INTRADAY RETURN AND VOLATILITY RELATIONSHIPS BETWEEN THE IBEX 35 STOCK INDEX AND STOCK INDEX FUTURES MARKETS

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Abstract

This paper analyses the intraday lead and lag relationships between return and volatilities in the Ibex 35 spot and futures markets. With hourly data we jointly perform the analysis estimating a bivariate error correction model with GARCH perturbations, which captures stochastically the presence of an intraday U shaped curve for both spot and futures volatility. Consistent with previous studies for U.S., our findings show an unidirectional causal relationship from the futures to spot market, both in returns and volatilities. This empirical pattern suggests that futures markets leads spot market to incorporate the arrival of new information.

Key words: Futures; Stock Index; GARCH; Causality

JEL classification: C51, G13, G14

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1 Introduction

Since January 14, 1992, it is possible to trade futures contracts on the Spanish stock index Ibex 35. The Spanish stock index futures market has become one of the fastest growing emerging futures markets in the world, being the futures contract on the Ibex 35 the derivative instrument with the highest trading activity in *Meff Renta Variable.* Hence, this is an interesting market to investigate in an area of intense empirical analysis: the interaction and information transmission between returns in spot and futures markets, as well as the linkages between their volatilities.

According to the cost of carry valuation (the most used forward pricing model), which assumes perfect markets and non stochastic interest rates and dividend yileds, the theoretical price at time t of an index futures contract which matures at time T, equals the opportunity cost of keeping a basket replicating the spot index from t to T, that is:

$$F_{t,T} = S_t \, e^{(r-d)\,(T-t)}, \tag{1}$$

where $F_{t,T}$ is the futures price; S_t is the index value and $(r-d)$ is the nest cost of carry associated to the underlying stocks in the index, i.e., the riskless rate of return minus the yield of dividends from the stocks in the index. Alternatively, equation (1) can be expressed:

$$r_{s,t} = r_{f,t} + (r-d), \tag{2}$$

where $r_{s,t} = \ln\left(\frac{S_t}{S_{t-1}}\right)$and $r_{f,t} = \ln\left(\frac{F_t}{F_{t-1}}\right)$, are the returns in the spot and futures market, respectively. Under the previous assumptions the relationship in (2) implies that: a) the variance of return in the spot market equals the variance of return in the futures market, b) the contemporaneous rates of return on the underlying stock index and the futures contract are perfectly and positively correlated, and c) the non-contemporaneous rates of return are uncorrelated and no lead-lag relationship should appears. However, in the presence of market imperfections such as transactions costs, asymmetric information, capital requirements and short-selling restrictions there might be a lead-lag relationship between spot and futures returns, as well as between volatilities. Therefore, the analysis of the causal relationship between the spot and futures markets concerning both, returns and volatilities, becomes a very relevant issue. The presence of lead-lag relationships may allow for anticipating price movements and the level of risk in one market from past information in the other one, a relevant question when using the futures contract as a hedge instrument for risk stock portfolios.

Most studies carried out so far implement the analysis separately, estimating volatilities from return innovations. Generally, the studies concerning return interactions find that the futures market leads the spot market [Kawaller et. al (1987), Stoll and Whaley (1990), Wahab and Lasghari (1993) and Pizzi et al. (1998), among many others]. The fact that price discovery occurs more significantly in the futures market compared to the cash market can be attributed to two factors: a) the stocks in the index have no identical trading activity, so that the index responds to new information with a lag, and b) the futures contract allows to trade with the market stock exchange portfolio with significant lower transaction cost and also saving for the necessary time to carry out the operation. Consequently, reactions in futures markets are faster, and movements in futures prices lead spot prices fluctuations. For the Spanish stock index futures market, Blanco (1998), and Lafuente (1998), among others, show that to be the case. Blanco (1998) suggest that the first factor is basically the principal reason behind futures prices leading spot prices[1].

On the other hand, there are numerous studies in the literature concerning with the analysis of the causal relationship between spot and futures volatilities [Kawaller et al. (1990), Chan et al. (1991), Chan and Chung (1993), Abhyankar (1995) and Min and Najand (1999), among others]. Contrary to consistent empirical evidence on the causal relationship between spot and futures market returns, the findings about volatility relationships are not similar in all markets, showing a dependency on the sample period analyzed and the volatility measure considered.

