# TECHNICAL ANALYSIS IN THE MADRID STOCK EXCHANGE*

Fernando Fernández-Rodríguez
(Universidad de Las Palmas de Gran Canaria)
Address: Departamento de Economía Aplicada
Universidad de Las Palmas de Gran Canaria
Campus de Tafira, 35017 Las Palmas de Gran Canaria, Spain
Tel: (+34) 928 451 802
Fax: (+34) 928 451 829
E-mail: fernando@empresariales.ulpgc.es

Corresponding author: Simón Sosvilla-Rivero
(FEDEA and Universidad Complutense de Madrid)
Address: FEDEA
Jorge Juan 46, 28001 Madrid, Spain
Tel: (+34) 914 350 401
Fax: (+34) 915 779 575
E-mail: simon.sosvilla@fedea.es

Julián Andrada-Félix
(Universidad de La Laguna)
Address: Departamento de Economía Aplicada
Universidad de La Laguna
Campus de Guajara, 38207 La Laguna, Spain
Tel: (+34) 922 317 030
Fax: (+34) 922 253 742
E-mail: jandrada@ull.es

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ABSTRACT

In this paper we assesss whether some simple forms of technical analysis can predict stock price movements in the Madrid Stock Exchange. To that end, we use daily data for General Index of the Madrid Stock Exchange, covering the thirty-one-year period from January 1966-October 1997.

Our results provide strong support for profitability of these technical trading rules. By making use of bootstrap techniques, we show that returns obtained from these trading rules are not consistent with several null models frequently used in finance, such as AR(1). GARCH and GARCH-M.

RESUMEN

Este trabajo evalúa la capacidad predictiva de las algunas formas simples de análisis técnico a la hora de explicar los movimientos de las cotizaciones en la Bolsa de Madrid. Para ello, utilizamos datos diarios del Indice General de la Bolsa de Madrid para el período de treinta y un años comprendido entre Enero de 1966 y Octubre de 1997.

Nuestros resultados ofrecen evidencia empírica favorable a la rentabilidad de dichas reglas técnicas de contratación. Mediante el uso de técnicas de simulaciones sucesivas (*bootstraping*), comprobamos que los rendimientos obtenidos a partir de dichas técnicas no son consistentes con distintos modelos empleados frecuentementes en Finanzas, tales como el AR(1); GARCH o GARCH-M.

JEL classification numbers: G12, G15

KEY WORDS: Stock market, Technical trading rules.

*"Time present and time past*
*are both perhaps present in future time*
*and time future*
*contained in time past"*
*T. S. Eliot ("Burnt Norton", Four Quarters)*

## 1. Introduction

Technical analysis test historical data attempting to establish specific rules for buying and selling securities with the objective of maximising profits and minimising risk of loss. The basic idea is that "prices moves in trends which are determined by changing attitudes of investors toward a variety of economic, monetary, political and psychological forces" (Pring, 1991, p. 2).

Although technical trading rules have been used in financial markets for over a century (see, e. g., Plummer, 1989), it is only during the last decade, with growing evidence that financial markets may be less efficient than was originally believed, that the academic literature is showing a growing interest in such rules. Furthermore, surveys among market participant show that many use technical analysis to make decisions on buying and selling. For example, Taylor and Allen (1992) report that 90% of the respondents (among 353 chief foreign exchange dealers in London) say that they place some weight on technical analysis when forming views for one or more time horizons.

A considerable amount of work has provided support for the view that technical trading rules are capable of producing valuable economic signals. On the one hand, technical analysis has been placed on more firmer theoretical foundations. Brown and Jennings (1989), for instance, demonstrate that, under a dynamic equilibrium model with heterogeneous market participants, rational investors use past prices in forming their demands. Neftci (1991) shows that trading rules derived by technical analysis could be formalized as nonlinear predictors. Finally, Clyde and Osler (1997) provide a theoretical foundation for technical analysis as a method for doing nonlinear forecasting on high dimension systems.

On the other hand, in empirical work, Brock *et al.* (1992) (BLL from now on) use bootstrap simulations[1] of various null asset pricing models and find that simple technical trading rule profits cannot be explained away by the popular statistical models of stock index returns. Levich and Thomas (1993) use the same bootstrap simulation technique to provide evidence on the profitability and statistical significance of technical trading rules in the foreign exchange market with currency future data. Finally, Gençay (1998) investigates the nonlinear predictability of stock market combinibg simple technical trading rules and feedforward networks. His results indicate strong evidence of nonlinear predictability in the stock merket returns by using the buy-sell signals of the moving average rules.

These are findings of potential importance, and we consider that it is of interest to investigate whether similar results hold for other stock markets. Therefore, the purpose of this paper is to examine the predictive ability of technical trading rules in the Madrid Stock Exchange, by analysing daily data on the General Index for the thirty-one-year period from 1966 to 1997.

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[1] Bootstraping is a method, introduced by Efron (1979), for estimating the distributions of statistics that are otherwise dificult or imposible to determine. The general idea behind the bootstrap is to use resampling to estimate an empirical distribution for the targert statistic. Artificial samples are drawn from the original data, being the statistic of interest recalculated on the basis of each artificial sample. The resulting "bootstrapped" measures are then used to construct a sampling distribution for the statistic of interest.

Our study can be viewed as contributing to a growing body of research testing nonlinear dependencies in financial prices. Early tests for the presence of nonlinearities, testing the null hypothesis of independent and identical distribution (*iid*), indicate that nonlinearities are indeed present in stock markets [see Ramsey (1990), Hsieh (1991) and Pununzi and Ricci (1993) among others, and, for the Spanish case, Olmeda and Pérez (1995) and Fernández-Rodríguez *et al*. (1997)].

The rest of the paper is organised as follows. In Section 2 we describe the data set and introduce the technical rules used. Section 3 offers some preliminary results. In Section 4 the empirical results from the bootstrap simulations are presented. Finally, Section 5 provides some concluding remarks.

**2. Data and technical trading rules**

The database used is composed of 6931 observations (from 4 January 1966 to 15 October 1997) of daily closing prices of the General Index of the Madrid Stock Exchange (IGBM). This index is sufficiently representative of the Spanish Stock Market, since it accounts for more than 90 percent of total trading volume.

