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DOES TECHNICAL ANALYSIS GENERATE PROFITABILITY IN THE COLOMBIAN STOCK MARKET?

ABSTRACT

In this study, we test for the weak market efficiency hypothesis in the Colombian stock market through two technical analysis strategies, Simple Moving Averages and Moving Average Convergence and Divergence, on eighteen stocks that have been part for a longer period of time in the COLCAP index. By simulating buy and sell positions under each strategy, it is found that none the strategies generate returns higher than the passive strategy obtained using the Capital Asset Pricing Model, besides, the returns obtained from the strategies are negative. In this sense, these technical analysis strategies are not profitable on the Colombian stock market.

1. INTRODUCTION

The weak market efficiency hypothesis proposed by Fama (1970), states that it is impossible to obtain profits with the same available information for all market agents. Therefore, when markets are efficient, the price adjustment to new information operates in an automatic way, and technical analysis becomes obsolete.

On the first part of this study, we compile studies concerning the application of technical analysis on different financial securities. As the main reference, we start with the weak form market efficiency hypothesis proposed by Fama (1970), and this is the principal hypothesis on which this study is based on. Additionally, it is found in the study of Lukac et al. (1988), that 50% of market speculators in the futures market use technical analysis. Moreover, in this paper the authors methodology consists on using the Capital Asset Pricing Model to test for three market disequilibrium hypotheses. Likewise, other studies consider technical analysis strategies such as Bollinger Bands, filter rules, simple moving averages, among others during different periods of time and financial securities.

On the second part of this study, are the data and the methodology. We took the eighteen stocks that have been part of the COLCAP Index for the longer period, between 2008 and 2015. This index was chosen considering it gathers the 20 most important companies of the Colombian stock market. For each stock, we applied the trading rules for buy and sell positions, we calculated the returns obtained, they were compared to a passive strategy to a benchmark obtained using a Capital Asset Pricing Model, and finally we tested for the statistically significance of the returns.

In the third part of the study, are the results concerning whether it is possible to obtain higher returns through technical analysis instead of investing in a passive strategy. We tested for: if the returns for each strategy generate returns different from zero, if the buy or sell positions were better within each strategy, and finally, if the strategies are more profitable than the COLCAP benchmark.

Finally, we concluded that the empirical studies that evaluated the technical analysis profitability support the weak market efficiency hypothesis, where it is impossible to obtain profits and statistically significant following the strict rules of SMV and MACD strategies. We found that none of the strategies generate higher returns than the returns obtained from a passive strategy obtained from the CAPM benchmark.

This study, initially begins with the stock market, one of the most used asset used in the Colombian's capital market. With the intent to investigate in the future the wide range of markets, such as the futures market, we decided to start with a simple market, with the information available online or in a platform such as Bloomberg, that provided us a robust start point to explore with a solid basis for other markets.

2. LITERATURE REVIEW

2.1 Efficient markets hypothesis

Considering the efficient capital market model, Fama (1970) stated that "a market in which prices always 'fully reflect' available information is called 'efficient'" (p. 383). According to the paper, the market efficiency hypothesis has been studied regarding three different forms tests. The first one, weak form test, is related to random walk models and concerns only the information of past prices or historical returns. The second one, semi-strong form of efficiency, centers in "the speed of price adjustment to other obviously publicly available information (e.g. announcements of stock splits, annual reports, new security issues, etc.)" (p. 388). And the last, the strong form of market efficiency, refers to as to whether there exists monopolistic access to relevant information related to the formation of new prices, by groups such as management funds, or investors (p. 388),

In its paper, Fama proposed three models in which the formation of prices would be testable for market efficiency: The Expected Return of "Fair Game" models, the Submartingale Model, and the Random Walk Model. Moreover, Fama (1970) determines three conditions that are sufficient for capital market efficiency: First, there are no transaction costs in trading securities; second, all information has no cost, and it is available for all market participants; and third, all market participants agree in both implications of all information in current prices and in the distribution of future market prices of each security (p. 387).

On local studies, Echeverri (2012) addressed the hypothesis of the existence of weak form efficiency of the Colombian stock market. The study uses daily prices from the Índice General de la Bolsa de Valores de Colombia. These prices, are the closing prices of each trading day, and the returns are calculated as compound percentages returns. The model used is an ARFIMA-HYAPARCH, and it is also considered under the investigation possible calendar effects in both the mean process and the conditional volatility process. The investigator found that under a ARFI-HYAGARCH model is the generating process of returns of the prices, and therefore, rejecting the hypothesis of weak form efficiency in the Colombian stock market.

Moreover, Agudelo Rueda & Uribe Estrada (2009), is a study that most closely resembles the present investigation. They support the weak market efficiency hypothesis, where they could not find significant and statistically strong economic profits. They used 10 trading rules, and applied them in 19 Colombian stocks, included out-of-sample tests in order to avoid data snooping, and included transaction costs. They find that the Colombian stock market is efficient, and therefore, technical analysis rules are not profitable.