This article examines the intraday interactions between spot and futures returns as well as the dynamic relationship between volatilities in the Spanish stock index futures market. Our investigation differs from previous studies on the Spanish market because we jointly analyze these two questions, rather than separately. Taking hourly data along the period covering 20/12/93 to 20/12/96, a bivariate error correction model with GARCH perturbations is used. Our model significantly differs from the previous GARCH methodolgy

[1]This author constructs a proxy for the *fair* Ibex 35 index taking the middle point of the bid-ask price interval for each individual asset, and shows that the explanatory power of futures returns reduces in relation to that observed with actual Ibex 35.

considered in the literature for jointly analizing the main international stock index futures markets in two ways: a) our model does not impose a constant conditional correlation coefficient in the second moment matrix of market returns, and b) the model captures the presence of an *U-shaped intraday pattern* for volatility both in the spot and futures market. Our modelization, representation and technique estimation allows for capturing stochastically, rather than trough deterministic variables, this intraday seasonal pattern for market volatilities. These two characteristics are extremely relevant when applying a methodology of this type to estimate hedge ratios for stock exchange portfolios.

Our empirical findings reveal a unidirectional causal relationship from the futures market to the spot market, both for returns and volatilities, and suggest that the futures markets behaves as a leader when incorporating the arrival of new information. On the other hand, the explanatory power of the spot market over the futures market, when arising, extends no longer than 60 minutes. The model not only shows a changing volatility, for both spot and futures market, during the trading session, but also provide empirical evidence supporting that the *opening* and *close* daily session are systematically the trading periods with higher volatility.

The rest of the paper is organized as follows. Section 2 describes the data set used in the analysis. Section 3 presents the econometric approach. The empirical results and their implications are discussed in section 4. Finally, section 5 summarizes and shows concluding remarks.

2 The Data

The data used in this study are provided by MEFF RV (*Mercado Español de Futuros, Renta Variable*) for the period December 15, 1993-December 15, 1996. This period is interesting in three ways: a) By December 1993 the initial exponential growth of the Spanish stock index futures market had already ended, becoming a highly liquid market; b) along the period 1994-1997 the number of contracts negotiated stabilized around three millions per year (indeed the multiplier of the futures contract has show no change along this period, staying at 100 *ptas.* per basic point), and c) the sample period cover three different behaviors for the Spanish spot market, that can be summarized as follows: during the year 1994 the market basket value registered an annual lose proxy to the 7%; the year 1995 is characterized by high level price fluctuations, and finally the year 1996 has shown a systematic growth in the Ibex 35, being the annual yield proxy to the 40%. This way, the period analyzed can be considered as a representative sample of the market behavior.

The first set of data contains information concerning with the futures contract on *the* Ibex 35 index, that is: a) trading price, b) transaction hour, c) bid price, d) ask price, and e) accumulated negotiated volume (millions of *ptas.*) until the registered transaction. The second set of data consists of the minute by minute Ibex 35 index level, as well as the traded volume corresponding the 35 shares on the index. Since the nearest to maturity contract is systematically the most actively traded, only data for the nearby futures contracts is used. Therefore, we handle 36 futures contract along the sample.

Since the opening cash index is reflecting closing spot prices from the previous day, we remove the first hour trading interval for spot market[2]. Then, from 11:00 hours to 17:00 hours we select hourly market prices. Therefore, we have seven observations for spot and futures prices for each trading day.

An important source of bias in testing the lead-lag relationships is the use of non-synchronous data. We remove this possibility by matching each futures price with the cash index value observed at the same minute. This way, we have two perfectly matched hourly price series. From hourly prices we generate the percentage return series for each market by taking the first difference of the natural logarithm of prices and after multiplying by 100, resulting seven hourly returns including the overnight and weekend returns. Finally we exclude overnight and weekend returns because they are measured over a longer time period. Consequently, the data set used in the analysis has six hourly returns per day. The number of trading days is equal to 743[3]. Overall, we have 4,458 return observations for each market.

2.1 Descriptive statistics and autocorrelations functions

Tables 1 to 3 present descriptive statistics for intraday hourly returns, as well as for the squared returns, in both markets. Table 1 shows the mean,

[2]The futures markety opnes at $10{:}45^{AM}$. For the period December 1993 to November 1994, Fernández and Yzaguirre (1996) show that the 35 assets integrating the Ibex 35 are first negotiated, in avergage, after the $11{:}00^{AM}$.

[3]We can not include data from: a) 02/14/95, b) 12/27/96, c) 05/27/96 and 07/29/96 because they were not avalaible from *Meff Renta Variable.*

standard deviation, skewness, kurtosis and autocorrelation functions for spot and futures market returns. As expected, the mean is similar in both markets, and the null hypothesis of a zero mean is not rejected in either case. There is a slight negative skewness in both markets, being more significant in the cash market, and empirical distributions of both intraday market returns show heavy tails, compared with the Normal distribution. The central cluster is sharper in the spot market. Both return series exhibit positive first order autocorrelation, that is, for each market the observed return in the previous hour anticipates a return of identical sign. However, only the first order autocorrelation coefficient for spot market is significant at the 5% level. This is consistent with the argument that infrequent trading of stocks in the index portfolio causes a larger inertia in the stock index (see, for example, Miller et al. (1994)).

