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ON METEOR SHOWERS IN STOCK MARKETS

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Abstract

The relationship between the Dow-Jones Index returns and Madrid Stock Index returns is observed. Using daily data for the period 1988-1989 significant effects are found, being the Dow-Jones Index returns a leading indicator for Madrid returns' conditional mean. The effects are asymmetric: negative changes in the Dow-Jones Index returns have twice the effect than positive ones; and nonlinear, as the influence of Black Friday, October 13, 1989 suggests. The "meteor shower" effect between both markets' volatilities is documented. Daily trading volume has some explanatory power for the conditional variance of daily returns. Day of the week effects are examined and it is found that the average return on Thursday is abnormally high.

Key words
GARCH Models; Asymmetric and nonlinear effects; Stock Index; Trading Volume; "Meteor Shower" effect.

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Further, using the analogies first put forth by Engle et al. (1990) a "meteor shower" effect is detected between the volatilities in both markets. The New York news (day before) have a large impact on Madrid returns volatility.

Day of the week effects are taken into account, although its form is different than the reported results for other countries (Lakonishok y Maberly (1990)). Further, the conditional variance in IM is positively related to the rate of daily information arrival represented by daily trading volume (Lamoreux y Lastrapes (1990)). However interest rate influence is not relevant for this sample data, in contrast with other published studies (Breen et al. (1989)).

The paper is structured as follows. The econometric framework is presented in section 2. Summary statistics and univariate ARMA-GARCH analysis are considered in section 3. The variable selection problems and maximum likelihood estimation for the econometric model are studied in section 4. Concluding remarks are presented in section 5.

1.- INTRODUCTION

Stock returns volatility is a growing interest subject, specially since the October 19, 1987 stock market crash. The consequences of the Kuwait crisis and its effect on the world stock markets, underline the volatile behaviour of these markets and the difficulties in understanding their basic mechanisms.

In that framework, is specially interesting the study of the effects transmission patterns between markets. If we consider that the U.S.A. account for approximately 60% of the world's market value of exchange-listed securities (Jaffe and Westerfield (1985)) and that New York Stock Exchange (NYSE) is the most representative of the U.S. stock markets, is not terribly hazardous to guess that this market keeps an essential role as indicator and leader in stock price changes, all over the world.

This work focuses on the form of the transmission of the influences of NYSE (represented by Dow-Jones Index) over an small market, the Madrid Stock Market (represented by the General Stock Index), using daily data. The model we estimate, shows a statistically significant relationship between the Madrid Index (IM) returns conditional mean and Dow-Jones (DJ) previous day returns. This relationship is asymmetric because the negative index variations have a higher (double) effect than positive ones. Also there is a nonlinear effect in the dates near Black Friday October 13,1989 where the negative effect increased almost six times the usual one.

2.- ECONOMETRIC FRAMEWORK

To model the dynamic relationships of interest, one single-equation econometric model with conditional heteroscedasticity ARCH-GARCH following Engle(1982) and Bollerslev(1986) is used. If we define the daily return for one financial asset r_t as follows $r_t = \ln(x_t) - \ln(x_{t-1})$ where x_t is the spot price, then we propose the following model for IM returns

$$r_t = \mu_{t|t-1} + \epsilon_t \tag{1}$$

$$\mu_{t|t-1} = \Sigma_i \Sigma_j \, \beta_{ij} \, Z_{i,t-j} + \Sigma_q \, \theta_q \, \epsilon_{t-q} \tag{2}$$

$$\epsilon_t | (\epsilon_{t-1}, \epsilon_{t-2}, \ldots) \sim N(0, h_t) \tag{3}$$

$$h_t = \alpha_0 + \Sigma_k \Sigma_l \, \delta_{kl} \, Y_{k,t-l} + \alpha_1(B) \epsilon^2_{t-1} + \alpha_2(B) h_{t-1} \tag{4}$$

where $\mu_{t|t-1}$ is the return's conditional mean, $Z_{i,t-j}$ and $Y_{k,t-l}$ are two (possibly overlapping) sets of explanatory variables (stochastic and/or deterministic, v.gr. day-of-the-week dummies) with appropriated lagged values, B is the backshift operator and $\alpha_0 >$ 0. The polynomials $\alpha(B)_{1,2}$ are stationary and invertible respectively and are of order a and b. The model is similar to Baillie and Bollerslev(1989) for foreign exchange rates. However we do not impose the efficient market restriction and allow for MA terms in the equation, as well as stochastic regressors.

