varepsilon_{2t-1}^2 I(\varepsilon_{1t-1}<0)$	0.3166	2.5870	2.0743	55.6470***
$\varepsilon_{2t-1}^2 I(\varepsilon_{2t-1}<0)$	0.3065	2.5053	2.0079	55.0708***

Panel (B). VECM- Asymmetric BEKK model.

Generalised residual tests

	$\upsilon_{12t}=\varepsilon_{1t}\varepsilon_{2t}-h_{12t}$	$\upsilon_{11t}=\varepsilon_{1t}^2-h_{11t}$	$\upsilon_{22t}=\varepsilon_{2t}^2-h_{22t}$	$\upsilon_{beta\ t}=\varepsilon_{1t}\varepsilon_{2t}/\varepsilon_{1t}^2-h_{12t}/h_{11t}$
$I(\varepsilon_{1t-1}<0;\varepsilon_{2t-1}<0)$	0.00914	0.39252	0.2297	0.0368
$I(\varepsilon_{1t-1}<0;\varepsilon_{2t-1}>0)$	1.50912	0.04206	1.92339	0.1173
$I(\varepsilon_{1t-1}>0;\varepsilon_{2t-1}<0)$	0.00769	0.10958	0.45041	0.1131
$I(\varepsilon_{1t-1}>0;\varepsilon_{2t-1}>0)$	0.15527	0.3273	0.17754	0.0885
$I(\varepsilon_{1t-1}<0)$	7.16526***	1.05423	3.25917*	0.0004
$I(\varepsilon_{2t-1}<0)$	1.38256	0.00536	1.48498	0.0459
$\varepsilon_{1t-1}^2 I(\varepsilon_{1t-1}<0)$	0.33422	0.62012	0.25339	1.0712
$\varepsilon_{1t-1}^2 I(\varepsilon_{2t-1}<0)$	0.09787	0.33743	0.06865	0.6277
$\varepsilon_{2t-1}^2 I(\varepsilon_{1t-1}<0)$	1.00249	0.34513	3.39857*	0.6866
$\varepsilon_{2t-1}^2 I(\varepsilon_{2t-1}<0)$	0.29722	0.62012	0.25339	0.2370

Panel (A) gives the robust conditional moment test statistic applied on unconditional moment estimates where h_{11}, h_{22}, h_{12} and beta coefficient are unconditional estimates of IBEX-35 variance, IBEX-Complementario variance, its covariance and beta, respectively. Panel (B) gives the robust conditional moment test on the conditional moment estimates, where h_{11t}, h_{22t}, h_{12t} and beta coefficient are the conditional estimates of IBEX-35 variance, IBEX-Complementario variance, its covariance and beta, respectively, obtained from the asymmetric GARCH model. The misspecification indicators are listed in the first column and the remaining columns in each panel give the test statistic computed for the generalised residual calculated as the first row in each panel shows. ε_{1t-1} is the return shock to the IBEX-35 and ε_{2t-1} is the return shock to the IBEX-Complementario. The indicator function $I()$ takes the value one if the expression inside the parentheses is satisfied and zero otherwise. All the statistics are distributed as a $\chi^2(1)$. Test values highlighted with one (*), two (**) and three (***) asterisks are significant at 90%, 95% and 99% of confidence level, respectively.

Table VIII
Cross-correlation in the levels and squares of standardised residuals

	Panel (A) Standardised residuals from theVECM		Panel (B) Standardised residuals from the VECM-GARCH	
Lag k	$\rho(\hat{\varepsilon}_{1,t}, \hat{\varepsilon}_{2,t-k})$	$\rho(\hat{\varepsilon}^2_{1,t}, \hat{\varepsilon}^2_{2,t-k})$	$\rho(U_{1,t}, U_{2,t-k})$	$\rho(U^2_{1,t}, U^2_{2,t-k})$
-5	-0.0169	0.0855*	-0.0337	0.0267
-4	-0.0221	0.0731*	0.0062	-0.0181
-3	0.0037	0.1038**	-0.0017	0.0153
-2	-0.0002	0.0199	0.0041	-0.0231
-1	0.0065	0.0921**	0.0329	-0.0135
0	0.7985**	0.5786**	0.8107**	0.6333**
1	-0.0040	0.1173**	0.0077	0.0114
2	-0.0050	0.0265	-0.0034	-0.0366
3	0.0058	0.0713*	0.0133	0.0302
4	0.0078	0.0452	0.0432	0.0146
5	-0.0334	0.0142	-0.0424	-0.0345