Autocorrelation coefficients for the squared intraday returns are displayed in Table 2. Estimated coefficients for this function slowly decrease to zero revealing the existence of non-linear dependence in the return series, both in the spot and futures markets. Therefore, to analyze the intraday causal relationship between spot and futures markets the methodology representing the dynamics of market returns must take into account higher order dependence, possibly as a result of changing volatility over time. Interestingly enough, we observe that estimated coefficients for lags multiple of six are systematically positive and significant, being much higher than the rest. This structure suggests an intraday seasonal pattern in volatility in both markets, that is, the risk in the *opening* and *close* trading intervals is higher than in other trading periods.

To reinforce the previous argument we also calculated intraday volatility in the spot and futures markets using Garman and Klass (1980) measure. We computed hourly volatilities from the stock index and the traded futures price matched every five minutes. Table 3 presents the mean volatility values along the 743 trading days for each trading hour interval. The results suggests not only that volatility is changing over time, but also the presence of an intraday U-shaped curves in volatility. The *opening* and *close* daily session seem to be the highest volatility trading periods. This initial empirical evidence is consistent with Daigler (1997) and Chan et al. (1991) for both the S$P 500 and the MMI stock index futures markets.

We implement such dependences betwen second order moments using a GARCH methodology (Bollerslev (1986)). As we will see in Section 3, our model representation and technique estimation captures stocastically the presence of intraday seasonality patterns in volatilities.

2.2 Cross correlations functions

Table 4 shows the cross correlation functions between the intraday cash and futures returns. Even though we find a high value for the unconditional contemporaneous correlation of about 0.67, it is not close to one, the expected value according from the cost of carry model. The first lagged futures return seems to contain some forecasting power to explain the current stock index return. The first leading cross correlation coefficient (predictability from spot to futures market) is also positive, showing that, in the short-run, price movements occur in the same direction in both markets. However this estimated coefficient is also significative, the empirical test statistic is close to the critical region at the 5% significance level.

Table 4 also presents the cross correlations for the squared hourly returns. This statistic represents a rough measure of intermarket association in volatility[4], since the average squared return is a good proxy for the unconditional variance of returns. The estimated coefficients do not decrease to zero quickly, suggesting highly persistent cross-market volatility interactions.

These preliminary results indicate that a lead-lag relationship exists not only between market returns, also between their volatilities. We incorporate these findings in the modeling strategy that follows in Section 3.

2.3 Long-run equilibrium relationship between market prices.

Before to analyze whether there is a cointegration relationship between two variables it is necessary to investigate the order of integration of each variable. The augmented Dickey-Fuller tests (not reported in the paper) confirm that the natural logarithm of the spot and futures market prices are integrated of order one. Therefore, it is possible that a linear combination of the natural logarithm of market prices be stationary. In this case, both variables are said to be cointegrated of order zero. Following Engle and Granger (1987) a two-step estimation procedure to test cointegration between the natural logarithm of spot and futures prices is used. First, we estimate by ordinary least squares

[4]We must take into account that if X is a random variable with $E_t(X) = 0$, then $Var_t(X) = E_t(X^2)$.

the cointegration equation imposing unidirectional causal relationship from the futures to the spot market, that is:

$$s_t = \gamma_1 + \gamma_2 f_t + u_t, \tag{3}$$

where s_t and f_t being the natural logarithm of spot index and trading futures price respectively, and u_t the random disturbance. We use three of the seven tests proposed by these authors. The first one uses the augmented Dickey-Fuller to examine whether estimated residuals for the cointegration equation are stationary. The second and third tests are based on the augmented restricted and unrestricted vector autoregression representation. Results are reported in table 5. They provide empirical evidence supporting the presence of a long-run equilibrium relationship between the natural logarithm of spot and futures market prices. Consequently, we include an error correction term to specify the joint dynamics of spot and futures returns.

3 The Bivariate Error Correction GARCH Model

To investigate the intraday relationships between spot and futures markets, the previous analysis of autocorrelations and cross-correlations functions, as well as the estimated hourly intraday Garman-Klass volatilities, suggest that to represent the dynamics of intraday returns in both the spot and futures market a model should be used capturing a) the intermarket dependence between returns, b) the cross-interactions between volatilities, and c) the presence of an intraday seasonal pattern in spot and futures volatility.