Drawing from previous academic studies and the technical analysis literature, in this paper we employ two of the simplest and most common trading rules: moving averages and support and resistance. BLL (1992) stress the substantial danger of detecting spurious patterns in security returns if trading strategies are both discovered and tested in the same database. To mitigate the danger of "data snooping" biased, we do not search for ex-post "successful" technical trading rules, but rather evaluate a wide set of rules that have been known to practitioners for at least several decades. Also, like BLL (1992), we report the results of all trading rules we evaluate.

According to the moving average rule, buy and sell signals are generated by two moving averages of the level of the index: a long-period average and a short-period average. A typical moving average trading rule prescribes a buy (sell) when the short-period moving average crosses the long-period moving average from below (above) (i. e. when the original time series is rising (falling) relatively fast). As can be seen, the moving average rule is essentially a trend following system because when prices are rising (falling), the short-period average tends to have larger (lower) values than the long-period average, signalling a long (short) position.

We evaluate the following popular moving average rules: 1-50, 1-150, 5-150, 1-200 and

2-200, where the first number in each pair indicates the days in the short period and the second number shows the days in the long period. These rules are often modified by introducing a band around the moving average, which reduces the number of buy (sell) signals by eliminating "whiplash" signals when the short and long period moving averages are close to each other. We are going to evaluate two moving average trading rules.

The first moving average rule we examine, called the variable length moving average (VMA), implies a buy (sell) signal is generated when the short period moving average is above (below) the long period moving average by more than one percent. If the short period moving average is inside the band, no signal is generated. This method attempts to simulate a strategy where traders go long as the short moving average moves above the long and short when it is below. With a band of zero, this method classifies all days into either buys or sells.

The second moving average trading rule that we analyse is called a fixed-length moving average (FMA). Since it is stressed that returns should be different for a few days following a crossover, in this strategy a buy (sell) signal is generated when the short moving average cuts the long moving average from below (above). Following BLL (1992), we compute returns during the next ten days. Other signals occurring during this ten-day period are ignored.

Finally, we consider the trading range break-out (TRB) rule. With this technical rule, a buy signal is generated when the price penetrates a resistance level, defined as a local maximum. On the other hand, a sell signal is generated when the price penetrates a support level, defined as a local minimum. As with the moving average rule, maximum (minimum) prices were determined on the past 50, 150 and 200 days, and the TRB rules are implemented with and without a one percent band.

## 3. Preliminary empirical results

Panel A and B in Table 1 reports some summary statistics for daily and 10-day returns series, respectively. Returns are calculated as daily changes in logarithms of the IGBM level, and thus exclude dividends yields. As can be seen, these returns exhibit excessive kurtosis and (marginal) negative skewness, indicating nonnormality in returns. On the other hand, the first order serial correlation coefficient is significant and positive. Autocorelations at a higher lag are considerably closer to zero.

[Table 1 here]

If technical analysis does not have any power to forecast price movements, then we should observe that returns on days when the rules emit by signals do not differ appreciably from returns on days when the rules emit sell signals. To evaluate the forecast power of technical trading rules, we compute mean return and variance on buy and sell days for each rule described.

In Table 2 we present the results from VMA trading strategies. As mentioned above, we examine ten rules (*s*,*l*,*b*), differing by the length of the short and long period (*s* and *l*, respectively, in days) and by the of size the band (*b*: 0 or 1%). In particular, in Table 2 we report the number of buy and sell signals generated during the period ["N(Buy)" and "N(Sell)", respectively], the mean buy and sell returns ("Buy" and "Sell", respectively), the fraction of buy and sell returns greater than zero ("Buy>0" and "Sell>0") and the difference between the mean daily buy and sell returns ("Buy-Sell"). The *t*-statistics for the "Buy" ("Sell") statistics are computed using the following formulae (see BLL, 1992, footnote 9):

$$\frac{\mu_r - \mu}{\sqrt{\frac{\sigma^2}{N} + \frac{\sigma^2}{N_r}}}$$

where $\mu_r$ and $N_r$ are the mean return and the number of signals for the buys and sells, and $\mu$ and N are the unconditional mean and the number of observations. $\sigma^2$ is the estimated variance for the entire sample. For the "Buy-Sell", the *t*-statistic is

$$\frac{\mu_b - \mu_s}{\sqrt{\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s}}}$$

where $\mu_b$ and $N_b$ are the mean return and number of signals for the buys, and $\mu_s$ and $N_s$ are the mean return and the number of signals for the sells.

[Table 2 here]

As can be seen in Table 2, the buy-sell differences are significantly positive for all rules. The introduction of the one percent band increases the spread between the buy and sell returns. The number of buy signals generated by each rule always exceeds the number of sell signals, by between 44 and 76 percent, which is consistent with an upward-trending market.

The mean buy returns are all positive with an average daily return of 0.10 percent, which is about 28.4 percent at an annual rate[2]. All *t*-statistics reject the null hypothesis that the returns equal the unconditional returns (0.039 percent from Table 1). For the sells, all means returns are negative, with an average daily return of -0.06 percent, or -16.2 on an annualized basis, and all but one of the *t*-statistics are significantly different from zero.

Regarding "Buy>0" and "Sell>0" statistics, the buy fraction is consistently greater than 50 percent, while that for all sells is considerably less, being in the region of 43.6 to 44.4 percent. Under the hypothesis that technical trading rules do not produce useful signals, these fractions should be the same: a binomial test shows that these differences are highly significant and the null of equality can be rejected.

These results are strikingly similar to those reported by BLL (1992, Table II)[3], who emphasised the difficulty in explaining them with an equilibrium model that predicts negative returns over such a fraction of trading days.

Results for the FMA trading rule are presented in Table 3 in the same format as Table 2. We examine fixed 10-day holding periods after a crossing of the two moving averages. As can be seen in Table 3, the buy-sell difference is positive for all the tests. Nevertheless, only in 3 of the 10 tests the null hypothesis that the difference is equal to zero can be rejected. As before, the

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[2] Throughout this paper, we compute approximate annualized returns on the basis of 250 trading days per year as exp(250*r*)-1, where *r* is the mean daily return.