Let us denote the parameter vector in model (1)-(4) as $\phi'=(\alpha',\beta',\theta',\delta')$ an mx1 vector where m=i+j+q+k+l+a+b+1. Then the log-likelihood function conditional on the initial values can be expressed as

$$L(\phi)= \Sigma_t L_t(\phi) \qquad (5)$$

$$L_t(\phi)=-\log h_t -\epsilon^2_t/2h^2_t \qquad (6)$$

Noting S the Txm array of first derivatives, a ready solution to the maximization of this likelihood function is to adopt the Berndt,Hall,Hall y Hausman(1974) approach using the iteration

$$\phi^{i+1} = \phi^i + \tau(S'S)^{-1} S'i \qquad (7)$$

where i is a Tx1 unit vector and τ is the step length which is adjusted from its a priori value of unity by a simple line search, and S as the matrix of first derivatives evaluated at Φ^i . It is well known (Engle et al.(1987)) that under sufficient regularity conditions, a solution to (7) will have the property that

$$(S'S)^{1/2} (\phi^* - \phi^0) \overset{A}{\sim} N(0,I) \qquad (8)$$

where ϕ^* is the maximum likelihood estimator obtained from (7) and ϕ^0 is the true value of the parameters.

3.- UNIVARIATE ANALYSIS

We use in this paper daily data of General Index of Madrid Stock Market (IM) from January 1, 1988 to December 31, 1989 that is 506 data points. Data are from the weekly Business supplement by EL PAIS newspaper. The series are clearly nonstationary with high values (0.99) in the autocorrelation function. A formal extended Dickey-Fuller test does not reject the null of unit root, so it seems reasonable to work with the returns of this series as previously defined. Table 1 summarizes the relevant statistics describing our data set.

The mean is near zero and there is some negative skewness as well as strong leptokurtosis as is usual in financial time series. The Bera and Jarque(1982) normality test LR(2) shows high values, so at reasonable significance levels, the null hypothesis of normality is rejected.

The Q-Ljung-Box (L-B Q(12)) statistic is large and statistically significant at low significance levels. The estimated alpha value for Pareto Stable distribution is well below 2 (Gaussian) but the coefficient b_4 (see Lau et al. (1990)) is small even for this sample size, so it is actually dubious that Pareto Stable (alpha < 2) distributions are worth of consideration for this sample.

There is a very low value on October, 16 1989 (Monday) where a drop of 5% was registered (the "mini-crash" of Black Friday October 13,1989 made a 3.3% decrease in DJ Stock Index). Its standardized value is almost 9 standard deviations. If we replace this nasty value for the mean, the skewness is -0.045 with t-value -0.41. However the normality test still reject the null at any reasonable levels due to high kurtosis. The Q(L-B) increases (70.6), the mean also increases slightly an variance decreases about 9%.

We build an ARMA-GARCH model for this series, taking into account the extreme data for the "mini-crash" with one dummy impulse variable, $Z464_t$. The estimated model is in Table 2.

All the coefficients are significant at a 5% level including the MA parameters (the polynomial is invertible with roots 0.65 and -0.24), which suggest failures of market efficiency.
The persistence in volatility as measured by $(\alpha_1+\alpha_2)$ is not high (0.4254). Thus, the conditional variance model is stationary, see Bollerslev(1988). The unconditional variance of r_t is $3.8186x10^{-5}$ and the unconditional variance of the residuals is $1.7586x10^{-5}$, so the model explains approximately 53% of the unconditional variance of r_t. The Q-Statistics L-B Q and Q_{aa} (McLeod y Li(1983)) do not signal strong specification problems, and the LR(4) test for constant mean and variance clearly rejects the null. Skewness are close to normality but normality test LR(2) and the kurtosis value suggest lack of normality, so standard errors may be biased.

4.-VARIABLE SELECTION AND THE ECONOMETRIC MODEL

The initial selection for variables Ys and Zs in (1)-(4) is not a straightforward problem. As an example, Tohuey(1980) in a somewhat informal discussion, suggests the following variables as specially relevant for stock price changes

- 90-day Treasury Bill Yield
- Total Time Savings Deposits
- Authorized Housing Permits
- Broker's Cash Accounts
- Stock Exchange Call Loan Interest Rate
- True Weekly Earnings (Inflation)
- Banker's Security Loans
- Broker's Total Margin Credit
- The Price of Gold
- Ratio of Corporate Bond Interest Rate to Prime Rate
- The U.S. Federal Deficit

Campbell(1987) documents evidence that the state of the term structure of interest rates predicts excess stock returns with monthly data for five U.S. firms. Breen et al.(1989), also with monthly data, present empirical results pointing out that the knowledge of one-month interest rate is useful in forecasting the sign as well the variance of the excess returns on stocks. Taking another point of view, Schwert(1989) suggests as determinants of stock volatility, expected values of inflation volatility, money growth, industrial production and degree of financial leverage, notwithstanding that there is weak evidence that macroeconomic volatility can help to predict stock return volatility, and that financial leverage affects stock volatility, but this effect explains only a small proportion of the changes in stock volatility over time. Also he suggests the possible relation between volume trade and stock volatility. This idea is further explored in Lamoreux and Lastrapes(1990) which show how daily trading volume, have significant explanatory power regarding the variance of daily returns for 20 selected U.S. firms.