3.1 Description of the model

In this paper we use a statistical model based on the generalized autoregressive conditional heteroskedasticity family of models. Let $r_{s,t}$ and $r_{f,t}$ the market returns, that is, $r_{s,t} = s_t - s_{t-1}$, and $r_{f,t} = f_t - f_{t-1}$. The dynamics governing intraday market returns is described by the following equations:

$$\begin{pmatrix} r_{s,t} \\ r_{f,t} \end{pmatrix} = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix} \begin{pmatrix} r_{s,t-1} \\ r_{f,t-1} \end{pmatrix} + \begin{pmatrix} \beta_s \\ \beta_f \end{pmatrix} (s_{t-1} - (\gamma_1 + \gamma_2 f_{t-1})) + \begin{pmatrix} \varepsilon_{s,t} \\ \varepsilon_{f,t} \end{pmatrix}, \tag{4}$$

with ε_t, the disturbance vector of innovations having a conditional distribution: $\varepsilon_t = \begin{pmatrix} \varepsilon_{s,t} & \varepsilon_{f,t} \end{pmatrix}' \mid \Omega_{t-1} \tilde{} N(0, \Sigma_t)$, where Ω_{t-1} is the information set available at time $t-1$ and Σ_t is the conditional covariance matrix of returns. We include $(s_{t-1} - (\gamma_1 + \gamma_2 f_{t-1}))$, an error correction term incorporating the short-run adjusting device when deviations from the long- run equilibrium relationship appear.

With standard notation, the dynamics of the variance-covariance matrix corresponding a GARCH(p,q) model can be represented as follows:

$$vech\Sigma_t = vech\bar{\Sigma} + \Theta_q(B)\, vech\left(\varepsilon_t \varepsilon_t'\right) + \Psi_p(B)\, vech\Sigma_t, \tag{5}$$

with $\Psi(0) = \Theta(0) = 0$, B is the backshift operator, ε_t is the innovations vector, $vech\Sigma_t = \begin{pmatrix} \sigma^2_{s,t} & \sigma_{sf,t} & \sigma^2_{f,t} \end{pmatrix}'$, $vech\bar{\Sigma} = \begin{pmatrix} \sigma^2_s & \sigma_{sf} & \sigma^2_f \end{pmatrix}'$ and $vech\left(\varepsilon_t \varepsilon_t'\right) = \begin{pmatrix} \varepsilon_{s,t} & \varepsilon_{s,t}\varepsilon_{f,t} & \varepsilon_{f,t} \end{pmatrix}'$. However, we use an alternative VARMA (vectorial autoregressive moving average) representation for the previous equation. Consider the next trivariate stochastic vector:

$$\xi_t = vech\left(\varepsilon_t \varepsilon_t'\right) - vech\Sigma_t \tag{6}$$

Substituting equation (6) in equation (5) and rearranging:

$$\Gamma_r(B)\, vech\left(\varepsilon_t \varepsilon_t'\right) = vech\bar{\Sigma} + \Phi_p(B)\, \xi_t, \tag{7}$$

where $\Gamma_r(B) = [I - (\Psi_p(B) + \Theta_q(B))]$, with $r = \max\{p, q\}$, and $\Phi_p(B) = [I - \Psi_p(B)]$, that is, an ARMA$(r,p)$representation. According to equation (7), we posit a pure moving average process governing second order moments of intraday returns:

$$vech\left(\varepsilon_t \varepsilon_t'\right) = vech\bar{\Sigma} + \left(\phi_1 B + \phi_2 B^6 + \phi_3 B^{12} + \phi_4 B^{18}\right) \xi_t, \tag{8}$$

If the moving average polinomial has no roots inside the unit circle, this representation captures a time dependence among squared innovations spanning a long period of time[5]. The following restrictions are introduced: a) matrices ϕ_2, ϕ_3, and ϕ_4 are diagonal, and b) denoting the (i, j) element in the matrix $\phi_1$by $\phi^1_{ij,}$ we impose: $\phi^1_{12} = \phi^1_{21} = \phi^1_{22} = \phi^1_{23} = \phi^1_{32} = 0$. These restrictions are not relevant concerning the objectives of the paper, and they only pursuit to avoid numerical problems when estimating the model. An over parametrized model would produce numerical problems due to a lack of identification of all parameters in the model. We still permit cross-market interactions between volatilities trough the elements $\phi^1_{31}$and ϕ^1_{13} in matrix ϕ_1. The intraday seasonal pattern in volatilities is captured by the diagonal elements in the matrices ϕ_j $(j = 1, 2, 3)$ since it relates the conditional volatility at a given hour to that of previous days. The same appears to the conditional variance. This is a more general model than those in Park and Switzer (1995), Iihara et al. (1996), Koutmos and Tucker (1996), Racine and Ackert (1998), among others, for previous analysis of the main international stock index futures markets, since it not only allows for conditional covariances to change over time, but also it does not impose that the ratio between conditional covariances and conditional standard deviations be constant over time.