2.2 Profitability of Technical Analysis

Park & Irwin (2007) gathered many papers containing literature about the profitability of technical analysis, surveying a literature review in a systematical and comprehensive way. They divided the empirical studies about the usefulness of technical analysis in two types of studies: the early and the modern studies. Since technical analysis have a long history between participants in speculative markets, they do not fully trust in the usefulness of trading rules and get skeptical about technical analysis.

A starting point, is the hypothesis proposed by Fama (1970), as described before, of an efficient market in which it is possible to make profits out of the available information, such as past prices. Then, they included the negative empirical findings in several studies about this field applied on markets, and complemented it with Jensen (1978), that subdivided the efficient market hypothesis in three types based on the available information (weak, semi-strong and strong form of efficiency). This implies that the last price already reflects what all can be known; therefore, the expected return on technical analysis is zero.

The early empirical studies (1960-1987) investigated diverse trading systems such as filters, stop-loss, moving averages, channels, oscillators and relative strength. Fama and Blume (1966) concluded that the excess of profit in long transactions over buy and hold strategies may be negative including the use of a brokerage. Moreover, according to James (1968), moving average or relative strength techniques are not profitable on the stock market, unlike the majority of technical trading rules applied on foreign exchange market and futures markets that obtain substantial net profits.

Leuthold (1972) applied six filters rules over 1965 to 1970 in futures contracts and found that four of them where profitable after transactions costs during the sample period. It would perhaps be appropriate to digress in order to show that, in this same period, was mentioned in (Ready, 1998) that profits from technical analysis were higher before 1986, “we know that BLL rules would have generated substantial after-transaction-cost excess returns over 24 years from 1963-1986” (p. 43-61). Continuing, this evidence suggests that stock markets were more efficient than foreign and futures markets before 1986. These results are consequence of numerous limitations found in the early studies, such as small trading systems, neither handled statistical test of significance of the returns, the riskiness is often ignored, that the performance of trading rules are presented in average and data snooping.

In contrast, modern studies use parameters of optimization and out-of-sample verifications, unlike early studies as Lukac, Brorsen & Irwin (1988) have shown, where they assured that parameters used over tests were optimized through time, every three years from 1975 to 1984. Hence, in the adaptive simulation of twelve trading rules, they used a null hypothesis in which returns generated from technical trading are zero, and t-tests for statistical significance for returns after transition costs and a Capital Asset Pricing Model (CAPM) to determine the significance of risk-adjusted return.

Other modern studies such as Model-based Bootstrap showed that stock indices in emerging markets are profitable after transactions costs, but for developed markets, the returns have declined over time. The reality check studies such as (White, 2000), can quantify the effects of data snooping by applying the best trading rule from a group of trading rules in the sample period. Genetic programing studies, such as (Ready, 1998), compared performance of technical trading rules formed by genetic programing from (Brock, Lakonishok, & LeBaron, 1992a) moving averages rules for the Dow Jones index. Non-linear studies, measure the probability or predictability of a trading rule from a non-linear model. Chart pattern studies test the ability of forecasting from visual aids used by technical analysts.

To summarize the results of modern studies, Park & Irwin (2007) identified that from 1960 to 2004 there are a number of studies about: stock markets (66), Foreign Exchange markets (44) and future markets (27), to an overall of 137 studies. They concluded that the number of studies that had positive profits (56) is greater than those that had negative profits (20) and 19 studies indicated mixed results in the stocks, foreign and future markets.

Aditionally, Lukac et al. (1988) presented twelve technical systems for twelve commodities from 1978-1984 to test market disequilibrium in the futures market. What is interesting in this paper is that it used a similar methodology of what we would like to use for the purposes of this paper. Starting with surveys that show how some speculators in the future markets use their trading decisions based on technical analysis, they found that 50% of all speculators consulted charting services. Through disequilibrium theory, they found that it might be a theoretical reason for trading systems to work.

The methodology used in this paper considered transaction costs and risk aversion using the Capital Asset Pricing Model (CAPM). Additionally, the efficient market hypothesis (EMH) where the prices reflect all available information, which means that technical analysis of price movements will not be profitable. They suggested three hypotheses about market disequilibrium. The first one is that no trading system could produce positive gross returns (random walk model), the second hypothesis consist in a trading system cannot produce returns above transaction costs (efficient markets), and finally the third hypothesis is that even if returns are greater than transaction costs, they cannot be above return to risk (Jessen test of efficient markets).

The trading model is a computer program that simulates trading of technical systems, including price channels, momentum oscillators, trailing stop systems and combination systems. For these trading rules, they applied the trading systems to a diversified portfolio composed of corn, cocoa, copper, live cattle, limber, pork bellies, soy beans, silver, sugar, US Treasury Bills, British pound, and Deutsch mark in the range between 1978-1984. The trading parameters were adapted and adjusted every three years and generated returns out of sample. They used a two-tailed test on the gross returns, they also included transactions costs and thus a one-tailed test for net returns, a t-test used to test these hypothesis, (Kolmogorov-Smirnov) KS test for monthly returns for normality, autocorrelation coefficients to determine if monthly returns are positively correlated and its significance levels.