Notes: The k-order cross-correlation coefficient between two standardised data series x and y is estimated as $\rho(x_t, y_{t-k}) = \sum x_t y_{t-k} \Big/ \sqrt{\sum x_t^2 \sum y_t^2}$ where k represents the number of lags (leads when negatives) of y with respect x. The standardised residuals in panel (A) are computed as $\hat{\varepsilon}_{1,t} = \varepsilon_{1,t} / \sigma(\varepsilon_{1,t})$ and $\hat{\varepsilon}_{2,t} = \varepsilon_{2,t} / \sigma(\varepsilon_{2,t})$ where σ (.) means the sample standard deviation. The standardised residuals in panel (B) are computed as $U_{1,t} = \varepsilon_{1,t} / \sqrt{h_{11,t}}$ and $U_{2,t} = \varepsilon_{2,t} / \sqrt{h_{22,t}}$ where $h_{ii,t}$ represents the conditional variance series estimated in Table V. For a sample size of T observations, the asymptotic distribution of the $\sqrt{T}$ times the cross-correlation coefficient is a zero-one normal distribution, that is $\sqrt{T}\rho(x_t, y_{t-k}) \to AN(0,1)$ (see Cheung and Ng (1996) for more details). Significant coefficients are highlighted with one (*) and two (**) asterisks are significant at 90% and 95% of confidence level, respectively.

Table IX trading rules according to the 'feedback' hypothesis on volatility

Panel (A): Trading after bad news

Panel (A.1): 'Direct' strategies on the IBEX-35

Strategy	Signal in 't–1'	Position to take in 't–1'
1A	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} < 0] > 0$	Short IBEX-35
1B	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} < 0] < 0$	Long IBEX-35

Panel (A.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35

2A	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} < 0] > 0$	Short IBEX-Compl.
2B	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} < 0] < 0$	Long IBEX-Compl.

Panel (A.3): 'Direct' strategies on the IBEX-Compl.

3A	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} < 0] > 0$	Short IBEX-Compl.
3B	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} < 0] < 0$	Long IBEX-Compl.

Panel (A.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.

4A	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} < 0] > 0$	Short IBEX-35
4B	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} < 0] < 0$	Long IBEX-35

Panel (B): Trading after good news

Panel (B.1): 'Direct' strategies on the IBEX-35

5A	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} > 0] > 0$	Short IBEX-35
5B	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} > 0] < 0$	Long IBEX-35

Panel (B.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35

6A	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} > 0] > 0$	Short IBEX-Compl.
6B	$E_{t-1}[\Delta h_{11t} \| \varepsilon_{1,t-1} > 0] < 0$	Long IBEX-Compl.

Panel (B.3): 'Direct' strategies on the IBEX-Compl.

7A	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} > 0] > 0$	Short IBEX-Compl.
7B	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} > 0] < 0$	Long IBEX-Compl.

Panel (B.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.

8A	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} > 0] > 0$	Short IBEX-35
8B	$E_{t-1}[\Delta h_{22t} \| \varepsilon_{2,t-1} > 0] < 0$	Long IBEX-35

Where h_{11t} and h_{22t} are the conditional estimates of IBEX-35 variance and IBEX-Complementario variance, respectively, obtained from the asymmetric GARCH model. ε_{1t-1} is the return shock to the IBEX-35 and ε_{2t-1} is the return shock to the IBEX-Complementario. And $E_{t-1}[\cdot]$ is the expectation operator conditioned to information available in 't–1'.