[3] Note that, while in BLL (1992) the buy returns from VMA rules yield an average return of 12 percent at an annual rate for the Dow Jones Index from 1897 to 1986, using the same VMA rules we obtain a return of 28.4 percent at an annual rate.

addition of a one percent band increases the buy-sell difference, except for those rules with long-period moving average equal to 150 days.

The buy returns are again all positive with an average daily return of 1.03 percent during the 10-day period following the signal[4]. None of the *t*-statistics reject the null hypothesis that the returns equal the unconditional 10-day return (0.30 percent from Table 1). For the sells, all means returns are negative, with an average daily return of -0.64 percent, but only 2 of the 10 *t*-statistics are significantly different from zero. For all the individual rules examined, the fraction of buys greater than zero exceeds the fraction of sells greater than zero.

[Table 3 here]

Table 4 presents the results for the TRB rule. As shown in that table, the buy-sell difference is always positive and in all cases the null hypothesis that the difference is equal to zero can be rejected. The buy returns are again all positive with an average daily return of 1.7 percent. The *t*-statistics suggest that the buy returns are significantly different from the unconditional 10-day return. Regarding the sells, the returns are always negative, being only 1 of the 6 *t*-statistics are significant. The fraction of buys greater than zero exceeds the fraction of sells greater than zero.

[Table 4 here]

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[4] This is approximately twice the average daily return found by BLL (1992) for the Dow Jones Index from 1897 to 1986.

Given that the period covered is very long and heterogeneous, with a number of important events that could affect the structure of the series, we have also considered two nonoverlapping subperiods, being 19 October 1987 the breaking point, including in the second period the effects of the "crash" of 1987 and the readjustments of 1989 and 1991, as well as the change in the clearing and settlement procedures and the inception of the IBEX35 futures market. The results (not present here, but available from the authors upon request) are similar to those reported for the complete sample and, therefore, we found no evidence that the results are different across subperiods.

**4. Bootstrap results.**

The results presented in Section 3 indicate that trading rules produce higher returns than the unconditional mean return. However, this conclusion is based on inference from *t*-statistics that assume independent, stationary and asymptotically normal distributions. As we have seen from Table 1, these assumptions certainly do not characterise the returns from the IGBM series. Following BLL (1992), this problem can be address using bootstrap methods (see Efron and Tibshiarani, 1993), which also facilitate a joint test across different trading rules that are not independent of each other. The basic idea is to compare the time series properties of a simulated data from a given model with those from the actual data. To that end, we first estimate the postulated model and bootstrap the residuals and the estimated parameters to generate bootstrap samples. Next we compute the trading rule profits for each of the bootstrap samples and compare this bootstrap distribution with the trading rule profits derived in Section 3 from the actual data.

Using information up to and including day $t$, the trading rules classify each day $t$ as either a buy ($b_t$), a sell ($s_t$) or, if a band is used, neutral ($n_t$). If we define the $h$-day return at $t$ as:

$$r_t^h = \log(p_{t+h}) - \log(p_t)$$

(where $p$ is the level of the index), then the expected $h$-day return conditional to a buy signal can be defined as

$$m_b = E(r_t^h | b_t)$$

and the expected $h$-day return conditional to a sell signal can be defined as

$$m_s \;=\; E(r_t^{\,h} | s_t)$$

The conditional standard deviations may then be defined as

$$\mathbf{ó}_b \;=\; (E[(r_t^{\,h} \;-\; m_b)^2 | b_t])^{1/2}$$

and

$$\mathbf{ó}_s \;=\; (E[(r_t^{\,h} \;-\; m_s)^2 | s_t])^{1/2}$$

These conditional expectations are estimated using appropriate sample means calculated from the IGBM series and compared to empirical-distributions from simulated null models for stock returns. Therefore, the bootstrap methods are use both to assess the profitability of various trading strategies and as a specification tool to obtain some indication of how the null model is failing to reproduce the data.

Regarding what model should be used to simulate the comparison series, following BLL (1992) we consider several commonly used models for stock prices: autorregressive process of order one (AR(1)), generalised autorregressive conditional heteroskedasticity model (GARCH) and GARCH in-mean model (GARCH-M).

The first model for simulation is the AR(1)

$$r_t \;=\; \mathbf{ä} \;+\; \mathbf{ñ} r_{t-1} \;+\; \varepsilon_t, \quad |\mathbf{ñ}|<1$$

where $r_t$ is the return of day *t* and $\mathbf{å}_t$ is independent, identically distributed. The parameters (**ä** and **ñ**) and the residuals $\mathbf{â}_t$ are estimated from the IGBM series using ordinary least squares (OLS).

The residuals are then resampled with replacement and the AR(1)s are generated using the estimated parameters and crumbled residuals.

The second model for simulation is the GARCH(1,1) model

$$r_t = \text{ä} + \text{æ}r_{t-1} + \text{å}_t$$

$$h_t = \text{ø} + \text{Æ}\text{å}^2_{t-1} + \text{â}h_{t-1}$$

$$\text{å}_t = h_t^{1/2} z_t, \quad z_t \sim N(0,1)$$

where the residual (å$_t$) is conditionally normally distributed with zero mean and conditional variance ($h_t$) and its standardized residuals ($z_t$) is i.i.d. N(0,1). This model allows for the conditional second moments of the return process to be serially correlated. This specification incorporates the familiar phenomenon of volatility clustering which is evident in financial market returns: large returns are more likely to be followed by large returns of either sign than by small returns. The parameters of the GARCH(1,1) model are estimated from the IGBM series using maximum likelihood. To adjust for heteroskedasticity, the resampling algorithm is applied to standardized residuals. Therefore, the heteroskedastic structure captured in the GARCH(1,1) model is maintained in simulations, and only the i.i.d. standardized residuals ( $\hat{z}_t = \text{å}_t/\hat{h}_t^{1/2}$) are resampled with replacement.

