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Online Publication Date: 01 July 2005


URL: http://dx.doi.org/10.1080/09603100500107818

To link to this article: DOI: 10.1080/09603100500107818

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Optimization of technical rules by genetic algorithms: evidence from the Madrid stock market

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This paper investigates the profitability of a simple and very common technical trading rule applied to the General Index of the Madrid Stock Market. The optimal trading rule parameter values are found using a genetic algorithm. The results suggest that, for reasonable trading costs, the technical trading rule is always superior to a risk-adjusted buy-and-hold strategy.

I. Introduction

A considerable amount of work has provided support for the view that simple technical trading rules (TTRs) are capable of producing valuable economic signals (see, Brock et al., 1992; Bessembinder and Chan, 1995; Mills, 1997; Fernández Rodríguez et al., 1999, among others). However, the majority of these studies have ignored the issue of parameter optimization, leaving them open to the criticism of data-snooping and the possibility of a survivorship bias (see Lo and MacKinley, 1990; Brown et al., 1995, respectively). To avoid this criticism, a more objective and valid approach consists in choosing TTRs based on an optimization procedure utilizing in-sample data and testing the performance of these rules out-of-sample. In this sense, a genetic algorithm is appropriate method to discover TTRs, as shown in Allen and Karjalainen (1999).

The aim of this paper is to investigate the profitability of some popular TTRs using genetic algorithm optimization procedures. Section II describes the TTRs examined in this paper, while Section III presents the genetic algorithms. The empirical results are shown in Section IV.

II. Technical Trading Rules

The simplest and most common trading rules are moving averages (MA). In particular, a generalized MA (GMA) rule that can be represented by the following binary indicator function is considered:

\[ S(\Theta)_t = MA(\theta_1)_t - (1 + (1 - 2S_{t-1})\theta_2)MA(\theta_2)_t \]

where \( \Theta = [\theta_1, \theta_2, \theta_3] \) denotes the parameters associated to the GMA rule, and \( MA(\theta) \) is a MA indicator defined as follows:

\[ MA(\theta) = \frac{1}{\theta} \sum_{t=0}^{\theta-1} P_{t-\theta}, \quad t = \theta, \theta + 1, \ldots, N \]

The lengths of the short and long MA are given by \( \theta_1 \) and \( \theta_2 \), while \( \theta_3 \) represents a filter parameter included to reduce the number of false buy and sell signals.

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generated by a MA rule when price movement is non-directional.

The GMA rule is used to indicate the trading position that should be taken at time \( t \). In particular, Equation 1 returns either a positive or negative number, corresponding to a buy or sell signal being codified as a one or zero, respectively.1

### III. Genetic Algorithms

Genetic algorithms (GA), developed by Holland (1975), are a class of adaptive search and optimization technique. A GA starts with a population of randomly generated solution candidates, which are evaluated in terms of an objective function. These candidates are usually represented by vectors consisting in binary digits. Promising candidates, as represented by relatively better performing solutions, are then combined through a process of binary recombination referred to as crossover. Finally, random mutations are introduced to safeguard against the loss of genetic diversity, avoiding local optima. Successive generations are created in the same manner and evaluated using the objective function until a well-defined criterion is satisfied.

In order to determine which solution candidates are allowed to participate in the crossover and undergo possible mutation, the genitor selection method proposed by Whitley (1989) is applied. This approach involves ranking all individuals according to performance and then replacing the poorly performing individuals by copies of better performing ones. In addition, the commonly used single point crossover is applied, consisting in randomly pairing candidates surviving the selection process and randomly selecting a break point at a particular position in the binary representation of each candidate. This break point is used to separate each vector into two subvectors. The two subvectors to the right of the break point are used to separate each vector into two subvectors. Finally, mutation occurs by randomly selecting a particular element in a particular vector. If the element is a one it is mutated to zero, and vice versa. This occurs with a very low probability in order not to destroy promising areas of search space.

### IV. Empirical Results

The data consists of daily closing prices of the General Index of the Madrid Stock Exchange (IGBM) and the daily 3-month rate in the interbank deposits markets, covering the 2 January 1972 to 15 November 1997 period (4376 observations). The total period is split into an in-sample optimization period from 2 January 1972 to 16 December 1988 and an out-of-sample test period from 16 December 1988 to 15 November 1997 (2188 observations in each subperiod).

The initial population was set at 150 candidates, while the maximum number of both generations allowed and iterations without improvement was fixed at 300. The maximum probabilities associated with the occurrence of crossover and mutation were set at 6% and 0.5%, respectively. These choices were guided by previous studies (see, Bauer, 1994) and experimentation with different values.

The signals from the trading rules are used to divide the total number of trading days (\( N \)) into either ‘in’ the market (earning the market return \( r_{mt} = \ln(P_t/P_{t-1}) \)) i.e. \( P_t/P_{t-1} \) or ‘out’ of the market (earning the risk-free rate of return \( r_{ft} \)). Therefore, the objective function used to evaluate the trading rules is given by the following expression:

\[
    r_{tr} = \sum_{i=1}^{N} S_{t-1} r_{mt} + \sum_{i=1}^{N} (1 - S_{t-1}) r_{ft} - T * c
\]

where \( T \) is the number of transactions and \( c \) is the cost per transaction.

As an appropriate benchmark, we consider the return from a risk-adjusted buy and hold strategy defined as

\[
    r_{bh} = \alpha \sum_{i=1}^{N} r_{ft} + (1 - \alpha) \sum_{i=1}^{N} r_{mt} - 2c
\]

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1 Three different MA rules are nested within the GMA rule and can be derived individually by imposing certain restrictions on Equation 1:

1. Simple MA: \( \theta_1 = 1, \theta_2 > 1, \theta_3 = 0 \)

\[
    S(\Theta)_t = P_t - MA(\theta_2)_t
\]

2. Filtered MA: \( \theta_1 = 1, \theta_2 > 1, \theta_3 > 0 \)

\[
    S(\Theta)_t = P_t - (1 + (1 - 2S_{t-1})\theta_3)MA(\theta_2)_t
\]

3. Double MA: \( \theta_1 > 1, \theta_2 > \theta_1, \theta_3 = 0 \)

\[
    S(\Theta)_t = MA(\theta_1)_t - MA(\theta_2)_t
\]
where \( \alpha \) is the proportion of trading days that the rule is out of the market.

Table 1 summarizes the results. As can be seen, the best GMA rules are double MA rules, without a filter parameter (except for the case of 0 transaction costs). The Sharpe ratio and the annualized returns corresponding to the best GMA rule are higher than those from the risk-adjusted buy and hold strategy, both for the in-sample and out-of-sample periods. It is interesting to note that this result holds for all transaction costs examined.

### Acknowledgements

We are very grateful to Mayte Ledo (BBVA) for kindly providing us with the data set used in this paper. Simón Sosvilla-Rivero also acknowledges partial financial support by the Spanish Ministry of Education, through DGICYT Project PB98-0546-C02-02. Fernando Fernández-Rodríguez also acknowledges support by the Spanish Ministry of Education, through the Project PB2001-3777.

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\[ \text{SR} = \frac{\bar{r}}{\sigma \sqrt{Y}} \]

\[ \bar{r} \] is the average annualized return of the trading strategy, \( \sigma \) is the standard deviation of daily trading rule returns, and \( Y \) is equal to the number of trading days per year.

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