Table X
Ex-post profitability of trading rules according to the 'feed-back hypothesis' on volatility
Period: January 2nd, 2001 to June 30th, 2002

Panel (A): Trading after bad news

Panel (A.1): 'Direct' strategies on the IBEX-35

Strategy	Weeks (+)	Weeks (-)	Transactions	Return (%)	TC: 0.1%	TC: 0.5%	TC: 1%	TC: 2%
1*A*	9	8	12	15.06	13.86*	9.06	3.06	-8.94
1*B*	12	10	14	3.99	2.59*	-3.01	-10.01	-24.01
Panel (A.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35								
2*A*	8	9	12	23.48	22.28	17.48	11.48**	-0.52
2*B*	13	9	14	4.49	3.09	-2.51	-9.51	-23.51
Panel (A.3): 'Direct' strategies on the IBEX-Compl.								
3*A*	7	5	9	26.46	25.56	21.96	17.46**	8.46
3*B*	9	8	10	6.14	5.14	1.14	-3.86	-13.86
Panel (A.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.								
4*A*	9	3	9	33.45	32.55*	28.95	24.45	15.45
4*B*	8	9	10	-2.68	-3.68	-7.68	-12.68	-22.68

Panel (B): Trading after good news

Panel (B.1): 'Direct' strategies on the IBEX-35

Strategy	Weeks (+)	Weeks (-)	Transactions	Return (%)	TC: 0.1%	TC: 0.5%	TC: 1%	TC: 2%
5*A*	5	3	7	2.81	2.11*	-0.69	-4.19	-11.19
5*B*	12	19	19	-16.75	-18.65	-26.25	-35.75	-54.75
Panel (B.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35								
6*A*	3	5	7	-4.60	-5.30	-8.10	-11.60	-18.60
6*B*	20	11	19	14.93	-13.03	-5.43	-4.07	-23.07
Panel (B.3): 'Direct' strategies on the IBEX-Compl.								
7*A*	6	6	10	-0.11	-1.11	-5.11	-10.11	-20.11
7*B*	27	10	20	20.75	18.75	10.75	0.75**	-19.25
Panel (B.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.								
8*A*	8	4	10	12.52	11.52*	7.52	2.52	-7.48
8*B*	20	17	20	18.03	16.03*	8.03	-1.97	-21.97

Panel (C): Buy and hold strategies

IBEX-35	35	43	0	-30.63				
IBEX-Complementario	47	31	0	0.54				
Risk-free	78	0	0	5.95				

Notes: The model for means and volatility is estimated for the whole sample and strategies results computed in the period January 2nd, 2001 to June 30th, 2002. In this period, the estimated conditional volatility is taken as 'forecasted' values and strategies results computed with the observed stock index values. The remaining comments can be seen in Table X notes.

Table XI
Ex-ante profitability of trading rules according to the 'feed-back hypothesis' on volatility
Period: January 2nd, 2001 to June 30th, 2002

Panel (A): Trading after bad news

Strategy	Weeks (+)	Weeks (-)	Transactions	Return (%)	TC: 0.1%	TC: 0.5%	TC: 1%	TC: 2%
Panel (A.1): 'Direct' strategies on the IBEX-35								
1*A*	8	7	11	15.10	14.00*	9.60	4.10	-6.90
1*B*	13	11	16	4.02	2.42*	-3.98	-11.98	-27.98
Panel (A.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35								
2*A*	7	8	11	24.80	23.70	19.30	13.80**	2.80
2*B*	14	10	16	5.81	4.21	-2.19	-10.19	-26.19
Panel (A.3): 'Direct' strategies on the IBEX-Compl.								
3*A*	7	7	9	26.05	25.15	21.55	17.05**	8.05
3*B*	6	8	11	0.08	-1.02	-5.42	-10.92	-21.92
Panel (A.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.								
4*A*	9	5	9	24.75	23.85*	20.25	15.75	6.75
4*B*	6	8	11	-10.69	-11.79	-16.19	-21.69	-32.69

Panel (B): Trading after good news

Strategy	Weeks (+)	Weeks (-)	Transactions	Return (%)	TC: 0.1%	TC: 0.5%	TC: 1%	TC: 2%
Panel (B.1): 'Direct' strategies on the IBEX-35								
5*A*	6	3	8	3.53	2.73*	-0.47	-4.47	-12.47
5*B*	12	18	19	-16.02	-17.92	-25.52	-35.02	-54.02
Panel (B.2): 'Crossed' Strategies on the IBEX-Compl. taking signals from the IBEX-35								
6*A*	3	6	8	-6.05	-6.85	-10.05	-14.05	-22.05
6*B*	19	11	19	13.03	11.13	3.53	-5.97	-24.97
Panel (B.3): 'Direct' strategies on the IBEX-Compl.								
7*A*	5	9	12	-0.53	-1.73	-6.53	-12.53	-24.53
7*B*	25	11	19	25.98	24.08	15.48	6.98**	-12.02
Panel (B.4): 'Crossed' Strategies on the IBEX-35 taking signals from the IBEX-Compl.								
8*A*	7	7	12	0.64	-0.46	-5.46	-11.46	-23.46
8*B*	17	19	19	5.46	3.56*	-4.04	-13.54	-42.54

