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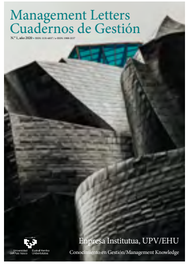

Temporal optimisation of signals emitted automatically by securities exchange indicators

Optimización temporal de las señales automáticas proporcionadas por indicadores técnicos bursátiles

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ABSTRACT

Stock exchange indicators deliver buy/sell signals that enable analysts to improve the results of a strategy based strictly on fundamental analysis. Nonetheless, since the automatic implementation of signals as they appear may not yield optimal returns, the present paper analysed the suitability of using a series of technical indicators as guidance for portfolio results. A second aim pursued was to study how delaying the implementation of indicator signals may enhance profitability.

A simulation was performed for the years 2005-2016 using the most representative index for the Spanish stock exchange, the IBEX35 and all its constituent securities, along with seven indicators (RoC, RSI, SMA, EMA, MACD, Bollinger bands and Stochastic Oscillator) and a total of 81 combinations of buy/sell lag times. The definition of three non-overlapping sub-periods to guarantee the reliability of the findings yielded a total of 61 236 simulated portfolios.

The conclusion drawn from the results was that for certain combinations of indicators, delaying the implementation of buy/sell signals improves returns. More specifically, optimal lag times identified for RSI and EMA signals were shown to deliver statistically significant improvements in portfolio returns, irrespective of the period studied. Those findings were consistent the results of an alternative simulation in which the five securities that were both the most liquid and had the greatest impact on the index were not considered, to rule out the possible effect of the relative weight of securities on either portfolio returns or their normalisation.

Keywords: Technical analysis, trading strategy, stock market, optimal lags, RSI, EMA.

RESUMEN

Los indicadores técnicos bursátiles transmiten al analista señales de compra/venta que, en el caso de ser ejecutadas en el momento de producirse, podrían no ser óptimas desde el punto de vista del resultado de la operación. El objetivo del presente trabajo es doble. En primer lugar, analizar la idoneidad del seguimiento de una batería de indicadores para la obtención de resultados en una cartera. En segundo lugar, estudiar cómo la introducción de retardos temporales entre las señales de los indicadores y la ejecución de las operaciones puede mejorar el resultado de la misma.

Se ha realizado una simulación, para el intervalo 2005-2016, con 35 títulos y un índice, sobre 7 indicadores técnicos bursátiles (ROC, RSI, Cruce SMA, Cruce EMA, MACD, Bandas de Bollinger y oscilador estocástico) y un total de 81 combinaciones de retardos de compra/venta. La definición del modelo y la división en tres periodos no solapados genera un total de 61.236 carteras.

Los resultados permiten concluir que existen combinaciones de indicador y retardos de compra/venta que proporcionan mejores resultados que la ejecución inmediata de la señal. Concretamente, se identifican retardos óptimos para RSI y cruce EMA que producen mejoras estadísticamente significativas en el resultado de una cartera de valores, independientemente del periodo estudiado.

Estos resultados son consistentes con una simulación alternativa en la que se excluyó a los cinco activos más líquidos y de mayor capitalización, para descartar el posible efecto generado por el peso relativo de los valores en la rentabilidad de la cartera o en su normalización.

Palabras clave: Análisis técnico, estrategia de trading, bolsa de valores, retardos óptimos, RSI, cruce EMA

1. INTRODUCTION

Technical stock market analysis, which generates buy or sell signals for equities based on their historic performance, has an objective and a subjective component. The former is the equity's historical performance, whereas the latter, fruit of the analyst's interpretation, consists in identifying and inferring future performance from price and indicator patterns. Choosing the tools to use and the indicator to follow where contradictions arise, identifying patterns, interpreting data, selectively parsing all the information analysed or establishing when an event is relevant (Lim 2015) are subjective decisions. This study aimed to identify the indicators with best past performance to divest this type of analysis of as much of the subjective component as possible. The focus is on retail investors, whose nil individual market power raises higher entry and operating barriers.

The paper is particularly timely, for a substantial proportion of stock market transactions are now estimated to be conducted by algorithms with no human intervention. Gerig (2015) found that such so-called high-frequency trading (HFT) accounts for approximately 55 % of the volume in US equity markets and 40 % in European equity markets, while it is growing rapidly in Asian, fixed income, commodity, foreign exchange, and nearly every other market. According to Lewis & Baker (2014), approximately half of the US daily volume consists in HFT, whilst in Australia around 27 % of total equity market turnover involves such trading (Australian Securities and Investments Commission 2015). The European values appear to be more difficult to estimate. ESMA, the European Securities and Markets Authority, an independent body tasked with safeguarding the stability of the European Union's financial system, premised that in 2014 HFT ranged from 3.6 % to 60 % of the total (ESMA 2015). Against that backdrop, this article proposes a tool to support human decision-making able to accommodate a limited number of signals generated by the most widely used indicators.

The primary objective of this study is to provide investors, retail investors in particular, with a simple tool to support investment decisions and improve their portfolio returns in the absence of advantages available to other market agents, such as vast computer power, complex models and learning algorithms. More specifically, two partial objectives are pursued: 1) to verify whether an indicator can be found that furnishes buy-sell signals able to improve equity portfolio profitability using a broader series of parameters than normally found in the literature; and 2) when a specific indicator emits a buy or sell signal, to determine the optimal lag time for implementing the operation, i.e., the lag that yields the best possible result. To put it another way, the possibility analysed is whether, after a signal from a given indicator is received, a higher profit can be obtained by delaying the order for a certain amount of time.

These two objectives are aligned with the general thrust of a series of papers on combining the variable time with indicators for decision-making, as observed in the review of the literature in section 2 below. The data and methodology used are described in section 3, which is followed by a discussion of the results in section 4. The conclusions drawn are set out in section 5.

