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ON METEOR SHOWERS IN STOCK MARKETS: NEW YORK vs MADRID

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Utilizando datos diarios 1988-1989 se detecta la presencia de efectos del Indice Dow-Jones sobre el Indice General de la Bolsa de Madrid. Estos efectos son asimétricos sobre la media, siendo los efectos de las bajadas mayores que los de las subidas y no lineales, ya que bajadas especialmente fuertes, como la del minicrash de octubre de 1989, tienen efectos adicionales. Asimismo se detecta un efecto sobre la volatilidad tipo «Meteor Shower», usando modelos GARCH. También se incluyen los efectos sobre la volatilidad del volumen de contratación así como de otras variables de día de la semana.

1. Introduction

One specially interesting area in financial time series analysis is the study of the transmission patterns between markets, specially volatility spillovers. Note that U.S.A. and Japan account for approximately 80% of world's market value of exchange-listed securities (see recent issues of Morgan Stanley Capital International Indices) being New York Stock Exchange (NYSE) and Tokyo Stock Exchange (TSE) the most representative stock markets. However, in spite of the total market value of equities listed on TSE is approximately 15 points larger than on the NYSE (see however the comments in French and Poterba (1989)), some published studies, Eun and Shim (1989), Hamao et al. (1990), Becker et al. (1990), suggest that the U. S. market is the essential leader in price moves and the most influential in the world. Similar results for the Spanish market are shown in Espitia and Santamaría (1991), and Manzano and Mateos (1991) using VAR methodology.

Thus, this work focuses on the influences of NYSE (represented by Dow-Jones Index) over an small market (about 1% world's market value), the Madrid Stock Market (represented by the General Stock Index), using daily data. The opening and closing times (in New York Time) for Madrid are from 5:00 a.m.

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to 8:00 a.m., so the return observations are nonsynchronous, and we could expect that Madrid's answer to U.S. shockn will have a one-day lag.

The model we present, shows a statistically significant relationship between the Madrid Index (IM) returns conditional mean and Dow-Jones (DJ) *previous day* returns. The relationship is probably *asymmetric* because negative returns have a higher (double) effect than positive ones. Also there is some suggestion of *nonlinear* effects in the dates near Black Friday October 13, 1989 where the negative effect increased almost six times.

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 «volatility surprise» (day before) have a large impact on IM volatility.

Day of the week effects are studied, although its form is different from reported results for other countries (Lakonishok and Maberly (1990)). Also, the conditional variance in IM is positively related to daily trading volume (Lamoreux and Lastrapes (1990)). Interest rate influence is not relevant for this sample data, in contrast with other published studies (Breen et al. 1989)).

The econometric framework is presented in Section 2. Summary statistics and univariate ARMA-GARCH analysis for Madrid series are considered in Section 3. Variable selection problems and maximum likelihood estimation for the econometric model are studied in Section 4. Concluding remarks are presented in section 5.

2. Econometric framework

To model the dynamic relationships of interest we use, a single-equation econometric model with conditional heteroskedasticity ARCH-GARCH following Engle (1982), Bollerslev (1986) and Baillie and Bollerslev (1989) model for foreign exchange rates, but we allow for MA terms in the equation, as well as stochastic regressors. If we define the daily return for one financial asset r_t as $r_t = \ln(x_t) - \ln(x_{t-1})$ where x_t is the spot price, then we propose the following model for IM returns.

$$r_t = \mu_{t|t-1} + \epsilon_t \quad [1]$$

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

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

$$h_t = \alpha_0 + \Sigma_k \Sigma_l \delta_{kl} Y_{k,t-1} + \alpha_1(B) \epsilon_{t-1}^2 + \alpha_2(B) h_{t-1} \quad [4]$$

where $\mu_{t|t-1}$ is the return's conditional mean, $Z_{i,t-j}$ and $Y_{k,t-1}$ 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 reason to allow for serial correlation in our stock index returns stem from the possible «Fisher effect» (nonsynchronous trading) and other frictions in the trading process, as discussed in Scholes and Williams (1977) and Lo and MacKinlay (1990).

Although we do not try to interpret our model [1]-[4] in terms of any equilibrium based asset pricing model (ICAPM, etc.), perhaps we could see it as one equation of the Factor ARCH model for Stock returns by Engle et al. (1989) which has a somewhat natural interpretation that are related to the well known international extension of Ross' APT [1].

Let us denote the parameter vector in model [1]–[4] as $\Phi' = (\alpha', \beta', \theta', \delta')$ an $m \times 1$ 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

$$L(\Phi) = \Sigma_t L_t(\Phi) \qquad [5]$$

$$L_t(\Phi) = -\log h_t - \epsilon_t^2/2h_t^2 \qquad [6]$$

Noting S the $T \times m$ 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, see Engle et al (1987) for details.

3. Madrid series univariate analysis

Daily closing data for General Index of Madrid Stock Market (IM) and Dow Jones Index (DJ) from January 1, 1988 to December 31, 1989, that is 506 data points, were obtained from the Studies Department of Madrid Stock Exchange (only closing data are available in the Madrid market). The IM series are clearly nonstationary with high values (near 0.99) in the first lags of 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 (the Hasza-Fuller test for a second unit root clearly rejects an additional unit root). 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 common in financial time series. 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 (characteristic exponent) 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.

[1] As one referee aptly pointed out there are some problems to interpret equations [1]-[4] in terms of taditional ICAPM models. Problems of exchange rate risk premium and validity of equilibrium PPP are obvious shortcomings.

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		

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 figure for the sample 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 and variance decreases about 9%.