Previous comments on some of the (abundant) publications on this area suggest as a reasonable candidates for Ys and/or Zs some measures of interest rates, money supply, monetary base, industrial production, inflation, expectations, etc. However, very few of these variables are available on daily data.

One clearly interesting variable is Trading Volume as a proxy for information arrival. If we interpret price changes as the market evaluation of new information, and the corresponding trade volume is considered an indication of the extent to which investors disagree about the meaning of the new information, Beaver(1968), the consequence is that return volatility increases when volume increases and so a strong increase in volume is usually coincident with strong price augments/decreases. Thus, Trade Volume could be included in the conditional variance equation. In the same way, It could be argued that the return conditional mean is proportional to new information arrival and use the proxy variable (Trade Volume) as regressor in the equation. However, apart from possible simultaneity bias, (if volume is not exogenous) the relationship between return mean and volume can be an extremely complex one (see Karpoff(1987), specially 120-121) and for that reason we do not include the variable in the conditional mean equation.

Also, for the small Madrid market,the "foreign news" effect can be represented by the Dow-Jones Index variations the day before, due to the fact of the 5-hour delay between Madrid and New York, that cause nonoverlapping trading hours. This idea is similar to Engle et al.(1990) "meteor shower" and "heat waves" effects for foreign exchange markets, where the daily change in exchange rates volatilities are explained by the influence of one market on others. Specifically they show how news in the New York market can predict volatility in the Tokyo market several hours later. The "heat wave" hypothesis is consistent with a view that major sources of volatility are country-specific, on the other hand "meteor shower" hypothesis is consistent with volatility spillovers form one country to another. The conclusion is that volatility appears to be a meteor shower rather than a heat wave for the Tokyo, New York, Pacific and Europe foreign exchange markets.

In summary, we use as explanatory variables in the model, the Interbank interest rate (one day, one week, one month, three months) and its first difference, Dow-Jones Index variations and volatility (we use the squared returns as a proxy for volatility because they follow a GARCH(0,0) process), Daily Trade Volume, and dummy variables for day-of-the week effects. Table 3 summarizes the relevant statistics for the model. Main points are

- All coefficients are significant at usual levels. Negative variations in DJ have double effect (0.2808) than positive ones (0.1269). This "pessimistic" influence is very significant, as the likelihood ratio test with null of coefficient equality for ZP_{t-1} and ZN_{t-1} shows (LR(1)=19.45). Also the October 1989 mini-crash (variable Z464) has a coefficient 1.85, six times the usual one, suggesting something like "panic" in this date at Madrid. Note that New York decrease was on Friday, and so the Madrid investor had one full weekend to realize the consequences, which lead to a strong bear market next Monday (5.73% decrease). Also note that MA coefficients remain significant, and even increase slightly, which suggest that explanatory variables do not modify greatly the process' inertia.

- Unlike the common weekend effect where average return on Friday is abnormally high, and average return on Monday is abnormally low, Jaffe and Westerfield(1985), only Thursday has a clear day-of-the-week effect, being the day with abnormally high mean returns (0.2%), and no weekday is specially volatile. There are various conjectures to explain these effects, related with market's institutional framework, but this is not the main target for the paper.

- No influence of interest rates (at various terms) are detected, possibly due to special institutional characteristic in the Interbank Market, see Escrivá(1990).

- Residual unconditional variance is 1.273×10^{-5}, so the model explains approximately 66% of the original variance, with 27% improvement over the univariate model, mainly due to DJ effects. Persistence in volatility (measured by $\alpha_1+\alpha_2$) mildly increases w.r.t. univariate model, and "basic" volatility (α_0) is scarcely 40% of the univariate model, suggesting that explanatory variables in the variance equation account for a somewhat high proportion of these basic volatility.

- Meteor shower effect is significant, pointing out that volatility variation in New York affect conditional volatility in Madrid next day. This result is consistent with failures of the strong form of market efficiency.

- Trade volume is also a relevant element in explaining conditional variance, although its coefficient is not strongly significant. Its small effect is underlined with no reduction in GARCH equation parameters, as opposed with findings in Lamoreux and Lastrapes(1990).

- Statistics L-B Q y Q_{aa} do not signal model misspecifications and LR(9) test for constant mean and variance rejects the null. Normality test suggests small departures from the null hypotheses, so standard errors might be mildly biased.

5.-CONCLUDING REMARKS

This paper provides empirical evidence consistent with the hypothesis that "meteor shower" effects between New York Stock Exchange and Madrid Stock Exchange are statistically significant. Also an asymmetric influence of NYSE daily (day before) returns over conditional mean in Madrid returns are documented. Negative "news" have double effect than positive ones, and significant nonlinear effects (six times the usual ones) happen when the news are really bad (Black Friday Oct 13, 1989). Weekend effects are not detected but average return on Thursday is abnormally high. However no day shows specially high(low) volatility.