2. REVIEW OF THE LITERATURE

Technical analysis is an historical performance-based asset management tool that aims to anticipate future outcomes. Whilst no proof of the benefits of analysing the profitability of simple strategies was in place authors such as Fama & Blume (1966) and Jensen & Bennington (1970) published the earliest papers, many subsequent studies have addressed the utility of applying the approach to securities, indices, futures and currencies. The perception of technical analysis has since undergone a radical about-face. One of the milestones in the discipline was Brown & Jennings' (1989) use of past prices in a context in which prices do not furnish all the information and agents rationally analyse the relationship between prices and signals. Later, Brock, Lakonishok, & LeBaron (1992) applied 90 years of daily DJIA equity prices to 26 indicators, concluding that an investor following any single one would have out-performed the market. In the same timeframe, Taylor & Allen (1992) observed that over 90 % of decision-makers used these 'non-fundamental' signals to manage their portfolios. More recent papers have focused on neural networks and vector support machines (VSM): Leigh, Modani, Purvis & Roberts (2002) for the NYSE; Kim & Shin (2007) in combination with genetic algorithms; Kara, Boyacioglu & Baykan (2011) for the Istanbul Securities Exchange; and Rosillo, Giner & De la Fuente (2014) for the Spanish bourse.

Among the key factors are data pre-processing, the selection of indicators and the establishment of decision-making criteria, the area addressed hereunder. A study by Cavalcante, Brasileiro, Souza, Nobrega & Oliveira (2016) provides an overview of the most significant papers from 2009 to 2015 on pre-processing and grouping historical data for technical analysis. Two basic approaches can be distinguished in these papers: statistical modelling and machine learning. Wang, Wang, Zhang & Guo's (2011) extensive review of the wide variety of learning algorithms is highly recommended. Park & Irwin (2007), in turn, classified studies into six groups depending on the methodology used: standard, bootstrapping, genetic programming, reality verification, graphic pattern recognition and non-linear. For a review of the studies on the returns delivered by these algorithms, see Serbera & Paumard (2016).

The variability in the indicators used can also be gleaned from the literature. Chaboud, Chiquoine, Hjalmarsson & Vega (2014) and Wang, An & Liu. (2015) used list prices and transactions; Yang, Zhou & Wang (2009), list prices and macroeconomic data (stage of the business cycle, inflation, monetary policy); Agudelo & Uribe (2009), supports and resistances; Wang & Chan (2007), Fernandes, Hamberger & do Valle (2015) and Cervelló-Royo Guijarro & Michniuk (2015), pattern recognition; Rodriguez-Gonzalez, Garcia-Crespo & Colomo-Palacios (2011), the relative strength index (RSI); Chong & Ng (2008), RSI and moving average convergence divergence (MACD); and Rosillo, De la Fuente & Brugos (2013), RSI, MACD, momentum and stochastics. The fairly small number of indicators used as a rule is a shortcoming that this study attempts to remedy.

Hudson, Dempsey & Keasey (1996), Mills (1997), Olson (2004), Bessembinder & Chan (1998), Ito (1999) and Day & Wang (2002) observed benefits of technical analysis to decline over time. That may be the result, among others, of sampling bias, data espionage (Ready 2002) or the effect of the quickly growing use of technical analysis (Chang, Wang & Yang 2004). Steep declines are now being recorded in high-frequency data trading returns (Serbera *et al.* 2016) relative to low-frequency, non-machine trading strategies. In highly volatility environments, algorithms enabled or disabled by human initiative fail (Chaboud *et al.* 2014). That, coupled with the close inter-correlations among learning algorithms (Serbera *et al.* 2016), translates into very positive human-mediated returns (contrary in sign to the results of machine trading models) during significant swings in trends.

Research in this area is widely diverse with: 1) algorithm advocates, such as Wang *et al.* (2011), mentioned earlier; 2) champions of human initiative, such as Serbera *et al.* (2016) and Chaboud *et al.* (2014); and 3) a group of authors who find no evidence that these techniques can enhance profits in practice (Teixeira & De Oliveira 2010; Taylor 2014), particularly for retail investors with smaller data processing capacities or who mistrust their long-term validity (Chang *et al.* 2004).

To the author's knowledge, the studies conducted to date have not dealt with delaying the implementation of stock market indicator signals.

This study constitutes a contribution to the second of the aforementioned three approaches, insofar as it furnishes a tool to support human decision-making based on the information provided by market operators to yield better results than machine tools, which are highly inefficient in detecting trend change (among others). In all, 81 lag time combinations are used to analyse the validity of the procedure proposed as a decision-making tool.

3. METHODOLOGY AND FIELD DATA

3.1. Methodology

The procedure deployed is illustrated in Figure 1.

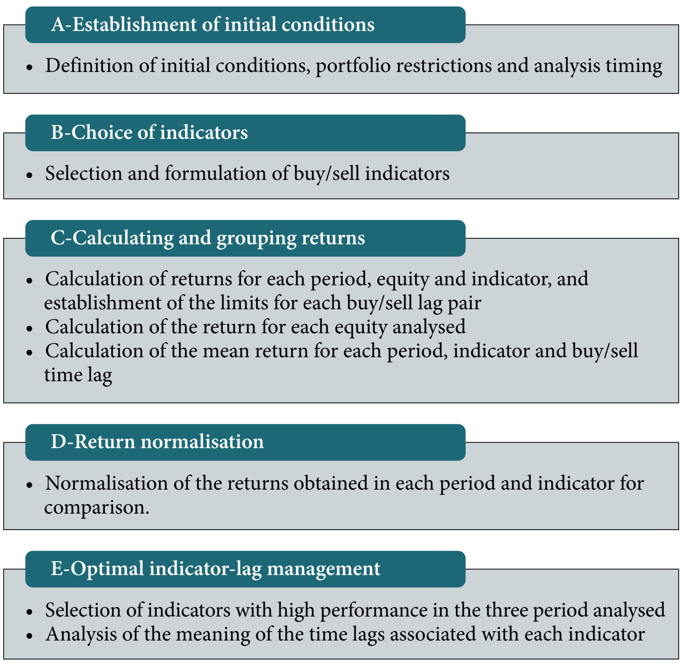


Figure 1
Procedure used, step-by-step

A. Establishment of initial conditions

The results for the period 01/01/2005-23/2/2016 were analysed. This 11-plus-year period was divided into three sub-periods (see Table 1) to identify the indicators and lag times exhibiting the highest performance in all three. The first two sub-periods had a duration of 5 years each, while the third covered just 13 months, in pursuit of an arrangement independent of market events (an alternative to the method proposed by Rosillo *et al.* 2013) to eliminate possible bias stemming from non-arbitrary choices of the start and end dates. In keeping with standard practice, closing prices were used in the simulations[1] [2].

Table 1
Sub-periods in period 01/01/2005-23/2/2016

	Start date	End date
Sub-period 1	01/01/2005	31/12/2009
Sub-period 2	01/01/2010	31/12/2014
Sub-period 3	01/01/2015	23/02/2016

The initial conditions and suite of operating restrictions for the buy and sell orders established for the model are given in Table 2.