The last model considered in the simulation is the GARCH(1,1)-M model

$$r_t = \text{ä} + \text{æ}r_{t-1} + {}^{a}h_t + \text{å}_t$$

$$h_t = \text{ø} + \text{Æ}\text{å}^2_{t-1} + \text{â}h_{t-1}$$

$$\text{å}_t = h_t^{1/2} z_t, \quad z_t \sim N(0,1)$$

In this specification, the conditional variance is introduced in the mean equation of the model. This is an attractive form in financial applications since it is natural to suppose that the expected return on an asset is proportional to the expected risk of the asset. As in the GARCH(1,1) model, the parameters and standardized residuals are estimated from the IGBM series using maximum likelihood. Once again, the standardized residuals are resampled with replacement and used along with the estimated parameters to generate GARCH-M series.

Table 5 presents the estimation results for the AR(1), GARCH(1,1) and GARCH(1,1) models. Panel A shows the results from the estimation of an AR(1) model using OLS. As can be seen, there is a significant first order autocorrelation in the IGBM series. Panel B contains the results from estimation of a GARCH(1,1) model using maximum likelihood. Note that the model estimated also contains an AR(1) term to account for the strong autocorrelation. The estimated parameters **á** and **â** indicate that the conditional variance is time varying and strongly persistent. The variance persistence measure (**á** + **â**) is 0.9828. The results are in line with those reported by Olmeda and Pérez (1995) who studied nonlinearity in variance in the IGBM over the 1989-1994 period using a GARCH(1,1) model for the AR(1) residuals of the returns. The **ñ** parameter, capturing the first orden autocorrelation in the series, is also significantly positive. Finally, Panel C presents the results for the GARCH(1,1)-M model. As can be seen, the estimate conditional expected return is positively related with the conditional variance (**ã**=3.02).

[Table 5 here]

4.1. AR(1) Process

In Table 6 we display the results for a simulated AR(1) process by using the estimated residuals from the original series for the entire sample. This experiment is designed to detect whether the results from the trading rules could be caused by daily serial correlation in the series, since results reported in Table 1 document a significant first order autocorrelation in the IGBM series. The numbers presented in Panel A are the fractions of the 500 simulations that result in larger statistics than those for the observed IGBM series. These statistics include, as in Tables 2-4, the mean buy, mean sell, and mean buy-sell difference returns, and the conditional standard deviations **ó**$_b$ and **ó**$_s$ defined above. For example, for the VMA(1,50,0) rule, Table 6 shows that, for the period 4/1/66 to 15/10/97, 0.6 percent of the simulated series generated a mean buy return as large as that form the actual IGBM series. This can be thought of as a simulated "*p*-value". On the other hand, all of the simulated series generated a mean sell returns larger than the IGBM mean sell return, while only 0.4 percent of the simulated series generated mean buy-sell differences larger than the mean difference for the IGBM. The **ó**$_b$ and **ó**$_s$ entries show that every simulated buy conditional standard deviation exceeded that of the analogous IGBM standard deviation, whereas none of the simulated sell standard deviations was larger than the corresponding value from the observed series. While the results for the returns are consistent with the traditional tests presented in the corresponding Table 2, the results for the standard deviations are new. As can be seen, the buy signals pick out periods where higher conditional means are accompanied by lower volatilities. These findings are similar to those found for the Dow Jones Index in the United States by BLL (1992), who emphasised that these are not in accord with any argument that explains return predictability in terms of changing risk.

[Table 6 here]

Almost identical results are found for all the other VMA rules, while the TRB rules produce similar, if not quite as conclusive, findings [except for the (1,150,0.01) and (1,200, 0.01) cases]. Finally, for the FMA rule, the results show a slightly different picture since a higher proportion (79 percent) of the simulated series generated a mean buy return as large as that form the actual IGBM series following a FMA(1,50) rule (both with and without the one percent band), while only 0.04 percent of simulated buy conditional standard deviation exceeded that of the analogous IGBM standard deviation. As a result, 28 percent (13 percent) of the simulated series generated mean buy-sell differences larger than the mean difference for the IGBM, when the one percent band is not (is) considered. Similarly, for the FMA(1,200) rule, 94 percent of the simulated series generated a mean buy return as large as that form the actual IGBM series, while 73 percent of the simulated series generated mean buy-sell differences larger than the mean difference for the IGBM. The introduction of the one percent band reduces this percentages to 60 percent and 66 percent, respectively.

In Panel B of Table 6 the results are summarized across all the rules. An average is taken for the statistics generated from each of the six rules. For the mean buys this would be

$$m_b = 1/6[m_b\,(1,50,0)] + 1/6[m_b\,(1,50,0.01)] + 1/6[m_b\,(1,150,0)] + 1/6[m_b\,(1,150,0.01)] + 1/6[m_b\,(1,200,0)] + 1/6[m_b\,(1,200,0.01)]$$

The results presented in the first row of Panel B (Fraction>IGBM), which follows the same format as Panel A, strongly agree with those for the individual rules. The second row (Mean) shows the returns and standard deviations of the buys, sells, and buy-sells, averaged over the 500 simulated AR(1) processes, and the third row (IGBM) shows the same statistics for the original IGBM series. As can be seen, the simulated buy mean returns in the column "Buy" are lower than the actual mean returns for the VMA and TRB rules. However, this difference is not significant as indicated by the "*p*-value" of 0.002 and 0.0637, respectively. In contrast, for the FMA rule, the opposite occurs, being the difference significant with a "*p*-value" of 0.569. On the other hand, for all three rules, the simulated sell mean returns are less negative than the actual sell mean returns, being the difference highly significant. Finally, the simulated buy-sell spreads are lower than the actual spread for all three rules, being the difference more significant for the FMA case. These results suggest that the simple serial correlation implied by the AR(1) model cannot explain the trading profits.

4.2. GARCH Process

Table 7 repeats the previous results for a simulated GARCH(1,1) model. This model allows for the conditional second moments of the return process to be serially correlated.

Checking the "Buy-Sell" column in Table 7, Panel B, the VMA rule shows that the GARCH model generated an average spread of 0.12 percent, compared with 0.16 percent for the IGBM series. Only 9.13 percent of the simulations generated buy-sell returns as large as those from the IGBM series. The GARCH model generated a positive buy-sell spread that is substantially larger than the spread under the AR(1) process, but this spread is still small when compared with that from the original IGBM series. In contrast, for both the FMA rule and the TRB rule,  the GARCH model generated an average spread higher than those from the IGBM series (2.02 percent and 2.41 percent, compared with 1.67 percent and 2.31 percent for the IGBM series, respectively). The percentage of simulated series that generated a buy-sell returns as large as those from the IGBM series is 56 percent for the FMA rule and 47 percent for the TRB rule.