3.2 Model Estimation

Under the previous assumption of conditional Gaussian bivariate distribution for the vector of innovations, the log-likelihood for the bivariate GARCH model can be written as follows:

$$L(\theta) = -T \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \left[\log |\Sigma_t| + \varepsilon_t \Sigma_t^{-1} \varepsilon_t^{'} \right] \qquad (9)$$

where θ is the parameter vector to be estimated, and $\varepsilon_t = (\varepsilon_{s,t}\, \varepsilon_{f,t})^{'}$. The log likelihood function is highly nonlinear in θ and a numerical maximization technique is required. We estimate by exact maximum likelihood with the

[5] As we will see in the next section the estimated vector moving average model can be represented as an infinite vector autoregressive process.

$E4$ toolbox (to be used with Matlab)[6], which represents the model in the state space form. The optimization algorithm used is the so called BFGS (Broyden, Fletcher, Goldfarb and Shanno). For model estimation we adopt the following strategy: a) we first estimate by ordinary least squares the cointegration equation, incorporating the residuals as an exogenous vector in the model, and b) we fix the three elements in vector $vech\bar{\Sigma}$ using the estimated unconditional second order moments of market returns in the global sample. Therefore, when the numerical algorithm iterates it is not taking into account these three parameters. Overall, we have nineteen paramaters to estimate in the bivariate model.

4 Empirical results

Tables 6 and 7 show the results of fitting the bivariate GARCH model to the intraday hourly stock index and futures returns. Table 6 presents the estimated coefficients for the mean equation (4). As expected, the estimations concerning the error correction term have opposite sign. Taking into account that the cointegration equation is previously estimated imposing unidirectional causal relationship from the futures to the spot market, we should expect $\hat{\beta}_f > 0$ and $\hat{\beta}_s < 0$. When, for example, $\hat{u}_{t-1} \simeq s_{t-1} - f_{t-1} < 0$[7] either the spot price must be higher in t relative to period $t-1$ or the futures price do decrease from $t-1$ to t, to recover the long-run equilibrium relationship. Consequently, the observed returns from $t-1$ to t must be positive in the spot market and negative in the futures contract. The contrary evolution in market prices should be observed when a positive departure from long-run equilibrium occurs. Estimated values in each equation for the respective parameters associated to the error correction term have the expected sign. The parameter $\hat{\beta}_s$ is significant at the 5% level. Therefore, the omission of the error correction term would lead to model misspecification. However, we do not reject the null hypothesis that $\hat{\beta}_f = 0$ at this significance level. Analysts generally regard the empirical basis (i.e. futures price minus the index value) as an indicator of the subsequent tendency for the spot market. In this sense, a large positive basis would indicate an increasing spot market. Taking into

[6]This toolbox has been developed in the *Departamento de Economía Cuantitativa, Universidad Complutense,* Madrid (Spain).

[7]Consistent with previous analysis, the estimated cointegration vector is aproximately (1, −1).

account that the error correction term is proportional to the empirical basis multiplied by -1, our result confirm this general belief, because when the basis is positive, the most observed event[8], the short-run adjustment estimated by the model forecasts a bullish stock market, rather than a downward futures market. Our empirical evidence supports this general belief, that is, the empirical basis can be used as an indicator of short-run future movements in the spot market.

Relative to return dynamics, the estimated coefficient α_{11} is significantly different from zero at the 5% significance level, reflecting that past hour spot returns contain relevant information to forecast current index returns. A similar characteristic is observed for the futures market, since α_{22} is also significant at the 5% level. Relative to cross-market interactions between market returns, we observe that past hourly futures return are correlated with current spot returns. However, the contrary effect is not empirically detected. Consequently, our findings suggests a unidirectional causal relationship from the futures to the spot market. This empirical evidence on the interactions between the conditional means of spot and futures market returns is consistent with the hypothesis that market-wide new information disseminates faster in the futures market than in the spot market. Our result is consistent with those in Blanco (1998) and Lafuente (1998), and they confirm that spot market return fluctuactions lead changes in futures returns by less than 60 minutes.

The average estimated conditional correlation coefficient is 0.87 (see table 8). This positive value reflects that innovations in both price processes have most often the same sign and, consequently, futures and spot prices fluctuactions have the same direction. However, the estimated correlation is below one, probably reflecting that the assumptions required for perfect correlation (no transactions costs and nonstochastic interest rates and dividend yields) are too restrictive.