Table 2
Initial model conditions and operating restrictions

PARAMETER	Euros	MEANING
(a) Initial cash assets	200 000	Cash initially available for operations
(b) Initial portfolio	40 000	Value of equities (shares or index) in initial portfolio
(c) Maximum value of sale	60 000	Maximum value of shares to be sold in the event of a sell signal
(d) Maximum value of purchase	60 000	Maximum value of shares to be bought in the event of a buy signal

(a) sum arbitrarily chosen to be able to base decisions on a given amount of capital

(b) initial portfolio defined to be able to associate the first operation implemented with a sell signal from the respective indicator; set here at 20 % of the initial cash assets to ensure a sufficient margin from the outset for normal buy and sell orders in a medium-large equity portfolio

(c), (d) sum equal to 30 % of the total initial cash assets to ensure a sufficient margin to absorb losses from ordinary (buy/sell) operations across the simulation period.

[1] Closing prices, used since 2000 (the former system was based on the average price), are computed on the grounds of a closing auction period consisting in a combination of five minutes plus a random closing (30 seconds during which —at any time and without prior notice— the market may close permanently).

[2] Prices are adjusted to accommodate corporate operations. The most common such operations and financial transactions affecting prices and volumes and requiring adjustments are: rights issues involving preferential subscription rights; extraordinary dividends; share amortisation- and share cancellation-mediated capital reductions; and mergers and acquisitions. Bolsas y Mercados Españoles (BME), the private company entrusted with the organisational administration of Spanish stock exchanges and financial markets, is responsible for making real-time adjustments as required to factor in financial operations that affect a traded security.

B. Choice of indicators

Lim (2015) and Achelis (2001), among others, have reviewed the wide spectrum of indicators currently in place. The seven chosen for this study are among the most widely used, alone or in combination, in most trading support tools (see Table 3). The details of these indicators are not described here, for they are regarded to be generally well known and available in the aforementioned references. Table 3 below does, however, describe the parameters used in their construction and the criteria that trigger buy and sell signals.

Table 3
Technical analysis indicators: construction parameters and signal emission criteria

INDICATOR	ABBREVIATION	CONSTRUCTION PARAMETER	SELL SIGNAL CRITERION	BUY SIGNAL CRITERION
Rate of change	(RoC)	Number of periods: 12	The indicator crosses 0 on a downward slope	The indicator crosses 0 on an upward slope
Relative strength index	(RSI)	Number of periods: 14	The indicator crosses 70 on an upward slope	The indicator crosses 30 on a downward slope
Simple moving average	(SMA)	Comparison of means for periods of 25 and 50 sessions	The short period mean crosses the long period mean on a downward slope	The short period mean crosses the long period mean on an upward slope
Exponential moving average	(EMA)	Comparison of means for periods of 25 and 50 sessions	The short period mean crosses the long period mean on a downward slope	The short period mean crosses the long period mean on an upward slope
Moving average convergence divergence	(MACD)	Number of periods: 12 and 26 EMA period for calculating signal: 9	The MACD histogram turns negative	The MACD histogram turns positive
Bollinger bands	—	SMA for 21 sessions No. of standard deviations for two	The price crosses the upper Bollinger band on an upward slope	The price crosses the lower Bollinger band on a downward slope
Stochastic oscillator	—	Window: 14 days	Stochastic oscillator crosses 80 on an upward slope	Stochastic oscillator crosses 20 on a downward slope

C. Calculating and grouping returns

Return was calculated for a portfolio with 36 components (the 35 equities in the IBEX 35 index at the time of the study, plus the index itself), running simulations for each of the following:

— the seven indicators described in Table 3
— the 81 lag combinations listed below, with lag time defined as the number of days lapsing between the date of the (buy or sell) signal generated by the indicator and the date of the transaction, adopting the closing price for both signal and transaction:

- nine buy lag times (0, 1, 2, 3, 5, 8, 10, 13 and 15 days) and
- nine sell lag times (0, 1, 2, 3, 5, 8, 10, 13 and 15 days)

— the three sub-periods listed in Table 1.

Lag pairs are represented as (a,b), where:

— *a* is the lag time between the indicator buy signal and the transaction
— *b* is the lag time between the indicator sell signal and the transaction.

The pair (0,5), for instance, would mean the buy order was implemented immediately and the sell order 5 days after receipt of the respective signal.

The above combinations yielded a total of 61 236 portfolios: i.e., the product of 36 equities times seven indicators, times 81 possible buy/sell lag pairs, times three sub-periods.

The simple, unweighted mean of the returns for each period and buy/sell lag pair could be used to group the portfolios thanks to the homogeneity of the initial conditions, the portfolio operating restrictions and the sub-periods for which each return was calculated.

Each indicator-lag pair requires its own data pool, leading to a different number of results. In some cases the outcome is that the first set of input data calls for vast amounts of raw data (from the market). EMA (or SMA), for instance, the two indicators necessitating most data, need input on 65 daily prices for the model to deliver the initial data with a 15 day lag. That situation appears only at the outset, however, for thereafter just one new raw data item is needed to replace each output item (as it is a moving indicator). Given that: 1) the Spanish stock market calendar comprises around 254 trading sessions per year; 2) the results are shown as means; and 3) the database used contained information for over eleven full years of stock trading, as noted earlier the sub-periods defined were of unequal duration in an attempt to separate results from the stock market cycle, with the only possible implications stemming exclusively from the length of the series.

D. Return normalisation

The return values generated by the simulations were normalised for classification and comparison by sub-period and indicator, attributing a value of 0 to the minimum and 100 to the maximum return recorded for an indicator in the sub-period analysed.

E. Optimal indicator-lag management

All the [indicator-lag] combinations with good performance in all the periods studied were selected. Good performance was defined as a higher than average normalised score in all sub-periods; in other words, a given [indicator-lag (a,b)] combination was regarded as optimal if it exhibited a normalised value greater than 50 in all three sub-periods (as shown in Table 4).

Two methods were deployed to guarantee that a lag detected as optimal actually was. On the one hand, the methodology described by Brock *et al.* (1992) was applied, which involved: 1) finding the results for all the indicators; 2) using long data series; and 3) focusing on the robustness of results between non-overlapping sub-periods. On the other, the statistical significance of the results was calculated to determine the likelihood that a lag detected as having higher than average performance actually did.