Regarding the simulated buy mean returns, they are lower than the actual mean returns for the VMA and TRB rules, being the associated "*p*-value" 0.11 and 0.30, respectively. For the FMA rule, the simulated buy mean returns are higher than the actual mean returns, being the difference highly significant with a "*p*-value" of 0.66. As for the simulated sell mean returns, they are less negative than the actual sell mean returns for theVMA rule, equal for the FMA rule and more negative for the TRB rule, and the "*p*-values" of these differences are 0.13, 0.45 and 0.56, respectively.

Turning now to volatility, it should be noted that for the IGBM series standard deviations are lower for the buy periods than for the sell periods. Panel B of Table 7 shows that, for all three trading rules, the average standard deviations for both buys and sells are larger from the GARCH model than those from the IGBM series. For most of the cases, the "*p*-values" support the significance of these differences. Hence, the GARCH model is substantially overestimating the volatility for both buy and sell periods.

[Table 7 here]

4.3. GARCH-M Process

Since a changing conditional mean can potentially explain some of the differences between buy and sell returns, the next simulations examine the GARCH-M model. These results are presented in Table 8.

In Panel B of Table 8, we see in the "Buy", "Sell" and "Buy-Sell" columns that the results are similar to those from the GARCH.

Simulated buy mean returns are similar to those from the GARCH: for the VMA and TRB rules they are lower than the actual mean returns (with associated "*p*-value" 0.06 and 0.20, respectively), while for the FMA rule, the simulated buy mean returns are higher than the actual mean returns (with a "*p*-value" of 0.61). In the case of the simulated sell mean returns, there are some differences with respect to the GARCH results. As can be seen, they are less negative than the actual sell mean returns for the VMA rule, and more negative for the FMA rule and TRB rule, being these differences highly significant as indicated by the "*p*-values" of 0.18, 0.49 and 0.64, respectively.

Regarding the volatility, as in the GARCH case, for all three trading rules, the average standard deviations for both buys and sells are larger from the GARCH-M model than those from the IGBM series. Nevertheless, we observe some changes in the results when compared to GARCH. For the VMA and the FMA rules, the conditional buy volatilities are lower for the GARCH-M than for the GARCH, while the opposite is true for the dell volatilities. For the TRB rule, the GARCH-M model generated higher buy volatility than the GARCH model, while the conditional sell volatilities are similar for the GARCH-M and for the GARCH.

[Table 8 here]

As in Section 3, we have also considered two nonoverlapping subperiods, being 19 October 1987 the breaking point. As before, the results (not present here, but available from the authors upon request) do not suggest significant differences across subperiods.

**5. Concluding remarks**

In this paper we have investigated the possibility that technical rules contain significant return forecast power. To that end, we have evaluated simple forms of technical analysis for the General Index of the Madrid Stock Exchange (IGBM), using daily data for the thirty-one-year period from 1966 to 1997.

On the one hand, our results suggest that technical trading rules generate buy signals that consistently yield higher returns than sell signals, suggesting that technical analysis does have power to forecast price movements. Moreover, the returns following buy signals are less volatile than returns on sell signals. This evidence could indicate the existance of nonlinearities in the IGBM data generating mechanism. In addittion, we find that returns following sell signals are negative, which are not easily explained by any of the currently existing equilibrium models.

On the other hand, we combine bootstrap methods and technical trading rules for the purpose of checking the adequacy of several models frequently used in finance [such as AR(1), GARCH and GARCH-M models]. We find that returns obtained from buy (sell) signals from the actual IGBM series are not likely generated by any of these models. Not only do they fail in predicting returns, but they also fail in predicting volatility (even in the case of the GARCH and GARCH-M models).

Given that the period covered is very long and heterogeneous, with a number of important events that could affect the structure of the series, we have also considered two nonoverlapping subperiods, being 19 October 1987 the breaking point. However, we found no evidence that the results are different across subperiods.

Therefore, our results provide strong support for profitability of simple technical trading rules and are in general consistent with those previously reported by BLL (1992) for the Dow Jones Index from 1897 to 1986, suggesting that earlier conclusions that found technical analysis to be useless might have been premature.

Nevertheless, the results should be taken with caution since reported gains may not seem to be high enough to translate into profits after transaction costs are considered. It would be worthwhile to investigate the performance of more elaborate trading rules and their profitability after transaction costs and brokerage fees are taken into account. This question is left for future research.

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Table 1: Summary statistics for daily and 10-day returns

| Panel A: Daily returns | |
|---|---|
| Sample size (n) | 6930 |
| Mean | 0.00039 |
| Std. deviation | 0.0091 |
| Skewness | -0.0656 |
| Kurtosis | 11.41 |
| **ñ**(1) | 0.323 |
| **ñ**(2) | 0.084 |
| **ñ**(3) | 0.039 |
| **ñ**(4) | 0.038 |
| **ñ**(5) | -0.001 |
| Barlett std. | 0.012 |
| **Panel B: 10-day returns** | |
| Sample size (n) | 692 |
| Mean | 0.0030 |
| Std. deviation | 0.0377 |
| Skewness | -0.6525 |
| Kurtosis | 10.03 |
| **ñ**(1) | 0.118 |
| **ñ**(2) | 0.030 |
| **ñ**(3) | 0.052 |
| **ñ**(4) | -0.024 |
| **ñ**(5) | 0.019 |
| Barlett std. | 0.038 |

Note: "Barlett std." refers to the Barlett standard error for autocorrelation, $(n)^{-1/2}$.