Table 7 shows the estimated coefficients for the variance equation in VARMA (vectorial autoregressive moving average) form, that is equation (8). We observe that the conditional variance in each market is affected by events in that market. To forecast volatility in the spot market, the estimated model suggests that the relevant past information is concerning with the volatility in the previous days in a similar hour interval, whereas the

[8]Along the sample period, for 74% of the hourly matched market prices, the empirical basis was positive.

volatility during the previous hour is not significant. Similar characteristic applies to the futures market, but now, we must also take into account volatility during the past hour. On the other hand, there is significant evidence of correlation in the conditional covariance of market returns between the same hourly intervals of successive days.

The coefficients that measure cross-market interactions between volatilities, ϕ_{13}^1 and ϕ_{31}^1 suggest an unidirectional causal relationship from the futures to the spot market. The estimated parameter $\hat{\phi}_{13}^1$ is positive and significant and the 5% level, showing that current spot volatility is positively correlated with volatility during the previous hour in the futures market. Taking into account that estimated conditional covariance is always positive, the empirical findings suggest that the futures market tends to transmit volatility to the spot markets in periods of large price fluctuations.

Table 8 presents the average statistics for the estimated variance-covariance matrices of market returns for each trading interval along the 743 trading sessions. An intraday seasonal pattern is detected for both spot and futures conditional volatility, showing a U shaped curve along the daily trading session, that is, the *opening* and *close* trading periods are those with higher volatility. Even though we detect a similar seasonal pattern for the conditional covariances, our model suggests that a restriction imposing a constant conditional correlation between spot and futures market returns is not realistic. This is a very important issue for hedging purposes. Dynamic hedging strategies should be adopted in preference to conventional techniques, in which the optimal hedge ratio is constant over time. Kroner and Sultan (1993) find that the reduction in risk from dynamic hedging in currency markets is worth even after transaction costs are taken into account.

Model diagnostics based on the standardized residuals (table 9) confirm that the bivariate error correction GARCH model successfully captures the cross-markets interactions between the first and second moments of intraday hourly returns.

5 Summary and conclusions

In this paper we examine the intraday relationships between returns and volatilities in the stock index and the stock index futures market in Spain. The sample covers from 12/20/93 to 12/20/96, a homogeneous period in terms of characteristics of negotiated futures contract, which contains three different tendencies in the Spanish stock market. Taking into account the presence of a long-run equilibrium relationship between market prices, we estimate a bivariate error correction GARCH model on hourly returns without imposing a constant conditional correlation coefficient between spot and futures market returns.

Our results show an unidirectional causal relationship from futures returns to spot returns, corroborating a similar result obtained in simpler specifications. The current return in the spot market is positively correlated with that from the previous hourly interval, showing the inertia in this process. On the other hand, an increase in trading price for futures contract tend to anticipate a similar evolution for the stock index. Even though we estimate a high contemporaneous conditional correlation between spot and futures market returns, our findings suggest that the trading futures price significantly departs from the standard cost-of-carry model valuation.

Similarly to interactions between returns, no bidirectional information flow between volatilities is detected. Our empirical findings suggest an unidirectional causal relationship from futures to spot market volatility. Current spot volatility is positively correlated with volatility in the previous hour in the futures market, suggesting that the futures markets does not contribute to stabilize the spot market in high fluctuaction trading periods. These two findings are consistent with the stock index futures market being the primary device for price discovery, in the sense that the new information disseminates first in the derivative market, and subsequently, in the spot market.

Finally, our findings show the presence of a seasonal intraday pattern for both, spot and futures volatility, revealing that the *opening* and *close* trading periods are systematically the intervals with higher volatility. Consequently, to forecast spot or futures market volatility, volatility in its own market at a similar hour in previous days must be taken into account. A similar pattern is detected for the conditional covariance. These two characteristics are relevant to apply GARCH models for dynamic hedging strategies, because optimal hedge ratio is changing along the daily trading session with a specific pattern.

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Appendix. Statistical Tables.

Table 1. Summary statistics for hourly returns

	Spot Market	Futures market
Mean$*10^4$	-0.2316	-0.0021
Standard deviation	0.0036	0.0030
Skewness	-0.7131	-0.0582
Excess of kurtosis	10.7904	3.4209
$\rho\left(r_t, r_{t-k}\right)^{(a)}$		
$k=1$	0.0758$^{(*)}$	0.0241
$k=2$	0.0073	0.0029
$k=3$	0.0542$^{(*)}$	0.0139
$k=4$	0.0232	0.0460$^{(*)}$
$k=5$	-0.0099	0.0181
$k=6$	-0.0175	0.0028
$k=7$	-0.0231	-0.0451$^{(*)}$
$k=8$	-0.0216	-0.0121
$k=9$	-0.0051	0.0001
$k=10$	0.0144	0.0408$^{(*)}$
$k=11$	0.0043	0.0110
$k=12$	0.0250	0.0406$^{(*)}$
$k=18$	0.0100	0.0296
$k=24$	0.1390$^{(*)}$	-0.0040
Ljung-Box statistics$^{(b)}$	73.41 (0.00)	54.39 (0.00)

Notes:$^{(a)}$Autocorrelation function. The standard error for the autocorrelation coefficients can be aproximated by $\frac{1}{\sqrt{4,468}} \simeq 0.0149$.$^{(b)}$Ljung-Box test uses 24 autocorrelation coefficients (p-value in parentheses).$^{(*)}$ Significant at the 5% level.