An ARMA-GARCH model was estimated for this series, including 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 reasonable significance levels (the MA polynomial is invertible with roots 0.65 and −0.24). This does not imply that these deviations form pure randomness are of significant magnitude to enable one to earn excess profits. To establish excess profit potential requires, as a minimum, that we adjust for risk and transaction costs, posit a specific trading strategy, and use out of sample data. The possible nonsynchronous friction problem in this sample is explored further in Peña (1992).

The persistence in volatility as measured by $(\alpha_1 + \alpha_2)$ is (0.4254), and the variance model is stationary, Bollerslev (1988). The unconditional variance of r_t is 3.818×10^{-5} and the unconditional variance of the residuals is 1.758×10^{-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 fat tailed distribution, so standard errors may be biased.

TABLE 2
Maximum likelihood estimation univariate model
MA(2)-GARCH(1,1) FOR IM

$$r_t = \beta\ Z464_t + \epsilon_t + \theta_1\ \epsilon_{t-1} + \theta_2\ \epsilon_{t-2} \quad ; \quad \epsilon_t \sim N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1\ \epsilon_{t-1}^2 + \alpha_2\ h_{t-1}$$

	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 $h_t^{1/2}$)

4. Variable selection and the econometric model

The initial selection for variables *Ys* and *Zs* in [1]−[4] is not a straightforward problem. 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 montly 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. Also, Schwert (1989) suggests as determinants of stock volatility, expected values of inflation volatility, money growth, industrial production and degree of financial leverage, but those effects explains only a small proportion of the changes in stock volatility over time. Lamoreux and Lastrapes (1990) show how daily trading volume, have significant explanatory power regarding the variance of daily returns for 20 selected U.S. firms.

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 pp. 120-121) and for that reason we do not include the variable in the conditional mean equation.

Another possible variable is Engle et al. (1990) «meteor shower» and «heat waves» effects, 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 close to close returns (we allow for asymmetric effects) and volatility (we use the squared returns as a «volatility surprise» following Hamao et al. (1990) because DJ returns follow a GARCH (0,0) process, i.e. no GARCH effect in our sample), Daily Trade Volume, and dummy variables for day-of-the week effects (both in mean and in variance equations). Table 3 summarizes the relevant statistics for the model, after discarding non significant variables. Main points are

— All coefficients are significant at usual levels. Negative variations in DJ_{t-1} 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 ($LR(1) = 19.45$)[2]. Also the October 1989 minicrash (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, leading to next Monday 5.73% decrease in Madrid General Index. It may be argued that Madrid also reflects what happens in Tokyo and other European markets, so there might be a spillover effect from Madrid to New York also, but we do not find these effects in our sample.

— 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 (settlement procedures), but more data should be collected before concluding that there is something special in the Spanish market. We do not detect day of the week effects in the conditional variance.

No influence of interest rates (at various terms) are detected, possibly due to

[2] The change from the traditional trading method (auctions) to a computerized trading system (Continuous Market) open from 11 AM to 5 PM, began at the end of 1989. However the Continuous Market was not fully operational until April, 1990. Elsewhere (Peña (1991)) it is shown that after the Continuous Market, the instantaneous relationships between NY and Madrid increases from 0.08 to 0.29 and the one-day lagged relationship decreases from 0.52 to 0.33. Note that the final (gain) effect remains approximately the same.

TABLE 3
Maximum likelihood estimation of econometric model
FOR IM

$r_t = \beta_1 ZP_{t-1} + \beta_2 ZN_{t-1} + \beta_3 Z464_t + \beta_4 J_t + \epsilon_t + \theta_1 \epsilon_{t-1} + \epsilon_{t-2} \quad \epsilon_t \sim N(0, h_t)$
$h_t = \alpha_0 + \delta_1 YV_t + \delta_2 YDJ_{t-1} + \alpha_1 \epsilon^2_{t-1} + \alpha_2 h_{t-1}$

	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
β_1	0.4846	10.19
θ_2	0.2006	4.04
θ_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 $t = 10\text{-}16\text{-}89$, 0.0 otherwise
$J_t = 1.0$ if t = Thursday, 0.0 otherwise
YV_t = Log (Trading Volume Madrid)
$YDJ_t = (\text{Log}(DJ_t) - \text{Log}(DJ_{t-1}))^2$

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_{gn} (12)	9.61
L-B $Q(12)$	10.92869
Sample Size	504

Residuals are normalized by $h_t^{1/2}$).

special institucional 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. Meteor shower effect is significant, pointing out that volatility variation in New York affect conditional volatility in Madrid next day.

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). However, including the contemporaneous volume, as in the above paper constitute a simultaneity problem, and might bias the results. Statistics *L-B* Q y Q_{ga} 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, because contemporaneous correlation is only 0.08 and non-significant) returns over conditional mean in Madrid returns are documented. The results suggest that 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), but these last result should be viewed with special caution, because we have only one single extreme observation. 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 for the conditional variance of daily Madrid returns. But in contrast with Lamoreux and Lastrapes's (1990) results this effect does not affect 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 to expand the model to include others stock market indexes (Tokyo, London, Frankfurt) in the line of multivariate-GARCH models. Testing why the influence of interest rates was not found, possibly due to data problems, explanations for the Thursday effect, and trading simulations to check if the excess profits the model could generate vanish when transaction costs and taxes are included.

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Abstract

Using daily data 1988-1989 the relationship of Dow-Jones Index returns and Madrid Stock Index returns in studied. Significant effects are found, being the Dow-Jones Index returns leading indicator for Madrid next day returns' conditional mean. The effects are possibly asymmetric, negative changes in Dow-Jones have double effect than positive ones; and nonlinear as the influence of Black Friday October 13, 1989 suggests. The «meteor shower» effect between both markets' volatilities are 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.

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