Panel (C): Buy and hold strategies

IBEX-35	35	43	0	-30.63
IBEX-Complementario	47	31	0	0.54
Risk-free	78	0	0	5.95

Notes: The model for means and volatility is estimated each week in the period January 2nd, 2001 to June 30th, 2002. In this period, the conditional covariance matrix is forecasted and trading strategies designed following Table IX, then each strategy result is computed with the observed stock index value. The 'Weeks(+)' ('Weeks(-)') column displays the number of weeks that each strategy has a positive (negative) return. The 'Transactions' column displays the number of trades by each strategy, taking into account only the weeks the portfolio position changes. Positive returns after taking realistic transactions costs away are highlighted with one asterisk (*) in the case of strategies on the IBEX-35 and with two asterisks (**) on the IBEX-Complementario strategies. Realistic transaction costs are about 0.1% per transaction on the IBEX-35 but trading with its futures contract and about 1% per transaction in the case of the IBEX-Complementario for institutional investors.

7. Figures

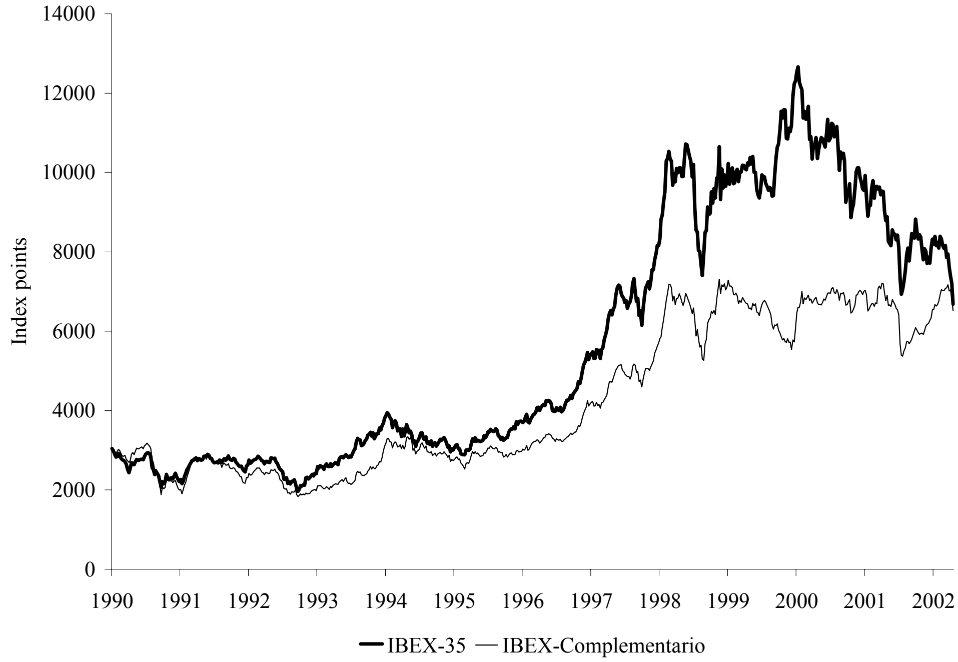

Figure 1. Evolution of the stock indices IBEX-35 and IBEX-Complementario

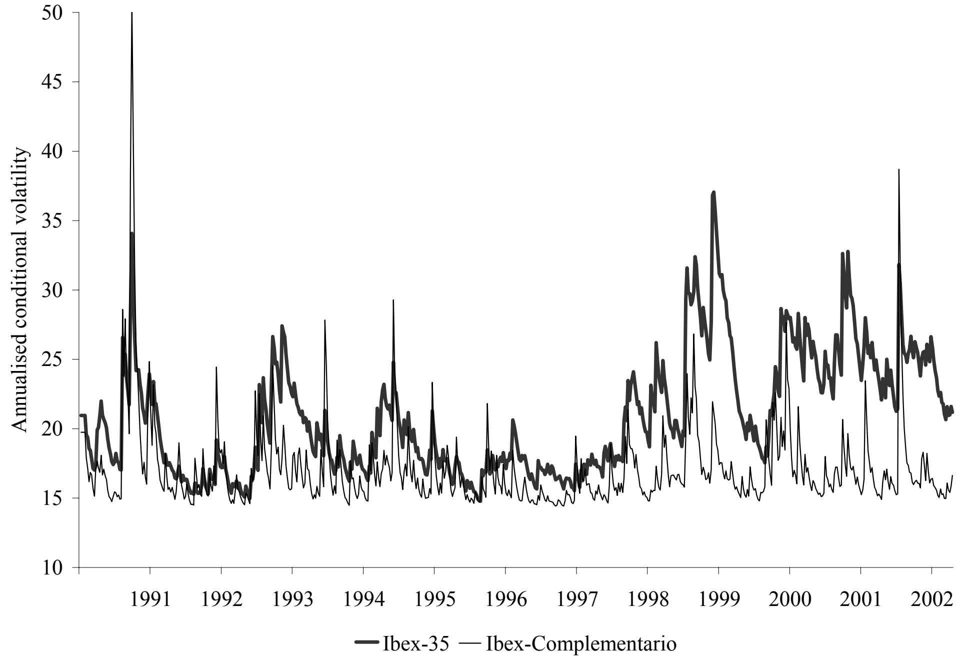

Figure 2. Annualised conditional volatility of the stock indices IBEX-35 and IBEX-Complementario

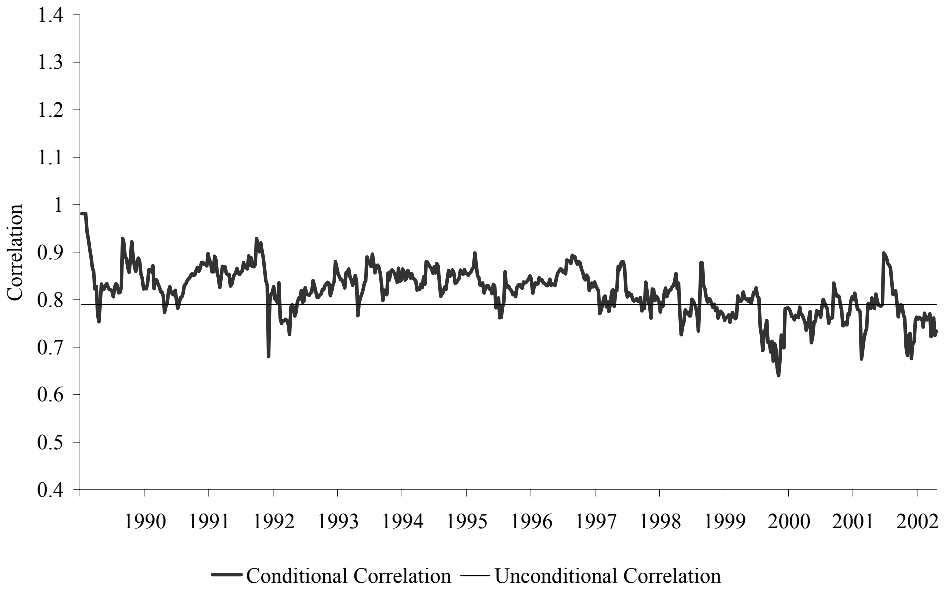

Figure 3-a. Unconditional and conditional correlation between the stock indices IBEX-35 and IBEX-Complementario