The final test was whether returns from technical analysis strategies were above the risk-adjusted returns, obtained using the CAPM. The results suggested that seven trading systems generate significantly positive gross returns, a strong evidence against the null hypothesis that futures prices were random walk and the most possible cause of disequilibrium is the large transaction costs. In addition, four of the twelve systems generated significant positive returns which implies that there is other disequilibrium in markets besides transaction costs owed to information shocks.

Brock et al. (1992) conducted a study using two basic technical trading rules: moving average-oscillators and trading range break-out, the latter concerning both resistance and support levels, on the Dow Jones Average index from 1897 to 1986. In order to make statistical inferences, they used a bootstrap methodology together with standard statistical tests. To proof that the technical trading strategies are profitable, they calculated the returns from buy and sell signals given by those strategies, and compared them “to returns from simulated comparison series generated by a fitted model from the null hypothesis class being tested. The null models tested are: random walk with a drift, AR(1), GARCH-M, and EGARCH” (p. 1757). They found support that the technical trading strategies are profitable and give higher returns than normal returns and have predictive power, however, they recognized that the lack of consideration of transaction costs could vary the implementation of those strategies.

Curcio, Goodhart, Guillaume, & Payne (1997) conducted a study to evaluate the profitability of trading strategies by using filter rules identified and supplied by technical analysts for two samples on the intra-daily foreign exchange market for the Mark (DEM), Yen (JPY) and Pound (GBP) against the US dollar (USD). The technical rules they employed are based on the movement of the exchange rate outside a pre-defined trading range, which is founded on four classes of trading rules definitions, that were constructed with the application of support and resistance levels.

In this sense, they defined a basic trading rule, in which they generated the signals to buy and sell currency: “[f]or each exchange rate, signals are generated according to the alternative range definitions and the mean return, number of buy/sell signals and a t- statistic for the significance of the mean rule return over the drift in the exchange rate” (p. 8). The initial trading rule had two restrictions: it does not take into account both the costs of opening and closing positions, and the risk incurred by taking such a position. A subsequent trading rule does take transactions costs into account.

Curcio et al. (1997) found, “that, on average, neither of these sets neither of these sets of rules generate profitable trading strategies”. (p. 16) However, the authors recognized there were sub periods in which profitability could be obtained under the trading rules, and that their results were consistent with efficiency in the foreign exchange market.

Ready (1998) provided a study comparing two trading rules that where highly used by traders since the positive results back in 1986. The first one, denominated BLL (Brock et al., 1992a), found that simple moving average trading rule could be performed in 1986, including transaction costs and its impact. In contrast with, the AK model, (Allen & Karjalainen, 1999), which is a genetic algorithm that builds trading rules that tries to exploit the predictability in a return series applied in 1963-1986, to switch between stocks and T-Bills. He also identified the principal reasons of why investors are interested in trending rules; therefore, he concluded that one of the principal reasons it's that companies are more likely to issue equity when they perceive their share price is tending to be high. In the conclusions, he realized that trading rules are more effective in short periods of time, which limits its usefulness. Finally, he also stated that BLL after 1987 performed poorly and the possible positives returns owing to a spurious success in the sample (data snooping).

Similarly, Coutts & Cheung (2000) studied the application of trading rules, and its validity, on stock returns in the Hang-Seng Index (HSI) on the Hong Kong Stock Exchange from 1987 to 1997. The aforementioned authors took three samples, two of them subsets of the bigger sample. They found that the two trading rules they used, moving average oscillators and a trading range break-out, were present to all samples, and that the trading range break-out was the strongest oscillator. Moreover, they came to the conclusion that for shorter data periods the rules were statistically significant (p. 585).

Coutts (2010) replicated the methodology used by the previous authors, but for the period from 1997 to 2008 for stock returns in the Hang-Seng Index (HSI). Therefore, he applied to the time series data two moving average oscillators (MAs): one for the short-run and for the long-run. Under this trading rule, the buy signal is given when the short-term moving average is greater than the long-term moving average, whereas a sell signal is given when the long-run oscillator is greater than the short-run oscillator (p. 1668). The paper proposed a second trading rule, denoted trading range break-out rule (TBR), that "initiates a 'sell' ('buy') signal if the security price falls below (rises above) some pre-specified support (resistance) level; the highest price of the security in the previous period" (p. 1668).

Coutts (2010) concluded that both trading rules, TBR and moving average oscillator, in the short-run are not profitable and are not statistically significant for all three samples. In this sense, the findings held by Coutts & Cheung (2000) are no longer possible as the rules are not applicable for subsequent periods (p. 1672).

Tai-leung, Wai, & Yin (2011) investigated the profitability of the ROC (rate-of-change) oscillator on the Chinese, Asian, European and U.S. indices. To calculate the profitability, they established these trading rules: first, a buy or sell signal occurs when the ROC rises above or falls below its own moving averages (simple moving average and exponential moving average); and second, a trading rule created by the crossing of the ROC and Bollinger bands (p. 72-73). They compared the profitability of the trading rules with the annualized rate of returns of 13 stock market indices.