Table 2. Autocorrelation functions for squared hourly returns

	Spot Market	Futures market
$\rho\left(r_t^2, r_{t-k}^2\right)^{(a)}$		
$k = 1$	0.0874$^{(*)}$	0.1435$^{(*)}$
$k = 2$	-0.0028	0.0760$^{(*)}$
$k = 3$	-0.0056	0.0261
$k = 4$	0.0255	0.0732$^{(*)}$
$k = 5$	0.1015	0.1001
k = 6	**0.2506**$^{(*)}$	**0.1982**$^{(*)}$
$k = 7$	0.0299	0.0630$^{(*)}$
$k = 8$	-0.0028	0.0397$^{(*)}$
$k = 9$	-0.0135	0.0389$^{(*)}$
$k = 10$	0.0028	0.0315$^{(*)}$
$k = 11$	0.0241	0.0820$^{(*)}$
k = 12	**0.1341**$^{(*)}$	**0.1464**$^{(*)}$
k = 18	**0.1697**$^{(*)}$	**0.1183**$^{(*)}$
k = 24	**0.1591**$^{(*)}$	**0.1325**$^{(*)}$
Ljung-Box statistics$^{(b)}$	724.08 (0.00)	800.83 (0.00)

Notes:$^{(a)}$Autocorrelation function.The standard error for the autocorrelation coefficients can be aproximated by $\frac{1}{\sqrt{4,468}} \simeq 0.0149$. $^{(b)}$Ljung-Box test uses twenty four autocorrelation coefficients. (p-value in parentheses).$^{(*)}$ Significant at the 5% level.

Table 3. Intraday Garman-Klass mean volatility

Trading hour intervals	Spot market	Futures market
11:00 - 12:00	0.1506	0.1365
12:00 - 13:00	0.0217	0.0267
13:00 - 14:00	0.0236	0.0429
14:00 - 15:00	0.0289	0.0467
15:00 - 16:00	0.0437	0.0649
16:00 - 17:00	0.0686	0.0952

Note: The Garman-Klass measure over a trading interval is defined as: $\frac{1}{2}\left[\ln(H) - \ln(L)\right]^2 - \left[2\ln(2) - 1\right]\left[\ln(O) - \ln(C)\right]^2$, where H, L, O and C denote the high, low, open and close price during the trading interval, respectively.

Table 4. Cross correlations functions

	Returns	Squares of returns
	$\rho\left(r_{s,t}, r_{f,t-k}\right)^{(a)}$	$\rho\left(r_{s,t}^2, r_{f,t-k}^2\right)$
$k=-24$	0.0062	0.0617$^{(*)}$
$k=-18$	0.0321$^{(*)}$	0.0618$^{(*)}$
$k=-12$	0.0415$^{(*)}$	0.0881$^{(*)}$
$k=-11$	0.0003	0.1191$^{(*)}$
$k=-10$	0.0353$^{(*)}$	0.0740$^{(*)}$
$k=-9$	-0.0051	0.0105
$k=-8$	-0.0066	0.0307$^{(*)}$
$k=-7$	-0.0281$^{(*)}$	0.0215
$k=-6$	-0.0081	0.1194$^{(*)}$
$k=-5$	-0.0179	0.2490$^{(*)}$
$k=-4$	0.0144	0.0527$^{(*)}$
$k=-3$	0.0281	0.0201
$k=-2$	0.0123	0.0195
$k=-1$	0.0309$^{(*)}$	0.1037$^{(*)}$
$k=0$	0.6708$^{(*)}$	0.3457$^{(*)}$
$k=1$	0.1275	0.1724$^{(*)}$
$k=2$	0.0198	0.0333$^{(*)}$
$k=3$	0.0358$^{(*)}$	0.0295$^{(*)}$
$k=4$	0.0255	0.0388$^{(*)}$
$k=5$	0.0314$^{(*)}$	0.0421$^{(*)}$
$k=6$	0.0102	0.0958$^{(*)}$
$k=7$	-0.0301$^{(*)}$	0.1187$^{(*)}$
$k=8$	-0.0392$^{(*)}$	0.0307$^{(*)}$
$k=9$	0.0007	0.0245
$k=10$	0.0117	0.0012
$k=11$	0.0149	0.0048
$k=12$	0.0268	0.0569$^{(*)}$
$k=18$	0.0232	0.0754$^{(*)}$
$k=24$	0.0094	0.0632$^{(*)}$

Notes:$^{(a)}r_{s,t}$ and $r_{f,t-k}$ denote spot and futures returns in period t and $t-k$, respectively. Standard errors for the cross-correlation coefficients can be aproximated by $\frac{1}{\sqrt{4.468}} \simeq 0.0149.$$^{(*)}$ Significant at the 5% level.