Daily trading volume is shown to have some explanatory power regarding the conditional variance of daily Madrid returns. But in contrast with Lamoreux and Lastrapes's (1990) results this effect does not delete the GARCH structure, that remains similar but with smaller α_0 value. This variance shows GARCH structure with low persistence in volatility and is stationary.

The implications for future research include why the influence of interest rates was not found, possibly due to data problems, and explanations for the Thursday effect.

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TABLE 1

Summary Statistics Madrid Index Returns

	Values	Std. Errors	T-Values
Mean	0.00037	0.00028	1.34934
Variance	0.00004		
Stand. Error	0.00619		
Median	0.00000		
Variation Coef.	16.63772		
Trimmed Mean10	0.00035		
Skewness	-1.36966	0.10911	-12.55313
Kurtosis	12.67820	0.21822	58.09882
LR(2) Normality	3508.1		
Max. Val	0.01951		
Min. Val	-0.05442		
Coef. b_4	991.25672		
Stable Alpha	1.58093		
L-B Q(12)	47.30284		
Sample Size	505		

TABLE 2

MAXIMUM LIKELIHOOD ESTIMATION UNIVARIATE MODEL

MA(2)-GARCH(1,1) FOR IM

$$r_t = \beta\ Z464_t + \epsilon_t + \theta_1\ \epsilon_{t-1} + \theta_2\ \epsilon_{t-2} \quad ; \quad \epsilon_t \sim N(0,h_t)$$

$$h_t = \alpha_0 + \alpha_1\ \epsilon^2_{t-1} + \alpha_2\ h_{t-1}$$

	Coefficient	T-Student (asint.)
β	-0.0589	-40.58
θ_1	0.4058	8.45
θ_2	0.1675	3.39
α_0	0.1021×10^{-4}	5.07
α_1	0.2529	3.41
α_2	0.1725	2.99
$\alpha_1+\alpha_2$	0.4254	

Log Likelihood	1940.54
Skewness	-0.2546
Kurtosis	2.116
L-B Q(12)	25.44 (coef. 6(0.09) and 10(0.11))
Q_{aa} (12)	7.13
LR(4) mean and var	184.16
LR(2) Normality	94.25

$Z464_t$ = 1.0 if t=10-16-89 0.0 otherwise

(Residuals are standardized by $h^{1/2}_t$)

TABLE 3

MAXIMUM LIKELIHOOD ESTIMATION OF ECONOMETRIC MODEL FOR IM

$r_t = \beta_1 ZP_{t-1} + \beta_2 ZN_{t-1} + \beta_3 Z464_t + \beta_4 J_t + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}$ $\epsilon_t \sim N(0, h_t)$

$h_t = \alpha_0 + \delta_1 YV_t + \delta_2 YDJ_{t-1} + \alpha_1 \epsilon^2_{t-1} + \alpha_2 h_{t-1}$

	Coefficient	T-Student (asint.)
β_1	0.1269	3.57
β_2	0.2808	8.63
β_3	1.8499	22.09
β_4	0.0022	5.84
θ_1	0.4846	10.19
θ_2	0.2006	4.04
α_0	0.0371×10^{-4}	4.22
δ_1	0.0928	1.90
δ_2	0.2667	3.94
α_1	0.2223	4.04
α_2	0.4845	7.61
$\alpha_1+\alpha_2$	0.7068	

Variables $ZP_t = (\text{Log}(DJ_t) - \text{Log}(DJ_{t-1})) > 0.0$

$ZN_t = (\text{Log}(DJ_t) - \text{Log}(DJ_{t-1})) < 0.0$ (without Z464)

$Z464_t = -0.03372$ if t=10-16-89 ,0.0 otherwise

$J_t = 1.0$ if t=Thursday ,0.0 otherwise

YV_t = Log(Trading Volume Madrid)

$YDJ_t = (\text{Log}(DJ_t) - \text{Log}(DJ_{t-1}))^2$

TABLE 3 (Cont.)

Log Likelihood	2037.43
LR(9) mean and var	378.84
LR(2) Normality	18.07
Mean	0.02938 (0.64940)
Variance	1.03162
Stand. Error	1.01569
Median	0.01260
Variation Coef.	34.57011
Trimmed Mean 10	0.01824
Skewness	0.09118 (0.83566)
Kurtosis	0.89484 (4.10069)
Max. Value	3.67510
Min. Value	-3.29580
Coef. B4	27.74786
Stable Alpha	1.84537
Q_{aa} (12)	9.61
L-B Q(12)	10.92869
Sample Size	504

(Residuals are normalized by $h^{1/2}_t$)