The significance of a lag associated with an indicator for a given sub-period and confidence level ($n_{sub\text{-}period}$) was calculated from the following expression:

$$\mathrm{Sign}_{\text{indicator-sub-period}} = (1 - n_{sub\text{-}period}) \quad (1)$$

Since the aim was to determine whether a given lag-indicator combination performed better than average in the three sub-periods studied to a pre-established likelihood, $n_{sub\text{-}period}$, the statistical significance of the combination ($\mathrm{Sign}_{\text{indicator}}$) would be:

$$\mathrm{Sign}_{\text{indicator}} = 1 - (1 - n_{sub\text{-}period})^3 \quad (2)$$

Table 4
Significance-confidence level table

Conf. level (%)	50	55	60	65	70	75	80	85	90	95
Significance (%)	87.5	90.8	93.6	95.7	97.3	98.44	99.2	99.66	99.9	99.99

3.2. *Market list price and trading volume data*

The data used were drawn from IBEX 35, the benchmark index for the Spanish securities exchange, comprising the 35 most liquid companies (weighted by market capitalisation) listed on the electronic system that interconnects its Madrid, Barcelona, Bilbao and Valencia exchanges and their equities. The following magnitudes were compiled for the index and each of its components: daily opening, maximum, minimum and closing prices, closing volume and closing price adjusted for dividends and splits, for the period 01/01/2005-23/2/2016. A total of 143 532 valid records were generated: 2903 records for each of the 36 items (index plus 35 components on the date the data were retrieved).

The composition of the index used (see Table 5) was as it appeared on the last date considered, which was also the day before retrieval. The IBEX 35 composition is revised quarterly (to compose and weight the constituent equities) and when its components are affected by financial operations. These include rights issues, extraordinary dividends, share consolidations, capital reductions, share buybacks, mergers, takeovers and spin-offs.

Table 5
Market capitalisation-weighted IBEX 35 composition used in this study (23/2/2016)

RANK	**Ticker**	**Company**	**Weight (%)**
1	ITX	Inditex	17.99
2	SAN	Banco Santander	11.92
3	TEF	Telefónica	9.02
4	IBE	Iberdrola	7.9
5	BBVA	Banco Bilbao Vizcaya Argentaria	7
6	ELE	Endesa	3.62
7	IAG	International Airlines Group	3.48
8	GAS	Gas Natural SDG	3.44
9	AMS	Amadeus	3.13
10	CABK	CaixaBank	3
11	AENA	AENA	2.94
12	FER	Ferrovial	2.82
13	REP	Repsol	2.65
14	ABE	Abertis Infraestructuras	2.46
15	GRF	Grifols	2.24
16	BKIA	Bankia	2.04
17	REE	Red Eléctrica Corporación	1.95
18	SAB	Banco de Sabadell	1.71
19	GAM	Gamesa Corporación Tecnológica	1.43
20	ACS	Actividades de Construcción y Servicios	1.4
21	POP	Banco Popular Español	1.25
22	ENG	Enagás	1.22
23	MAP	MAPFRE	1.18
24	BKT	Bankinter	1.08
25	MTS	Arcelor Mittal	0.99
26	DIA	Distribuidora Internacional de Alimentación	0.79
27	ANA	Acciona	0.77
28	MRL	MERLIN Properties	0.66
29	TL5	Mediaset España Comunicación	0.62
30	ACX	Acerinox	0.41
31	FCC	Fomento de Construcciones y Contratas	0.33
32	TRE	Técnicas Reunidas	0.32
33	IDR	Indra Sistemas	0.28
34	OHL	Obrascón Huarte Lain	0.28
35	SCYR	Sacyr	0.15

Source: Sociedad de Bolsas, S.A. (www.bmerv.es/).

Further to Sociedad de Bolsas, S.A., the formula for calculating the market capitalisation-weighted IBEX 35 composition is:

$$IBEX\,(35) = IBEX\,35\,(t-1) \cdot \frac{\sum_{i=1}^{35} Cap_i(t)}{\left[\sum_{i=1}^{35} Cap_i(t-1) \pm J\right]} \tag{3}$$

where:

t = date of calculation

i = company i

S_i = number of company i shares applicable for computing the index value

P_i = listed price of company i shares at time t

Cap_i = company i market capitalisation ($S_i \cdot P_i$)

$\Sigma\, Cap_i$ = summation of market capitalisation for all companies in the index

J = amount used to adjust the value of the index for rights issues and similar

Factor J is the adjusted market capitalisation to ensure index continuity, introduced on the occasion of financial operations defined in the *Normas Técnicas de Composición y Cálculo del Índice* [technical rules for index composition and weighting] and in routine and ad hoc index redefinitions. Component J ensures that the index value is not altered by any of the aforementioned financial operations. Its value reflects the difference in market capitalisation before and after the adjustment.

4. RESULTS

The results of the simulations discussed below are illustrated with tables and graphs containing numerical information on the lag times for each indicator that yielded higher than average performance in all three sub-periods[3].

Therefore, as this proposal is expressed in terms of mean values, the different duration of the sub-periods (the first sub-period is shorter than the second, for construction of the initial input data calls for several market prices, whilst the third sub-period is shorter than the other two) does not condition the validity of the results.

[3] An indicator-lag pair was deemed to exhibit good performance in a given sub-period when its normalised score was higher than the mean in that sub-period. Good performance across the full period was defined as a normalised score higher than the mean in all sub-periods.

Consequently, the only indicator-lag pairs relevant to the analysis were the ones exhibiting a normalised value of >50 in all three sub-periods. Two graphs were plotted for each indicator: one comparing sub-period 2005-2009 to sub-period 2010-2014 and the other sub-period 2005-2009 to sub-period 2015-2016. The good performers are listed in the tables included in each figure.

The same simulations were conducted for all 35 equities in the index, 20 412 simulations in all, the results of which were analysed and normalised for the three sub-periods studied. Table 6 ranks the best indicator-lag pair groups, i.e., the ones exhibiting a general confidence interval of over 65 % and significance of over 95.7 % (Table 4), by significance. The other indicator-lag pair groups described hereunder (with a general confidence interval of 50 % to 65 % and significance ranging from 87.5 % to 95.7 %) are listed in Appendix.