| Table 2: Standard results for the variable-length moving (VMA) rules | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Period | Test | N(buy) | N(sell) | Buy | Sell | Buy>0 | Sell>0 | Buy-sell |
| 4/1/66 to 15/10/97 | (1,50,0) | 4057 | 2824 | 0.0012 | -0.0007 | 0.5554 | 0.4418 | 0.0019 |
| | | | | (4.6153) | (-5.0125) | | | (8.1554) |
| | (1,50,0.01) | 3492 | 2332 | 0.0013 | -0.0009 | 0.5644 | 0.4358 | 0.0022 |
| | | | | (5.0544) | (-5.1658) | | | (8.3178) |
| | (1,150,0) | 4220 | 2561 | 0.0009 | -0.0005 | 0.5475 | 0.4437 | 0.0014 |
| | | | | (3.2164) | (-3.7041) | | | (5.7912) |
| | (1,150,0.01) | 3984 | 2358 | 0.0010 | -0.0005 | 0.5516 | 0.4408 | 0.0014 |
| | | | | (3.5038) | (-3.6219) | | | (5.8296) |
| | (1,200,0) | 4242 | 2489 | 0.0009 | -0.0004 | 0.5450 | 0.4439 | 0.0013 |
| | | | | (2.9315) | (-3.4622) | | | (5.3403) |
| | (1,200,0.01) | 4088 | 2328 | 0.0009 | -0.0005 | 0.5474 | 0.4430 | 0.0014 |
| | | | | (3.1446) | (-3.4644) | | | (5.4315) |
| | Average | | | 0.0010 | -0.0006 | | | 0.0016 |

Notes: Rules are identified as (*s*,*l*,*b*), where *s* and *l* are the length of the short and long period (in days) and *b* is the band (either 0 or 1%). "N(buy)" and "N(Sell)" are the number of buy and sells signals generated by the rule. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. Number in parentheses are standard *t*-statistics testing the difference, respectively, between the mean buy return and the unconditional mean return, the mean sell return and the unconditional mean return, and buy-sell and zero. The last row reports averages across all 10 rules.

Table 3: Standard results for the fixed-length moving (FMA) rules

| Period | Test | N(buy) | N(sell) | Buy | Sell | Buy>0 | Sell>0 | Buy-sell |
|---|---|---|---|---|---|---|---|---|
| 4/1/66 to 15/10/97 | (1,50,0) | 73 | 81 | 0.0073 | -0.0088 | 0.6164 | 0.4321 | 0.0161 |
| | | | | (0.7825) | (-2.4595) | | | (2.2991) |
| | (1,50,0.01) | 59 | 55 | 0.0075 | -0.0135 | 0.5932 | 0.3273 | 0.0211 |
| | | | | (0.7490) | (-2.8604) | | | (2.5864) |
| | (1,150,0) | 25 | 41 | 0.0202 | -0.0069 | 0.8400 | 0.4634 | 0.0271 |
| | | | | (3.3482) | (-1.4596) | | | (3.2869) |
| | (1,150,0.01) | 24 | 34 | 0.0152 | -0.0020 | 0.7500 | 0.4412 | 0.0172 |
| | | | | (2.1588) | (-0.6404) | | | (1.8270) |
| | (1,200,0) | 27 | 25 | 0.0022 | -0.0063 | 0.5556 | 0.3200 | 0.0085 |
| | | | | (0.1272) | (-0.8596) | | | (0.6897) |
| | (1,200,0.01) | 20 | 22 | 0.0093 | -0.0009 | 0.7000 | 0.5000 | 0.0102 |
| | | | | (1.0501) | (-0.3563) | | | (0.8366) |
| | Average | | | 0.0103 | -0.0064 | | | 0.0167 |

Note: See Table 2.

Table 4: Standard results for the trading range break (TRB) rules

| Period | Test | N(buy) | N(sell) | Buy | Sell | Buy>0 | Sell>0 | Buy-sell |
|---|---|---|---|---|---|---|---|---|
| 4/1/66 to 15/10/97 | (1,50,0) | 201 | 132 | 0.0150 | -0.0058 | 0.6368 | 0.4167 | 0.0208 |
| | | | | (3.8381) | (-2.2448) | | | (4.4024) |
| | (1,50,0.01) | 99 | 65 | 0.0177 | -0.0037 | 0.6667 | 0.4462 | 0.0239 |
| | | | | (2.9729) | (-1.4318) | | | (2.9695) |
| | (1,150,0) | 152 | 67 | 0.0155 | -0.0067 | 0.6316 | 0.4478 | 0.0192 |
| | | | | (3.5649) | (-1.1629) | | | (2.8413) |
| | (1,150,0.01) | 75 | 32 | 0.0170 | -0.0083 | 0.6533 | 0.3750 | 0.0253 |
| | | | | (2.3314) | (-1.4084) | | | (2.5285) |
| | (1,200,0) | 139 | 60 | 0.0167 | -0.0039 | 0.6403 | 0.4667 | 0.0206 |
| | | | | (3.7160) | (-1.1235) | | | (2.8451) |
| | (1,200,0.01) | 68 | 29 | 0.0197 | -0.0093 | 0.6912 | 0.3793 | 0.0290 |
| | | | | (2.6988) | (-1.4392) | | | (2.7504) |
| | Average | | | 0.0169 | -0.0062 | | | 0.0231 |

Note: See Table 2.

Table 5: Parameters estimates for the AR(1), GARCH(1,1) and GARCH(1,1)-M models

Panel A: AR(1) parameters estimate

$r_t$ = ä + æ$r_{t-1}$ + å$_t$

| ä | æ |
|---|---|
| 0.0002 | 0.3283 |
| (2.51) | (29.54) |

Panel B: GARCH(1,1) parameters estimate

$r_t$ = ä + æ$r_{t-1}$ + å$_t$

$h_t$ = ø + Æå$^2_{t-1}$ + â$h_{t-1}$

å$_t$ = $h_t^{1/2} z_t$,    $z_t \sim N(0,1)$

| ä | æ | ø | Æ | â |
|---|---|---|---|---|
| 0.0003 | 0.4105 | 1.70e-7 | 0.1502 | 0.8326 |
| (3.95) | (39.11) | (15.24) | (18.08) | (100.10) |

Panel C: GARCH(1,1)-M parameters estimate

$r_t$ = ä + æ$r_{t-1}$ + ª$h_t$ + å$_t$

$h_t$ = ø + Æå$^2_{t-1}$ + â$h_{t-1}$

å$_t$ = $h_t^{1/2} z_t$,    $z_t \sim N(0,1)$

| ä | æ | ª | ø | Æ | â |
|---|---|---|---|---|---|
| 0.0005 | 0.4114 | 3.0215 | 1.72e-6 | 0.1567 | 0.8267 |
| (2.08) | (39.11) | (2.88) | (15.35) | (18.06) | (97.48) |