In its study, Glabadanidis (2014), used monthly returns of both equal-weighted and value-weighted US REIT (Real Estate Investment Trust) indexes. The analyzed period was January 1980 to December 2010. The trading strategy applied in the paper was a moving average (MA), and it indicated the existence of a dominant buying and holding strategy of the underlying asset in a mean-variance sense. Using the closing price at the end of each month, the strategy consisted in comparing that price with the value given by the moving average: if the closing price is higher than the moving average this generates a buy signal (to invest in the portfolio) or to maintain the position; if the closing price is lower than the moving average, it a sell signal of the portfolio or a signal to stay invested in cash. The rule employed a proxy for the risk-free rate: the returns of a 30-day US Treasury Bill. (p.163)

Glabadanidis (2014) calculated the abnormal returns of the moving average portfolios using three different models: a Capital Asset Pricing Model (CAPM), a three-factor model proposed by Fama and French, and finally the Carhart four factor model. He found that the moving average strategies generated economically and significant alphas.

Even though Fernández-Rodríguez, González-Martel, & Sosvilla-Rivero (2000) conducted a study on the Madrid Stock Market in order to determine the profitability of technical trading rules using Artificial Neural Networks (ANNs), the output of the model and their findings are relevant for the present investigation. The predictions made by the model were transformed into a simple trading strategy, and its profitability was compared against simple buy-and-hold strategies. Therefore, the model's final output was "a value in the (-1, +1) interval. A value greater than 0 will be used as a buy signal, while a value lesser than 0 will be used as a sell signal" (p. 91). Under this model, they found that applying the investment strategy to the General Index of the Madrid Stock Market, the trading technique employed presents higher profitability than a buy-and-hold strategy for both "bear" markets and "stable markets". However, under a "bull" market, the buy-and-hold strategies presented higher returns.

3. DATA AND METHODOLOGY

The data used are the daily prices for eighteen (18) stocks that have been part of the COLCAP index. The COLCAP index is the main indicator that reflects the changes in prices of the twenty (20) most actively traded shares of the Colombia Stock Exchange (IGBC), where the market capitalization for each company determines periodically its inclusion in the index (Banco de la República de Colombia). For all data, it was established a time frame from 2008 to 2015 using daily prices of the index and the stocks.

Daily prices are obtained for trading days (excluding non-transactional days as weekends and holidays) from 01/02/2008 until 12/31/2015, covering a period of eight (8) years. All data was obtained and downloaded from Bloomberg. In Annex 1 are the summary statistics of the data: number of observations, mean, standard deviation, minimum and maximum value.

To determine which stock is to be considered for the investigation, the criterion was: the stocks that have been part of the COLCAP Index for a longer period of time, during the 8-year period considered. Therefore, we filtered the 18 stocks and counted the number of years that have been part of the COLCAP Index from 2008 to 2015, as shown in Table 1.

Table 1. Stocks that have been part of the COLCAP Index, 2008-2015.

Stock	Total trimesters	Years
CORFICOLCF	32	8.00
EXITO	32	8.00
ISA	32	8.00
ECOPETROL	31	7.75
ISAGEN	31	7.75
BVC	30	7.50
PFBCOLOM	29	7.25
CEMARGOS	27	6.75
PREC	23	5.75
FABRICATO	21	5.25
CNEC	20	5.00
ETB	20	5.00
GRUPO SURA	19	4.75

PFDAVVNDA	19	4.75
TABLEMAC	19	4.75
NUTRESA	18	4.50
PFAVAL	16	4.00
EEB	15	3.75

For purposes of the present investigation, we used both long and short positions for stocks in the Colombian stock market. It is important to highlight that short positions on stocks were not completely regulated under Colombian law until the Decree 4432 of 2006, which permitted short positions as ‘operations of temporary transfer of securities’. In this sense, these operations managed to materialize all the elements of a short position on stocks, as it contained all express authorizations, the assets involved, and the guarantees that permitted to bring transparency for all transactions and trust to the investors (Autorregulador del Mercado de Valores de Colombia, 2010).

The Decree was derogated and substituted by the Decree 2555 of 2010, that lays down all the rules governing the short sells operations in Colombia. Therefore, we will assume that it is possible to engage in short positions to comply with the established trading rules (SMV and MACD).

We will test the weak market efficiency hypothesis on the COLCAP Index, by comparing the returns obtained under a Capital Asset Pricing Model (hereinafter CAPM), as the benchmark, with the returns obtained using two technical analysis strategies: Simple Moving Averages (hereinafter SMV), and Moving Average Convergence Divergence (hereinafter MACD). In this sense, we are following the methodology employed by (Lukac et al., 1988), and (Agudelo Rueda & Uribe Estrada, 2009), simulating two trading systems or strategies in order to test market equilibrium by determining that these technical systems have returns that are significantly different from zero, and testing whether the returns from technical analysis were above a return to risk obtained from a CAPM. Moreover, we test for the profitability of the positions (buy or sell) under each strategy for each stock, to determine which position is more profitable.