Table 6
Indicator-lag pairs (optimal normalised results)

Indicator	Lag pair	2005-2009	2010-2014	2015-2016	Significance
SMA	00-01	99.11 %	73.90 %	71.85 %	97.77 %
SMA	05-01	71.01 %	77.36 %	89.07 %	97.56 %
RSI	02-15	70.40 %	78.59 %	83.29 %	97.41 %
SMA	00-00	100.00 %	84.92 %	69.94 %	97.28 %
EMA	08-03	69.87 %	90.53 %	83.74 %	97.26 %
EMA	05-03	69.00 %	91.82 %	84.75 %	97.02 %
SMA	00-03	87.23 %	68.42 %	72.43 %	96.85 %
SMA	02-01	84.46 %	73.63 %	67.12 %	96.45 %
RSI	02-13	74.93 %	82.74 %	66.96 %	96.39 %
EMA	08-02	76.73 %	79.04 %	66.96 %	96.39 %
SMA	01-01	98.13 %	77.78 %	66.56 %	96.26 %
SMA	05-02	70.72 %	65.38 %	76.82 %	95.85 %

4.1. Rate of Change (RoC)

Only one lag pair with higher than average normalised performance (>50 % of the scores) in the three sub-periods was found for this indicator, for a statistical significance of 87.63 % (see Table 7). Performance was similar in two of the three sub-periods. In this sole pair, orders lagged substantially behind the buy/sell signals. All the foregoing infers that as a guide for investment decisions, RoC exhibited low statistical significance for the lag times proposed. In Table 7 and Figure 2, the values for high performing pairs in the first period (2005-2009) are plotted against those in the second (2010-2014) and the third (2015-2016). That only one pair could be detected on each graph and that it was positioned near the minimum 50 % level (on the y-axis) are indications of the low statistical significance of RoC.

Table 7
RoC - optimal lag times

Lag pair	Normalised value			Significance
	2005-2009	2010-2014	2015-2016	
15-13	77.15%	50.18%	50.47%	87.63%

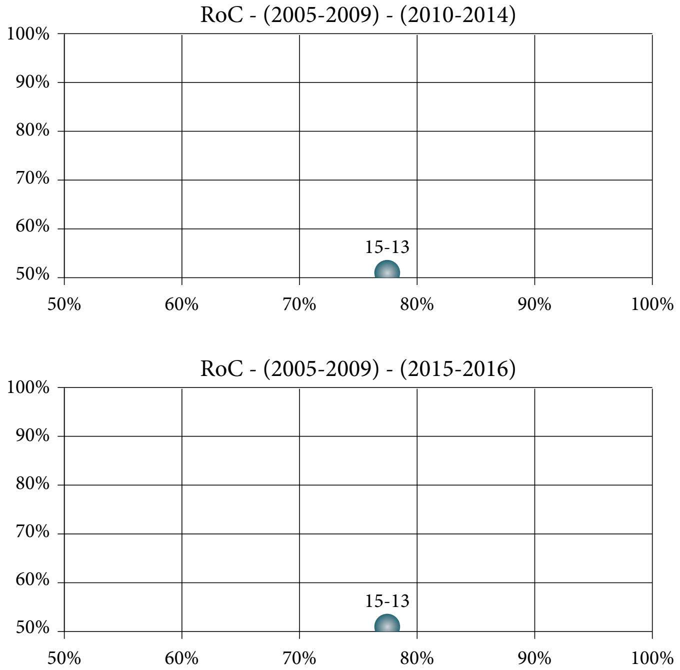


Figure 2
RoC - optimal lag times

4.2. Relative strength index (RSI)

RSI was highly statistically significant for up to 10 lag pairs. Good results were obtained for the portfolio with buy lag times of 0-3 days and sell lag times of 10-15 days (see Table 8 and Figure 2). The optimal result was obtained with the lag pair (01-15), where significance was over 95 % and the mean confidence level for the three sub-periods therefore greater than 65 %. The pairs (02-13) and (02-10) came close to that level. These findings infer that the RSI would be a good strategic guide if buy signals were implemented with a 1-2 day, and sell signals a 13-15 day lag. Groups of lag combinations also constituted a good guide for investors, who could obtain statistically significant results for their operations in windows wide enough for the confidence level associated with the results to afford a dual guarantee for their strategy.

Table 8
RSI - optimal lag pairs

Lag pair	**Normalised value**			**Significance**
	2005-2009	**2010-2014**	**2015-2016**	
00-08	51.92%	87.30%	72.94%	88.89%
00-10	53.34%	75.98%	66.00%	89.84%
01-13	54.76%	68.03%	59.38%	90.74%
01-15	67.38%	77.99%	65.19%	95.78%
02-08	52.69%	89.98%	70.45%	89.41%
02-10	58.56%	100.00%	59.66%	92.89%
02-13	67.06%	88.66%	62.23%	94.61%
02-15	53.31%	65.13%	73.39%	89.82%
03-13	61.53%	66.55%	56.38%	91.70%
03-15	73.41%	52.96%	66.49%	89.59%