Notes: Estimated on daily returns series for the 4/1/66-15/10/97 period. The AR(1) is estimated by OLS, while the GARCH(1,1) and GARCH(1,1)-M models are estimated using maximum likelihood. Numbers in parentheses are *t*-ratios.

| Table 6 : Simulation tests from AR(1) bootstraps for 500 replications | | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel A: Individual rules | | | | | | | |
| Rule | | Result | Buy | **ó**$_{b}$ | Sell | **ó**$_{s}$ | Buy-Sell |
| (1,50,0) | VMA | Fraction>IGBM | 0.0060 | 1.0000 | 0.0000 | 0.0000 | 0.0040 |
| | FMA | Fraction>IGBM | 0.7900 | 0.0360 | 0.0028 | 0.2180 | 0.2800 |
| | TRB | Fraction>IGBM | 0.0100 | 0.7460 | 0.0700 | 0.0180 | 0.0100 |
| (1,50,0.01) | VMA | Fraction>IGBM | 0.0040 | 1.0000 | 0.0060 | 0.0000 | 0.0040 |
| | FMA | Fraction>IGBM | 0.7940 | 0.0440 | 0.0080 | 0.2620 | 0.1260 |
| | TRB | Fraction>IGBM | 0.0860 | 0.0200 | 0.4100 | 0.0000 | 0.1820 |
| (1,150,0) | VMA | Fraction>IGBM | 0.0000 | 1.0000 | 0.0000 | 0.0000 | 0.0000 |
| | FMA | Fraction>IGBM | 0.0500 | 1.0000 | 0.2260 | 0.2100 | 0.0500 |
| | TRB | Fraction>IGBM | 0.0220 | 0.6200 | 0.3520 | 0.0120 | 0.0900 |
| (1,150,0.01) | VMA | Fraction>IGBM | 0.0020 | 1.0000 | 0.0000 | 0.0000 | 0.0000 |
| | FMA | Fraction>IGBM | 0.2420 | 0.9900 | 0.5800 | 0.1480 | 0.4000 |
| | TRB | Fraction>IGBM | 0.1740 | 0.0120 | 0.3040 | 0.1220 | 0.2080 |
| (1,200,0) | VMA | Fraction>IGBM | 0.0000 | 1.0000 | 0.0020 | 0.0000 | 0.0000 |
| | FMA | Fraction>IGBM | 0.9360 | 0.9440 | 0.3020 | 0.0100 | 0.7320 |
| | TRB | Fraction>IGBM | 0.0100 | 0.5280 | 0.3600 | 0.0080 | 0.0600 |
| (1,200,0.01) | VMA | Fraction>IGBM | 0.0000 | 1.0000 | 0.0020 | 0.0000 | 0.0000 |
| | FMA | Fraction>IGBM | 0.6020 | 0.9860 | 0.6420 | 0.0400 | 0.6600 |
| | TRB | Fraction>IGBM | 0.0800 | 0.0120 | 0.2740 | 0.1140 | 0.1380 |
| Panel B: Rule Averages | | | | | | | |
| Rule | | Result | Buy | **ó**$_{b}$ | Sell | **ó**$_{s}$ | Buy-Sell |
| Rule average | VMA | Fraction>IGBM | 0.0020 | 1.0000 | 0.0017 | 0.0000 | 0.0013 |
| | | Mean | 0.0007 | 0.0091 | -0.0001 | 0.0091 | 0.0009 |
| | | IGBM | 0.0010 | 0.0084 | -0.0006 | 0.0105 | 0.0016 |
| Rule average | FMA | Fraction>IGBM | 0.5690 | 0.6667 | 0.2977 | 0.1480 | 0.3747 |
| | | Mean | 0.0109 | 0.3867 | -0.0030 | 0.0390 | 0.0139 |
| | | IGBM | 0.0103 | 0.0334 | -0.0064 | 0.0455 | 0.0167 |
| Rule average | TRB | Fraction>IGBM | 0.0637 | 0.3230 | 0.2950 | 0.0457 | 0.1147 |
| | | Mean | 0.0114 | 0.0386 | -0.0034 | 0.0389 | 0.0148 |
| | | IGBM | 0.0169 | 0.0425 | -0.0062 | 0.0487 | 0.0231 |