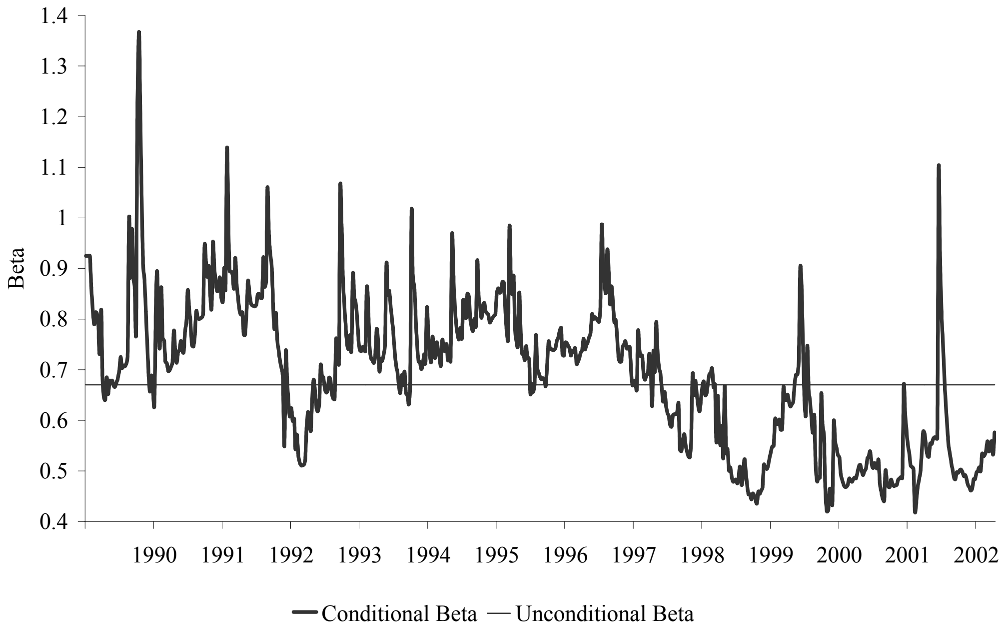

Figure 3-b. Unconditional and conditional Beta coefficients of IBEX-Complementario stock index with respect the stock index IBEX-35

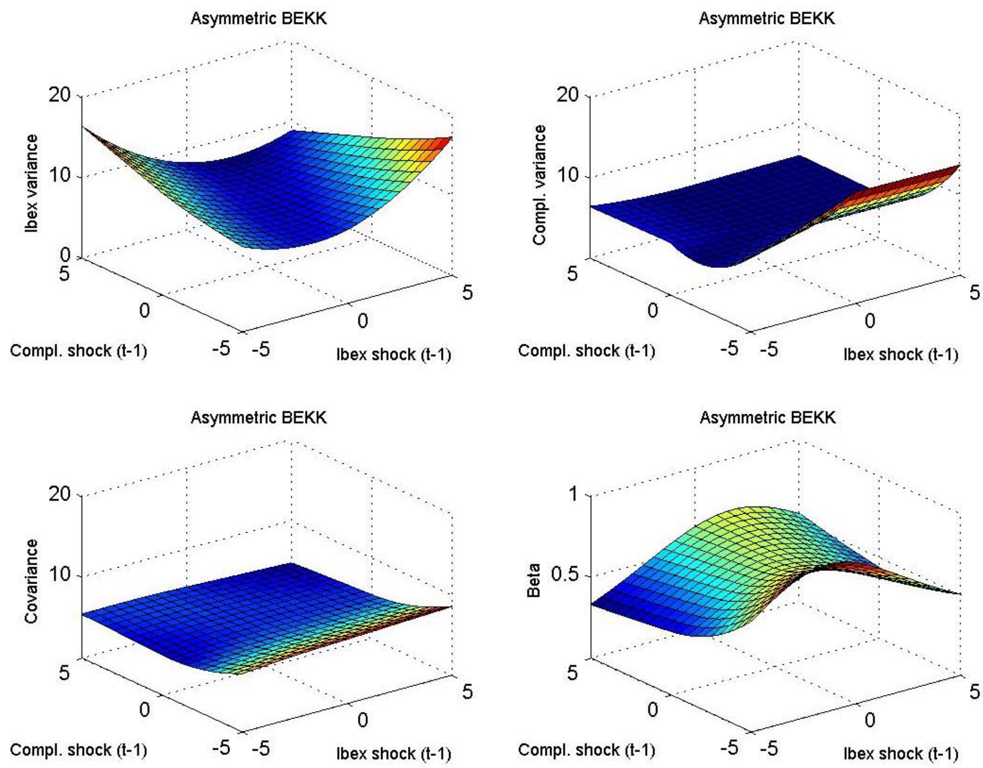

Figure 4. News impact surfaces for the asymmetric BEKK model.