3.1 CAPM-returns

The CAPM returns or beta-adjusted returns are used as the benchmark for comparison to the technical analysis strategies returns. We followed the model of Sharpe, which states that the appropriate rate of return on an asset is the sum of a risk-free rate and a risk premium, also, is the first strict model to describe the relationship between risk and return. However, the CAPM considers only the systematic risk rather than the total risk (Zhang, 2013).

Therefore, the expected return of an asset given its risk is:

$$\overline{r_a} = r_f + \beta_a(\bar{r}_m - r_f)$$

Where: $\overline{r_a}$ is the expected return of the asset, r_f is the risk-free rate, β_a is the *beta* of the asset, and $\bar{r}_m$ is the expected return of the market.

To obtain the CAPM returns as the benchmark, we first found the value of the *beta* for each stock using the following econometric model:

$$(r_a - r_f) = \beta_a(r_m - r_f)$$

Where: $r_a$is the logarithmic return of the asset: ln (price$_{t+1}$/ price$_t$),

r_f is the risk-free rate. We used as a risk free rate the rate of intervention of Colombia's Central Bank, Banco de la República. (Banco de la República de Colombia, 2016)

β_a is the *beta* of the security, or market risk of the stock, which is estimated by Ordinary Least Squares (OLS) regression without constant term β_0.

r_m is return of the market, the logarithmic returns of the COLCAP Index.

3.2 Technical Analysis

3.2.1 Simple Moving Averages (SMV)

To calculate the returns of each asset we used the SMV strategy, which consists in two simple moving averages, one for the short-term and one for the long-term. Coutts (2010) determined that the trading rule for moving averages oscillator is as follows: the buy signal is given when the short-term moving average is greater than the long-term moving average, whereas a sell signal is given when the long-run oscillator is greater than the short-run oscillator. Therefore, we established two moving averages strategies: a MA of 10 days with a 40 days MA; and a MA of 20 days with a 50 days MA.

In both 10-40 SMV and 20-50 SMV, the returns were calculated as daily logarithmic returns. For buy signals, the return was calculated as: ln ($price_{t+1}$/ $price_t$)/number of days between the buy signal and the next sell signal, in order to close the position. For sell signals, the daily logarithmic return was calculated as: - ln ($price_{t+1}$/ $price_t$)/number of days between the sell signal and the next buy signal. Then, the total return of the strategy is the summation of both buy and sell returns.

3.2.2 MACD

According to Bloomberg, Moving Average Convergence/Divergence (MACD) is an indicator of the change in a security's underlying price trend. The theory suggests that when a price is trending, it is expected, from time to time, that speculative forces "test" the trend. MACD shows characteristics of both a trending indicator and an oscillator. While the primary function is to identify turning points in a trend, the level at which the signals occur determines the strength of the reading.

First, we defined the MACD line as the difference between the faster (or short period of time) exponential moving average that will be more sensitive to price changes, and the slower (or long period of time) exponential moving average that will have more of a smoothing effect as the calculation is based on longer term movement. Then, we will look at whether the two moving averages are converging or diverging.

When MACD Line crosses over the MACD Signal Line, this can be regarded at as a positive turn in the market. A cross in the opposite direction, would be deemed a negative turn. These rules, help to define the trade position (long/short).

Therefore, we used the data available in Bloomberg to obtain the MACD line and the MACD signal applied to the 18 stocks and defined a conditional rule: if the faster exponential moving average is positive and crosses over the MACD signal, means that the trend of the stock is deemed bullish (long position); but if the MACD line crosses below the MACD signal its deemed as bearish (short position) for the trader. For the calculation of logarithmic returns for the buys and sells, we used the same formulas as in SMV strategies.

3.2.3 T-Statistics for the SMV and MACD strategies

First, to determine if the strategies generate returns different from zero, and are statistically significant, for each stock, the t-statistic is obtained through STATA, using the "ttest" function.

To determine the t-statistic to be used for both buy and sell signals, we will follow the t-statistics established by (Brock, Lakonishok, & LeBaron, 1992). For buys (or sells), the t-statistics are:

$$\frac{\mu_r - \mu}{(\frac{\sigma^2}{N} + \frac{\sigma^2}{N_r})^{1/2}}$$

Where, μ_r are the mean return for the buys or the sells, N_r is the number of signals for buys or the sells, μ is the unconditional mean, N are the number of observations and σ^2 is the variance of the entire sample.

For the buy-sell the t-statistics is calculated as:

$$\frac{\mu_b - \mu_s}{(\frac{\sigma^2}{N_b} + \frac{\sigma^2}{N_s})^{1/2}}$$

Where, μ_b is the mean return for the buys, N_b is the number of signals for buys, μ_s is the mean return for the sells, N_s is the number of sells, and σ^2 is the variance of the entire sample.