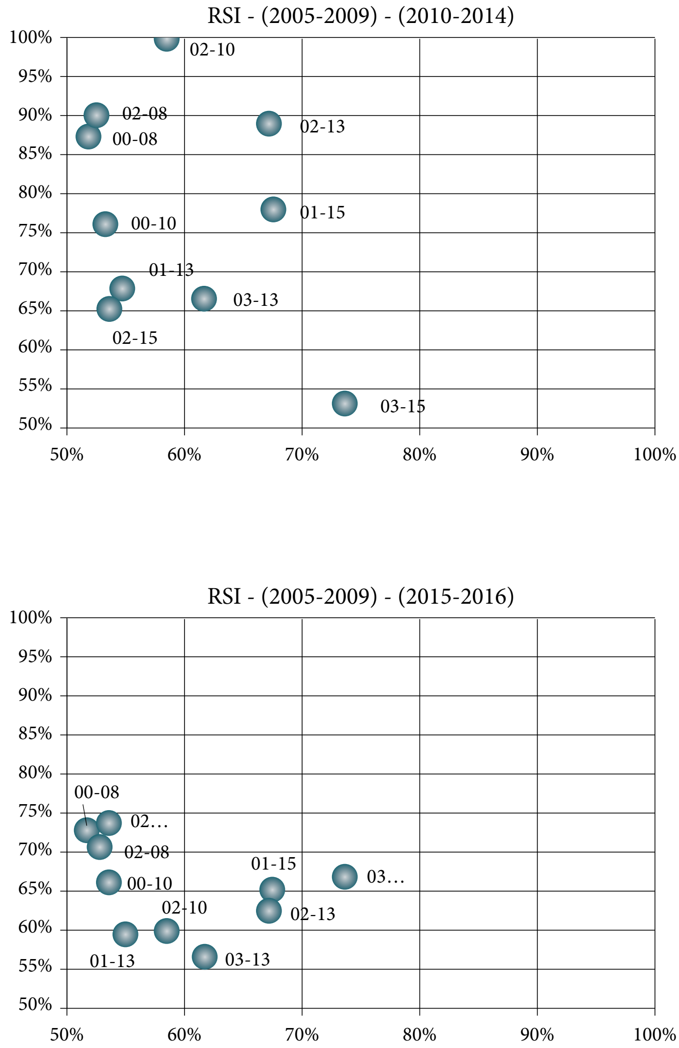


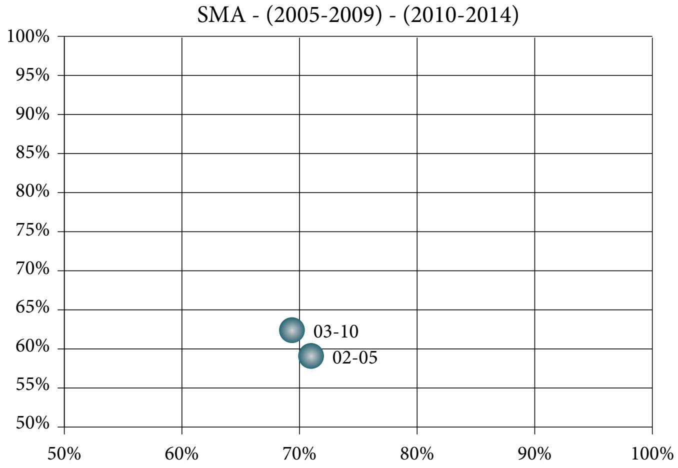
Figure 3
RSI - optimal lag pairs

4.3. Simple moving average (SMA) comparison

Comparing simple moving averages yielded good results for only two lag pairs. The buy lags generating the highest level of investor confidence when this criterion was applied to portfolio management merit analysis. The pair (03-10) exhibited 93.41 % significance, for a mean confidence level for the three sub-periods of over 60 % (see Table 9 and Figure 4).

Table 9
SMA - optimal lag pairs

Lag pair	**Normalised value**			**Significance**
	2005-2009	**2010-2014**	**2015-2016**	
02-05	72.07%	58.25%	50.74%	88.05%
03-10	68.71%	62.08%	59.61%	93.41%



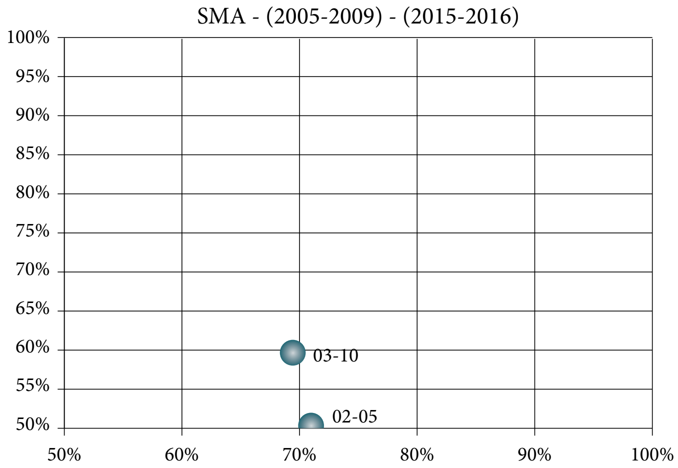
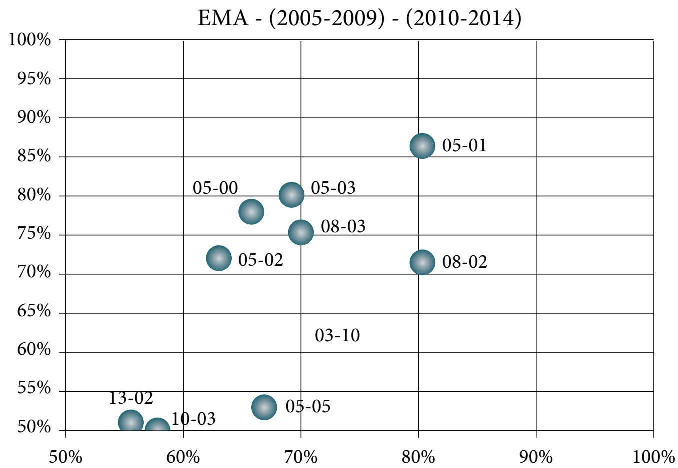


Figure 4
SMA - optimal lag pairs

Table 10
EMA - optimal lag pairs

Lag pair	Normalised value			Significance
	2005-2009	2010-2014	2015-2016	
08-03	70.03%	75.04%	100.00%	97.31%
05-03	69.10%	79.80%	95.41%	97.05%
08-02	80.55%	71.46%	83.55%	97.68%
05-02	63.16%	71.71%	78.37%	95.00%
05-00	65.77%	77.83%	61.94%	94.49%
05-01	80.39%	86.23%	57.22%	92.17%
05-05	67.08%	52.86%	60.93%	89.52%
10-03	57.45%	50.27%	96.05%	87.70%
13-02	55.55%	51.28%	50.74%	88.04%



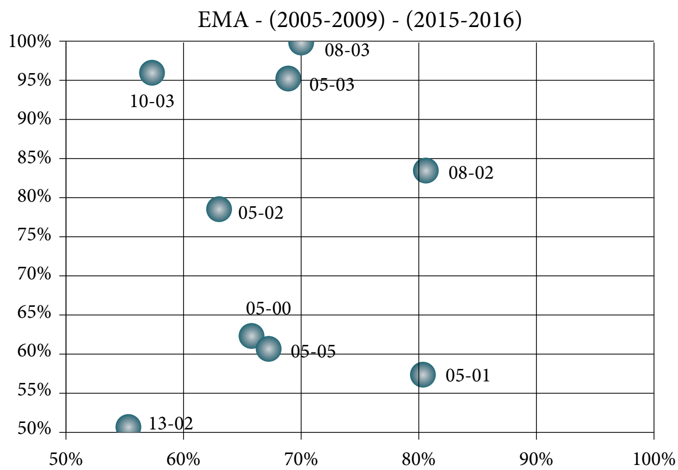


Figure 5
EMA - optimal lag pairs

4.4. Exponential moving average (EMA) comparisons

This indicator delivered the best results. As shown in Table 10 and Figure 5, five lag pairs showed significance of around 95 %, for mean confidence levels >70 % for the three sub-periods, as well as very homogeneous performance: a 5-8 day buy lag time and a shorter 0-3 day sell lag time.