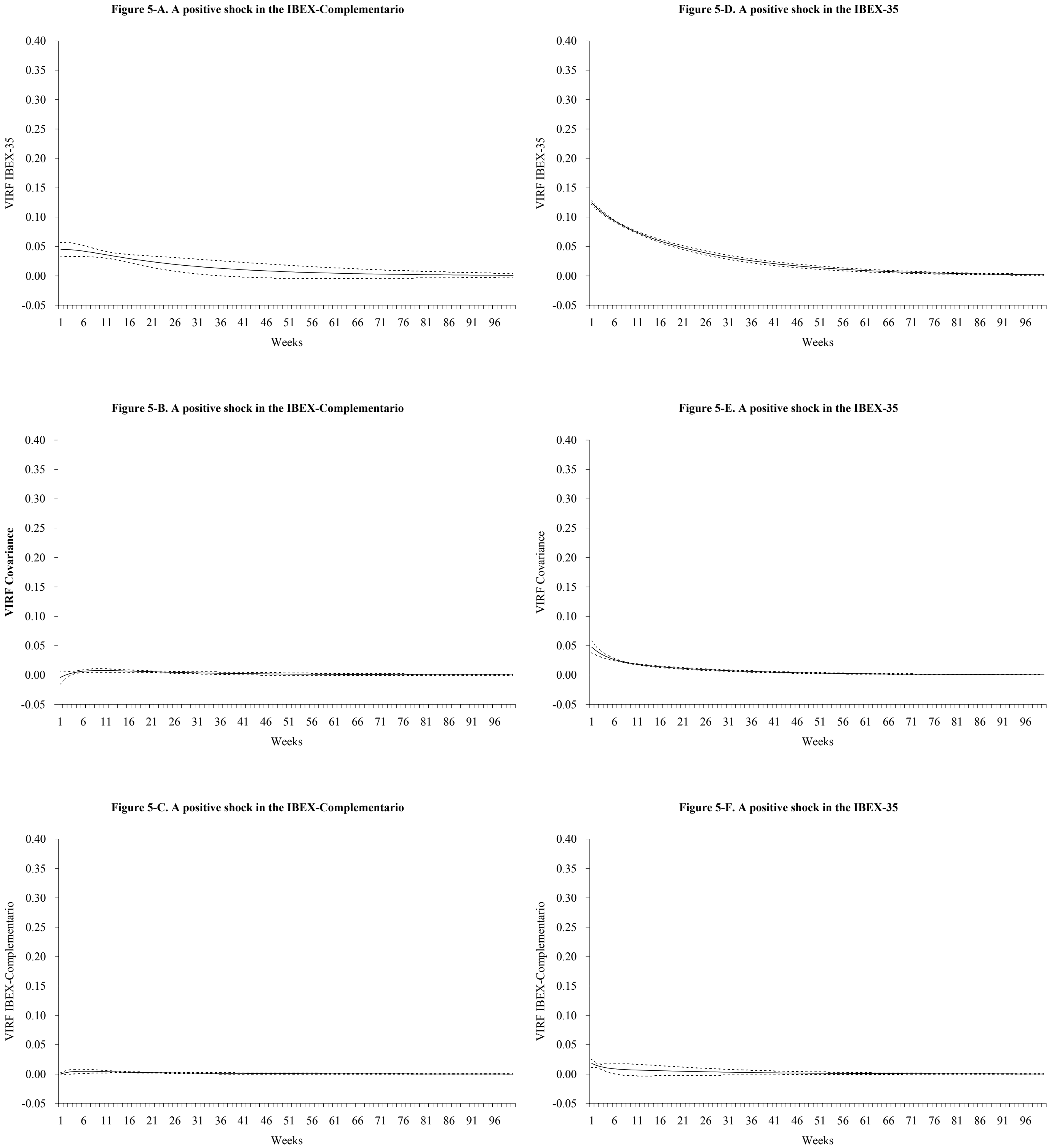

Figure 5. Asymmetric volatility impulse-response function to positive unexpected shocks from the VECM - Asymmetric BEKK