Table 5. Cointegration tests.

ADF[(1)]	ARVAR[(2)]	AUVAR[(3)]
-11.34 (-4.22)[(*)]	24.96 (15.80)	50.68 (22.60)

Note:[(*)] Critical values at the 1% level in parenthesis. [(1)] Augmented Dickey-Fuller test over residuals from the estimated cointegration equation. The number of lags used equals 3.[(2)] Augmented restricted vector autoregression.The number of lags used for the spot and futures market returns equals 3 and 6, respectively. [(3)]Augmented unrestricted vector autoregression. The previous lag structure is applied.

Table 6. Maximum likelihood estimation. Mean equation

coefficient[(a)]	Spot return	coefficient	Futures return
α_{11}	0.061[(*)] (0.017)	α_{21}	-0.006 (0.014)
α_{12}	-0.106[(*)] (0.021)	α_{22}	-0.032[(*)] (0.018)
β_s	-0.078[(*)] (0.014)	β_f	0.012 (0.012)

Note:[(a)]Estimated standard errors are in parenthesis. [(*)] Significant at the 5% level.

Table 7. Maximum likelihood estimation. Variance equation

coeff.[(a)]	$\varepsilon_{s,t}$	coeff.	$\varepsilon_{f,t}$	coeff.	$\varepsilon_{s,t}\,\varepsilon_{f,t}$
ϕ_{11}^{1} [(b)]	0.002 (0.004)	ϕ_{31}^{1}	0.004 (0.003)	ϕ_{22}^{2}	0.078[(*)] (0.008)
ϕ_{13}^{1}	0.065[(*)] (0.011)	ϕ_{33}^{1}	0.036[(*)] (0.008)	ϕ_{22}^{3}	0.012 (0.007)
ϕ_{11}^{2}	0.136[(*)] (0.004)	ϕ_{33}^{2}	0.036[(*)] (0.011)	ϕ_{22}^{4}	0.007 (0.005)
ϕ_{11}^{3}	0.077[(*)] (0.007)	ϕ_{33}^{3}	0.051[(*)] (0.008)		
ϕ_{11}^{4}	0.068[(*)] (0.004)	ϕ_{33}^{4}	0.035[(*)] (0.005)		

Notes:[(a)]Estimated standard errors are in parenthesis.[(b)]ϕ_{ij}^{r} denotes the *ith*-row *jth*-colum element in matrix ϕ_r (r=1,2,3,4). [(*)] Significant at the 5% level.

Table 8. Average intraday statistics from the GARH model

	Conditional second moments[a]			
Trading hour intervals	Spot Volatility	Futures Volatility	Spot-Futures Covariance	Conditional Correlation
11:00 - 12:00	0.091	0.160	0.092	0.762
12:00 - 13:00	0.083	0.089	0.077	0.895
13:00 - 14:00	0.081	0.084	0.076	0.924
14:00 - 15:00	0.083	0.086	0.078	0.919
15:00 - 16:00	0.086	0.090	0.079	0.900
16:00 - 17:00	0.101	0.112	0.089	0.834
Global	0.088	0.104	0.081	0.872

Note:[a] Each mean is computed from the 743 estimated daily GARCH second order moment at the upper hour interval.

Table 9. Model Diagnostics

Ljung-Box Q statistics for the standardized residuals				
	Number of lags			
	1	6	12	24
Spot	0.00(0.99)[*]	0.08(0.99)	5.02(0.95)	25.08(0.40)
Futures	0.00(0.97)	0.08(0.99)	2.18(0.99)	19.62(0.72)
Ljung-Box Q statistics for the squared standardized residuals				
	Number of lags			
	1	6	12	24
Spot	0.25(0.62)	3.78(0.71)	11.78(0.46)	27.84(0.27)
Futures	0.23(0.63)	3.25(0.77)	9.45(0.66)	30.45(0.17)
L-M ARCH(p) test for the standardized residuals				
	Number of lags (p)			
	1	2	6	
Spot	0.28(0.60)	0.91(0.63)	4.02(0.68)	
Futures	0.23(0.63)	0.94(0.63)	3.20(0.78)	

Note:[*] Critical significant levels of the test in parenthesis.