3.2.4 T-statistics for CAPM and technical analysis strategies

And finally, for the CAPM returns and technical analysis returns, the t-statistic is defined as:

$$\frac{\mu_{TS} - \mu_{CAPM}}{(\frac{\sigma^2}{N_{TS}} + \frac{\sigma^2}{N_{CAPM}})^{1/2}}$$

Where, μ_{TS} is the mean return for the technical analysis strategies, N_{TS} is the number of returns from the buy and sell position, μ_{CAPM} is the mean return of the CAPM-returns, N_{CAPM} is the number of returns used in the CAPM calculation, and σ^2 is the variance of the entire sample of daily returns.

4. RESULTS

4.1 CAPM benchmark

Table 2 shows the summary of the estimated *beta* for each stock. All calculated *betas* are statistically significant under a 5% level.

Table 2. Summary of non-constant regressions for CAPM. Column 2 shows the estimated coefficient, column 3 contains the standard error and column 4 shows the calculated t-statistic.

Stock	Coef.	Std.Err.	t
CORFICOL	0.7184892	0.0207467	34.63
EXITO	0.8571928	0.0296739	28.89
ISA	0.9455242	0.025571	36.98
ECOPETL	1.130724	0.0245495	46.06
ISAGEN	0.6855368	0.0267536	25.62
BVC	0.7724904	0.0336003	22.99
PFBCOLO	1.055286	0.0236191	44.68
CEMARGOS	1.066351	0.025986	41.04
PREC	1.629964	0.1012397	16.1
FABRI	0.9423493	0.1093081	8.62
CNEC	1.361937	0.0938819	14.51
ETB	0.6287963	0.0456121	13.79
GRUPOSUR	1.143785	0.0200969	56.91
PFDAVVND	0.783814	0.043932	17.84
TABLEMA	0.9714207	0.0512809	18.94
NUTRESA	0.7278088	0.020554	35.41
PFAVAL	0.649679	0.0344302	18.87
EEB	0.4994311	0.0624992	7.99

Therefore, we used those *betas* to calculate the expected return for each asset under the CAPM, shown in Table 3, in order to have the benchmark that will be compared to the technical analysis strategies returns.

Table 3. CAPM expected returns (β -adjusted returns).

Column 2 shows the β for each stock. In column 3 is the average risk-free rate. Column 4 contains the market excess returns, and column 5 shows the expected return for each stock.

Stock	Estimated	Risk-free rate	Market excess returns	CAPM
CORFICOL	0.7184892	0.019%	-0.01463%	8.58837E-05
EXITO	0.8571928	0.019%	-0.01463%	6.55929E-05
ISA	0.9455242	0.019%	-0.01463%	5.26711E-05
ECOPETL	1.130724	0.019%	-0.01463%	2.55785E-05
ISAGEN	0.6855368	0.019%	-0.01463%	9.07042E-05
BVC	0.7724904	0.019%	-0.01463%	7.79839E-05
PFBCOLO	1.055286	0.019%	-0.01463%	3.66142E-05
CEMARGOS	1.066351	0.019%	-0.01463%	3.49955E-05
PREC	1.629964	0.019%	-0.01463%	-4.74545E-05
FABRI	0.9423493	0.019%	-0.01463%	5.31355E-05
CNEC	1.361937	0.019%	-0.01463%	-8.24529E-06
ETB	0.6287963	0.019%	-0.01463%	9.90047E-05
GRUPOSUR	1.143785	0.019%	-0.01463%	2.36678E-05
PFDAVVND	0.783814	0.019%	-0.01463%	7.63274E-05
TABLEMA	0.9714207	0.019%	-0.01463%	4.88827E-05
NUTRESA	0.7278088	0.019%	-0.01463%	8.45203E-05
PFAVAL	0.649679	0.019%	-0.01463%	9.59498E-05
EEB	0.4994311	0.019%	-0.01463%	0.000117929

4.2 SMV strategies & MACD

In Table 4 are the expected returns of the 18 stocks under the SMV strategies and the MACD strategy.

Table 4. In columns 2, 3 & 4 are the logarithmic returns for the 18 stocks, under the three technical analysis strategies.

Stock	SMV 10-40	SMV 20-50	MACD
CORFICOL	-0.0847%	-0.1621%	-0.2431%
EXITO	-0.0949%	-0.0849%	-0.2512%
ISA	-0.1545%	-0.1265%	-0.2570%
ECOPETL	-0.1255%	-0.0292%	-0.2580%
ISAGEN	-0.1861%	-0.1555%	-0.3071%
BVC	-0.0785%	-0.0398%	-0.3417%
PFBCOLO	-0.1225%	-0.1393%	-0.1953%
CEMARGOS	-0.0869%	-0.0960%	-0.5702%
PREC	-0.3488%	-0.4588%	-0.8706%
FABRI	-0.3832%	-0.0677%	-1.0454%
CNEC	-0.1281%	-0.1498%	-1.1628%
ETB	-0.1977%	-0.3267%	-0.3989%
GRUPOSUR	-0.0912%	-0.1287%	-0.4119%
PFDAVVND	-0.0982%	-0.0626%	-0.6558%
TABLEMA	-0.2515%	-0.3972%	-0.6047%
NUTRESA	-0.1179%	-0.1312%	-0.2910%
PFAVAL	-0.1058%	-0.1283%	-0.3613%
EEB	-0.2070%	-0.2182%	-0.6595%

As shown in Table 4, the returns obtained under the strategies are all negative, and in general, are less profitable than the expected returns from the CAPM.