(Dashed lines displays the 90% confidence interval)

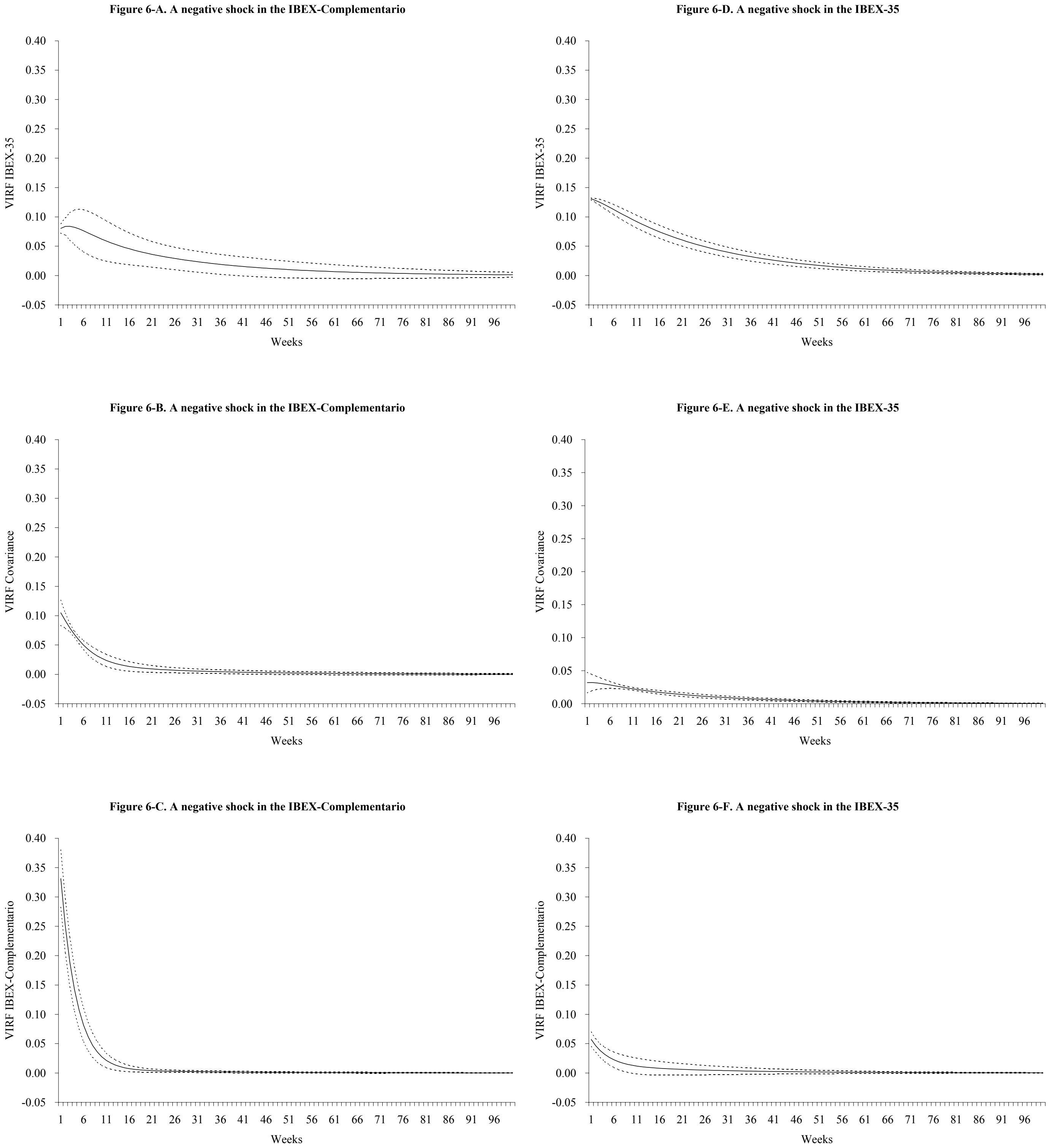

Figure 6. Asymmetric volatility impulse-response function to negative unexpected shocks from the VECM - Asymmetric BEKK

(Dashed lines displays the 90% confidence interval)

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