Very similar results were observed in other simulations performed but not reported here for all but the moving average indicators. For these, when the five largest companies in the index were included, the number of highly significant lag times was much lower than when the portfolio used comprised the IBEX 35 and its 30 lightest weighted equities. The effect of size was particularly significant for the simple moving average, very likely as a result of the decline in profitability deriving from the widespread use of this very popular indicator among market agents for operations with these blue chip securities.

4.5. Moving average convergence divergence (MACD)

This was the sole indicator studied for which no lag time was found to be optimal in all three periods, due to the concurrent results for different lag pairs. As that finding was consistent with the results of alternative simulations not discussed hereunder, both as regards the portfolio and the parameters used in its construction, and in keeping with standard practice, only the latter are shown (short EMA: 12 sessions; long EMA: 26 sessions; signal: 9).

Although consistent with observations reported by Wang *et al.* (2015) who, using particle swarm optimisation (PSO), found that combinations of two moving average indicators were not needed for investment decisions in over 70 % of the sessions, these findings did not concur with Chong *et al.*'s (2008) and Rosillo *et al.*'s (2013) results.

4.6. Bollinger bands

This indicator exhibited poor performance, with only one significant lag pair (see Table 11 and Figure 6). Despite the good results for the period 2015-2016, profitability was clearly below average for some of the other periods studied. These findings were consistent with the results of other simulations conducted on the occasion of this study.

Table 11
Bollinger bands - optimal lags

Lag pair	Normalised value			Significance
	2005-2009	2010-2014	2015-2016	
00-13	64.50%	60.79%	79.47%	93.97%

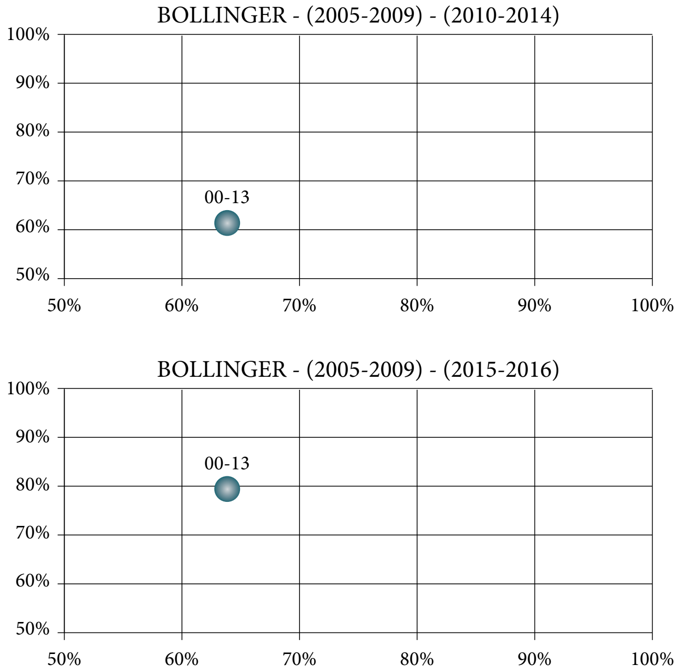


Figure 6
Bollinger bands - optimal lags

4.7. Stochastic oscillator

Three possibly optimal lags were found for this indicator, although their statistical significance was low. The confidence level was high for short (0-1 day) buy and longer (10-13 day) sell lag times (see Table 12 and Figure 7). The findings were consistent with simulations conducted with portfolios other than described here to verify indicator performance.

Table 12
Stochastic oscillator - optimal lags

Lag pair	Normalised value			Significance
	2005-2009	2010-2014	2015-2016	
00-10	69.12%	77.84%	57.30%	92.21%
01-13	71.17%	52.32%	52.02%	88.96%
01-10	64.92%	98.65%	51.70%	88.73%