| Table 7: Simulation tests from GARCH(1,1) bootstraps for 500 replications | | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel A: Individal rules | | | | | | | |
| Rule | | Result | Buy | **ó**$_b$ | Sell | **ó**$_s$ | Buy-Sell |
| (1,50,0) | VMA | Fraction>IGBM | 0.1520 | 0.9760 | 0.1360 | 0.4940 | 0.1120 |
| | FMA | Fraction>IGBM | 0.8320 | 0.5700 | 0.1900 | 0.8180 | 0.5080 |
| | TRB | Fraction>IGBM | 0.1320 | 0.9820 | 0.3100 | 0.7980 | 0.2100 |
| (1,50,0.01) | VMA | Fraction>IGBM | 0.2180 | 0.9920 | 0.1720 | 0.5260 | 0.1500 |
| | FMA | Fraction>IGBM | 0.8240 | 0.6320 | 0.0900 | 0.8800 | 0.3620 |
| | TRB | Fraction>IGBM | 0.4240 | 0.9000 | 0.6960 | 0.8260 | 0.6320 |
| (1,150,0) | VMA | Fraction>IGBM | 0.0820 | 0.9620 | 0.0980 | 0.4500 | 0.0640 |
| | FMA | Fraction>IGBM | 0.1760 | 1.0000 | 0.4580 | 0.8400 | 0.2560 |
| | TRB | Fraction>IGBM | 0.2220 | 0.9680 | 0.5840 | 0.7240 | 0.4220 |
| (1,150,0.01) | VMA | Fraction>IGBM | 0.0700 | 0.9700 | 0.1500 | 0.4900 | 0.0900 |
| | FMA | Fraction>IGBM | 0.4440 | 0.9980 | 0.6840 | 0.8020 | 0.6120 |
| | TRB | Fraction>IGBM | 0.04960 | 0.8100 | 0.6060 | 0.9020 | 0.5860 |
| (1,200,0) | VMA | Fraction>IGBM | 0.0740 | 0.9460 | 0.1060 | 0.4400 | 0.0620 |
| | FMA | Fraction>IGBM | 0.9360 | 0.9760 | 0.5260 | 0.4940 | 0.8320 |
| | TRB | Fraction>IGBM | 0.1520 | 0.9500 | 0.5820 | 0.7120 | 0.4240 |
| (1,200,0.01) | VMA | Fraction>IGBM | 0.0620 | 0.9460 | 0.1240 | 0.4840 | 0.0700 |
| | FMA | Fraction>IGBM | 0.7440 | 0.9960 | 0.7680 | 0.7000 | 0.7880 |
| | TRB | Fraction>IGBM | 0.3640 | 0.7980 | 0.6160 | 0.8880 | 0.5480 |
| Panel B: Rule Averages | | | | | | | |
| Rule | | Result | Buy | **ó**$_b$ | Sell | **ó**$_s$ | Buy-Sell |
| Rule average | VMA | Fraction>IGBM | 0.1097 | 0.9653 | 0.1310 | 0.4807 | 0.0913 |
| | | Mean | 0.0009 | 0.0101 | -0.0003 | 0.0112 | 0.0012 |
| | | IGBM | 0.0010 | 0.0084 | -0.0006 | 0.0105 | 0.0016 |
| Rule average | FMA | Fraction>IGBM | 0.6593 | 0.8620 | 0.4527 | 0.7557 | 0.5597 |
| | | Mean | 0.0138 | 0.0532 | -0.0064 | 0.0576 | 0.0202 |
| | | IGBM | 0.0103 | 0.0334 | -0.0064 | 0.0455 | 0.0167 |
| Rule average | TRB | Fraction>IGBM | 0.2983 | 0.9013 | 0.5657 | 0.8083 | 0.4703 |
| | | Mean | 0.0147 | 0.0564 | -0.0095 | 0.0726 | 0.0241 |
| | | IGBM | 0.0169 | 0.0425 | -0.0062 | 0.0487 | 0.0231 |

Table 8: Simulation tests from GARCH-M(1,1) bootstraps for 500 replications

Panel A: Individual rules

| Rule | | Result | Buy | **ó**$_{b}$ | Sell | **ó**$_{s}$ | Buy-Sell |
|---|---|---|---|---|---|---|---|
| (1,50,0) | VMA | Fraction>IGBM | 0.0760 | 0.9680 | 0.1840 | 0.5280 | 0.1160 |
| | FMA | Fraction>IGBM | 0.8080 | 0.5640 | 0.2200 | 0.8240 | 0.5140 |
| | TRB | Fraction>IGBM | 0.0700 | 0.9700 | 0.4320 | 0.7760 | 0.2140 |
| (1,50,0.01) | VMA | Fraction>IGBM | 0.1180 | 0.9840 | 0.2320 | 0.5640 | 0.1600 |
| | FMA | Fraction>IGBM | 0.7640 | 0.6020 | 0.1320 | 0.8720 | 0.3660 |
| | TRB | Fraction>IGBM | 0.3060 | 0.8980 | 0.7520 | 0.8200 | 0.6420 |
| (1,150,0) | VMA | Fraction>IGBM | 0.4400 | 0.9480 | 0.1460 | 0.4940 | 0.0760 |
| | FMA | Fraction>IGBM | 0.1700 | 1.0000 | 0.4920 | 0.8600 | 0.2560 |
| | TRB | Fraction>IGBM | 0.0980 | 0.9600 | 0.6700 | 0.7320 | 0.4500 |
| (1,150,0.01) | VMA | Fraction>IGBM | 0.0360 | 0.9600 | 0.2020 | 0.5260 | 0.0880 |
| | FMA | Fraction>IGBM | 0.4080 | 0.9980 | 0.7700 | 0.8420 | 0.6240 |
| | TRB | Fraction>IGBM | 0.3880 | 0.8380 | 0.6880 | 0.9040 | 0.6320 |
| (1,200,0) | VMA | Fraction>IGBM | 0.0360 | 0.9240 | 0.1520 | 0.5000 | 0.0560 |
| | FMA | Fraction>IGBM | 0.8780 | 0.9760 | 0.5780 | 0.5440 | 0.8220 |
| | TRB | Fraction>IGBM | 0.0820 | 0.9400 | 0.6700 | 0.7120 | 0.4300 |
| (1,200,0.01) | VMA | Fraction>IGBM | 0.0380 | 0.9140 | 0.1680 | 0.5240 | 0.0700 |
| | FMA | Fraction>IGBM | 0.6440 | 0.9960 | 0.7720 | 0.7040 | 0.7920 |
| | TRB | Fraction>IGBM | 0.2600 | 0.8240 | 0.6480 | 0.8860 | 0.5460 |
| Panel B: Rule Averages | | | | | | | |
| Rule | | Result | Buy | **ó**$_{b}$ | Sell | **ó**$_{s}$ | Buy-Sell |
| Rule average | VMA | Fraction>IGBM | 0.0580 | 0.9497 | 0.1807 | 0.5227 | 0.0943 |
| | | Mean | 0.0008 | 0.0099 | -0.0004 | 0.0113 | 0.0012 |
| | | IGBM | 0.0010 | 0.0084 | -0.0006 | 0.0105 | 0.0016 |
| Rule average | FMA | Fraction>IGBM | 0.6120 | 0.8560 | 0.4940 | 0.7743 | 0.5623 |
| | | Mean | 0.0126 | 0.0531 | -0.0077 | 0.0595 | 0.0204 |
| | | IGBM | 0.0103 | 0.0334 | -0.0064 | 0.0455 | 0.0167 |
| Rule average | TRB | Fraction>IGBM | 0.2007 | 0.9080 | 0.6433 | 0.8050 | 0.4857 |
| | | Mean | 0.0126 | 0.0567 | -0.0117 | 0.0712 | 0.0243 |
| | | IGBM | 0.0169 | 0.0425 | -0.0062 | 0.0487 | 0.0231 |