4.2.1 t-statistics for SMV strategies & MACD

Table 5 shows the calculated t-statistics for the SMV 10-40, SMV 20-50 and MACD strategies for each stock, in order to determine whether the technical analysis returns are statistically significant.

Table 5. In columns 2, 3 & 4 are the calculated t-statistics for SMV 10-40, 20-50 and MACD strategies, where it is tested if the log-returns are statistically different from zero, as: Ho: mean= 0, Ha: mean > or < 0. All t-statistics are to be considered under a 5% significance level. The numbers highlighted are statistically significant for a two-tailed test.

Stock	SMV 10-40	SMV 20-50	MACD
CORFICOL	**-3.6784**	**-3.6784**	**-6.2772**
EXITO	**-1.9856**	**-1.9856**	**-5.6934**
ISA	**-3.3318**	**-3.3318**	**-5.0568**
ECOPETL	**-2.5575**	-2.5575	**-5.6982**
ISAGEN	**-4.2058**	**-4.2058**	**-8.1418**
BVC	-1.3605	-1.3605	**-6.5236**
PFBCOLO	**-3.32**	**-3.32**	**-4.9717**
CEMARGOS	**-2.3946**	**-2.3946**	**-6.2308**
PREC	**-3.0757**	**-3.0757**	**-4.0787**
FABRI	**-2.7393**	-2.7393	**-4.4769**
CNEC	-1.3192	-1.3192	**-4.5181**
ETB	**-3.9949**	**-3.9949**	**-3.3164**
GRUPOSUR	**-2.1834**	**-2.1834**	**-5.2332**
PFDAVVND	**-1.7903**	**-1.7903**	**-6.6535**
TABLEMA	**-3.7258**	**-3.7258**	**-4.8898**
NUTRESA	**-3.0275**	**-3.0275**	**-4.4838**
PFAVAL	**-3.1235**	**-3.1235**	**-4.0891**
EEB	**-4.5524**	**-4.5524**	**-7.5955**

Table 6 shows the t-statistics for the SMV 20-50. In columns 1 and 2 are the t-statistics testing the difference of the mean buy and mean sell from the unconditional total mean, and column 3 contains the t-statistic testing the difference of buy-sell from zero.

Table 6. In each three columns under each strategy, are the calculated t-statistics for the 18 stocks. Under columns 1 and 2 are the t-statistics testing the difference of the mean buy and mean sell from the unconditional total mean, as follows: Ho: $\mu_{buy} - \mu_{total} = 0$ or Ho: $\mu_{sell} - \mu_{total} = 0$, Ha: $\mu_{buy} - \mu_{total} \neq 0$ o Ha: $\mu_{sell} - \mu_{total} \neq 0$.AT24:BF59 In column 3 are the t-statistic testing the difference of buy-sell from zero, as: . All t-statistics are to be considered under a 5% significance level. For purposes of interpretation, the t-statistics that are signifcant are highlighted.

Stock	SMV 10-40			SMV 20-50			MACD		
	Buys	Sells	Buys-sells	Buys	Sells	Buys-sells	Buys	Sells	Buys-sells
CORFICOL	1.25788553	-1.2866381	**2.20362213**	1.19760518	-1.1976052	**2.07431302**	0.00045525	-0.0004522	1.66254231
EXITO	-0.7283526	0.70879861	-1.2446095	0.32840401	-0.3178944	0.55971085	-0.0002796	0.00027605	-0.8934766
ISA	-1.0590879	1.03542034	-1.8138973	-0.0682323	0.06640051	-0.1165955	0.00013065	-0.0001332	0.43095606
ECOPETL	-0.4876144	0.50164717	-0.8567256	-0.7497161	0.78768235	-1.3314262	-6.913E-05	6.9133E-05	-0.2166212
ISAGEN	0.96352531	-0.9635253	1.66887478	0.80185762	-0.8018576	1.38885814	3.6182E-05	-3.557E-05	0.11240523
BVC	-0.445212	0.43024583	-0.7581687	-0.2835233	0.27229354	-0.4813515	-3.669E-05	3.6692E-05	-0.0994304
PFBCOLO	-0.0463049	0.04753155	-0.0812647	-0.2466605	0.25375905	-0.4333761	-3.601E-05	3.601E-05	-0.1300537
CEMARGOS	0.14769483	-0.1476948	0.25581494	0.75611636	-0.7561164	1.30963196	0.00244016	0.00159195	1.31507731
PREC	-0.7605697	0.78571415	-1.3391211	-0.6198953	0.6454607	-1.0958305	0.00201397	0.00414185	-1.4159969
FABRI	0.35967726	-0.3710064	0.6327906	0.15428059	-0.1606433	0.27273213	0.00400739	0.00338489	0.37865969
CNEC	-0.629417	0.66129124	-1.1177862	-0.4228108	0.45357045	-0.7589685	0.00389259	0.00432724	-0.2623488
ETB	-0.5077437	0.52235578	-0.8920923	-0.4907164	0.50693949	-0.8639953	0.00142382	0.00138466	0.06329937
GRUPOSUR	0.38760547	-0.3876055	0.67135238	-0.1031274	0.1031274	-0.1786219	0.00139904	0.00151351	-0.2063901
PFDAVVND	-0.6751035	0.67510349	-1.1693135	-0.7871676	0.83417288	-1.4041222	0.00214163	0.00249397	-0.5395297
TABLEMA	-0.0472531	0.0459313	-0.0807001	0.48848992	-0.4691419	0.82933346	0.0019891	0.00228811	-0.3215188
NUTRESA	-0.6160048	0.61600477	-1.0669516	-0.7780062	0.75624266	-1.3286985	0.00122063	0.00083679	0.83974483
PFAVAL	0.17330798	-0.1804554	0.30636811	-0.224867	0.23545036	-0.3986465	0.00148246	0.00107237	0.65922184
EEB	0.1121536	-0.1147172	0.19647587	0.62449463	-0.6451405	1.09953626	0.00234389	0.00231977	0.01200905