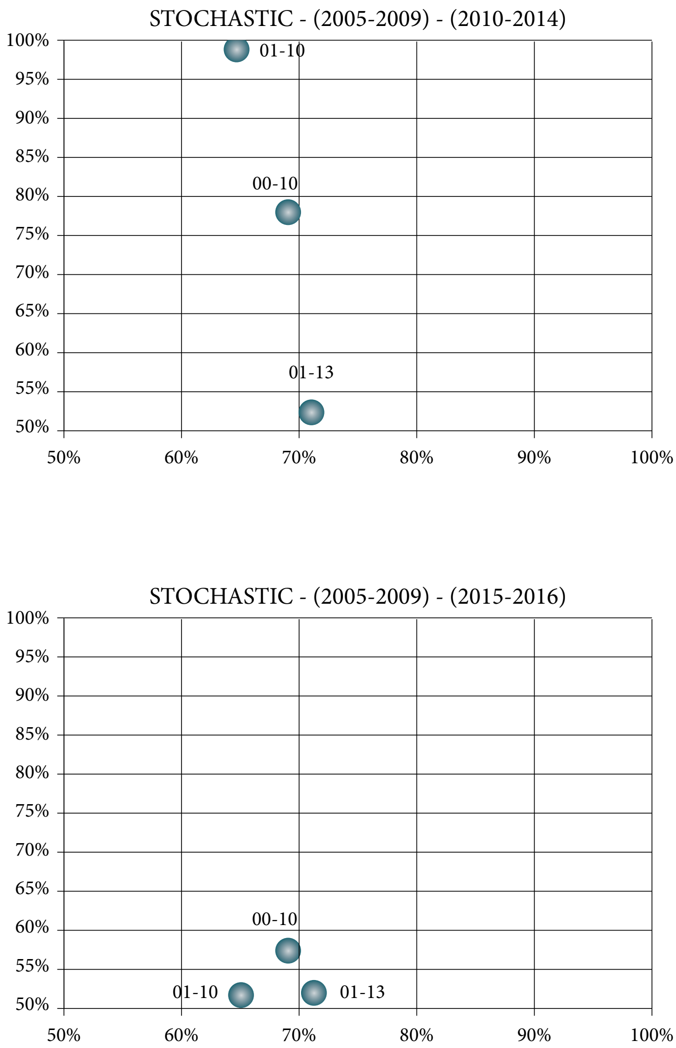


Figure 7
Stochastic oscillator - optimal lags

5. CONCLUSIONS

This study analysed the validity of buy/sell signals generated automatically by the most widely used indicators (RoC, RSI, SMA, EMA, MACD, Bollinger bands and Stochastic Oscillator) for the Spanish securities exchange and the effect of introducing lag times (a total of 81 combinations of buy and sell lags) in implementing the transactions recommended by each indicator. The aim was to maximise the return of a portfolio consisting in the market's benchmark index (IBEX 35) and its 35 constituent equities. The simulation sought to identify the indicator and buy/sell lag combinations which, irrespective of the period studied, consistently improved on the portfolio return. The model developed for that purpose was based on the consistency of results for non-overlapping, randomly selected sub-periods.

Indicator and buy/sell lag combinations were found for the market and period analysed that afforded statistically significant improvements over the immediate implementation of indicator signals. The highest performing indicators were EMA and RSI. The parallelism is unsurprising, for relative strength is based on the exponential moving average. High confidence levels were also observed for both indicators: for medium (5-8 day) buy lags and short (0-3 day) sell lags in the former and in the latter, for a short (0-2 day) buy lag and a long sell lag (the best result was recorded for a 15 day lag time).

The inter-sub-period analysis revealed no significant results for any of the other indicators. Notably, the moving averages (EMA and SMA comparisons) performed better than their synthetic grouping (MACD), a finding which while consistent with results reported by Wang *et al.* (2015), was not regarded as conclusive for the market analysed with the methodology described here. Rather, the present result would appear to be attributable to the construction of the synthetic indicator and therefore not applicable to those calculated with moving averages.

Some of the non-optimal indicators exhibited better results in certain periods than the ones identified as optimal. That does not question the validity of the former in predicting the performance of the equities to which they are applied. Rather, they were 'disregarded' due to the heterogeneity of the results for the parameters designed for the present simulation.

Several lines of follow-up research to this study can be identified. Firstly, the utility of the indicators and delays should be verified in connection with dividends: amount and both announcement and ex-dividend dates. Secondly, the consistency of these findings for both the indicators studied and others might be verified when period trends, volatility or even the daily volume of transactions recorded are factored into technical analysis. Thirdly, the validity of analysis and decision-making should be explored at times of trend change or high volatility and the results compared for simple versus more complex methodologies and algorithms to determine their respective utility in such periods, which impact long-term portfolio profitability so heavily.

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APPENDIX

Table 6 (continued)
Indicator-lag pair groups (optimal normalised results)

Indicator	Lag pair	2005-2009	2010-2014	2015-2016	Significance
SMA	01-00	90.80 %	80.04 %	64.94 %	95.69 %
RSI	01-15	64.44 %	100.00 %	75.25 %	95.50 %
SMA	03-00	82.89 %	74.50 %	64.16 %	95.40 %
SMA	05-00	62.99 %	77.96 %	87.01 %	94.93 %
SMA	02-00	78.57 %	62.96 %	65.43 %	94.92 %
EMA	05-02	62.67 %	84.15 %	67.57 %	94.80 %
SMA	00-02	75.47 %	78.45 %	61.14 %	94.13 %
RSI	00-13	61.05 %	77.35 %	78.46 %	94.09 %
RSI	08-15	72.75 %	60.42 %	63.28 %	93.80 %
SMA	01-03	67.68 %	60.17 %	65.24 %	93.68 %
SMA	08-01	60.12 %	63.92 %	91.20 %	93.66 %
STOCHASTIC	00-10	65.67 %	68.08 %	59.84 %	93.52 %
RSI	02-10	64.18 %	88.38 %	59.76 %	93.49 %
RSI	03-15	72.73 %	59.66 %	78.05 %	93.44 %
RSI	03-13	63.03 %	58.85 %	63.13 %	93.03 %
EMA	02-05	76.45 %	58.58 %	67.85 %	92.89 %
SMA	03-01	79.12 %	57.93 %	66.41 %	92.55 %
RSI	00-10	57.22 %	57.97 %	76.76 %	92.17 %
EMA	02-03	77.61 %	56.58 %	91.24 %	91.81 %
SMA	00-05	79.12 %	91.00 %	56.53 %	91.79 %
BOLLINGER	00-08	56.51 %	61.19 %	73.27 %	91.78 %
EMA	03-02	78.34 %	56.47 %	95.41 %	91.75 %
SMA	02-02	81.03 %	63.68 %	56.23 %	91.62 %
BOLLINGER	00-13	75.85 %	56.13 %	86.68 %	91.56 %
RSI	01-13	55.86 %	74.70 %	69.50 %	91.40 %
SMA	01-02	86.86 %	59.55 %	55.71 %	91.31 %
SMA	03-02	74.95 %	59.86 %	55.69 %	91.30 %
RSI	02-08	55.17 %	75.79 %	57.55 %	90.99 %
EMA	03-05	58.43 %	55.10 %	55.06 %	90.92 %
EMA	05-05	68.77 %	54.12 %	57.36 %	90.34 %
EMA	03-03	78.36 %	54.10 %	100.00 %	90.33 %
EMA	03-01	70.17 %	83.44 %	53.17 %	89.73 %
STOCHASTIC	01-13	58.00 %	52.75 %	55.80 %	89.45 %
RSI	01-10	52.09 %	85.90 %	73.28 %	89.00 %
ROC	15-13	57.92 %	71.29 %	51.95 %	88.90 %
SMA	08-00	51.91 %	53.82 %	89.12 %	88.88 %
RSI	00-08	51.80 %	71.85 %	64.24 %	88.80 %
RSI	05-13	66.27 %	69.61 %	51.67 %	88.71 %
EMA	05-10	51.54 %	61.72 %	53.46 %	88.62 %
EMA	03-08	60.79 %	51.36 %	65.41 %	88.50 %
SMA	08-02	50.70 %	58.52 %	83.26 %	88.02 %
STOCHASTIC	01-10	53.63 %	91.49 %	50.49 %	87.86 %
EMA	05-08	63.98 %	50.20 %	57.67 %	87.65 %
ROC	08-15	50.19 %	68.51 %	62.53 %	87.64 %