All t-statistics for buys and sells are not statistically significant under a 5% level of significance. By contrast, the only t-statistic that is significant is the buys-sells for Corficolombiana, showing that the difference between the buys and sells returns is statistically different from zero.

Like the results found for the SMV 10-40, all t-statistics for buys and sells returns under the SMV 20-50 are not statistically significant under a 5% level of significance. Again, the only t-statistic that is significant is the buys-sells for Corficolombiana.

Finally, in Table 7 are the t-statistics testing whether the differences between the SMV strategies and MACD returns with the CAPM returns are statistically significant.

Table 7. In columns 2, 3 & 4 are the calculated t-statistics for SMV 10-40, 20-50 and MACD strategies, where it is tested if the log-returns are statistically different from the CAPM return, as: Ho: µsmv/macd - µcapm=0 , Ha: µsmv/macd- µcapm≠ 0. All t-statistics are to be considered under a 5% significance level. The numbers highlighted are statistically significant for a two-tailed test.

Stock	SMV 10-40-CAPM	SMV 20-50-CAPM	MACD
CORFICOL	-0.543966132	-0.953523178	**-2.274389993**
EXITO	-0.398445715	-0.329521093	-1.765299368
ISA	-0.730135911	-0.550198843	-1.908857568
ECOPETL	-0.492691838	-0.093150126	-1.778052414
ISAGEN	-1.100374544	-0.843698284	**-2.47412229**
BVC	-0.286951752	-0.145839434	**-2.144098487**
PFBCOLO	-0.533057394	-0.58023293	-1.390004872
CEMARGOS	-0.365697896	-0.336227041	**-3.873084333**
PREC	-0.543882707	-0.645639103	**-2.247087173**
FABRI	-0.49903809	-0.082439563	**-2.146034544**
CNEC	-0.184254023	-0.181461734	**-3.168374935**
ETB	-0.609296498	-0.924312778	-1.86476552
GRUPOSUR	-0.401258827	-0.516142206	**-2.94640716**
PFDAVVND	-0.338160233	-0.196989286	**-3.889814619**
TABLEMA	-0.676970289	-0.893946771	**-2.440201198**
NUTRESA	-0.736349668	-0.722600118	**-2.52493188**

PFAVAL	-0.523623592	-0.587401629	**-2.598512077**
EEB	-0.703630409	-0.62018543	**-3.230804183**

According the results none of the SMV strategies (10-40 & 20-50) are statistically significant compare to the Capital Asset Pricing Model (CAPM). However, 13 of the 18 stocks for the MACD strategies are statistically significant.

5. CONCLUSIONS

Under the present investigation, we tested for the weak market efficient hypothesis in the COLCAP index, by comparing the returns obtained from technical analysis strategies (SMV and MACD) to a benchmark using the CAPM.

The empirical studies that evaluated the technical analysis profitability support the weak market efficiency hypothesis, where it is impossible to obtain profits and statistically significant following the strict rules of SMV and MACD strategies. We found that none of the strategies generate higher returns than the returns obtained from a passive strategy obtained from the CAPM benchmark. In this sense, for the two SMV strategies we found that the returns obtained for all 18 stocks compared to the CAPM returns were not statistically significant. For the MACD strategy, we found that 13 of the 18 stocks generate negative returns that are statistically significant. In this sense, all three strategies are not convenient as they generate losses, and that is better to invest in the COLCAP Index. These results are in accordance with the findings of (Agudelo Rueda & Uribe Estrada, 2009) for ten technical rules in Colombian stocks.

For the SMV 10-40 strategy, we found that strictly following this trading rule, sixteen out of eighteen stocks generate negative returns that are significant under a 5% level. The stocks that do not generate negative returns and therefore are statistically equal to zero are BVC, and CNEC. Hence, this strategy generates negative returns for the period of time considered. For the SMV 20-50 strategy, 14 of the 18 stocks generate significant negative returns. In the MACD strategy, all 18 stocks generate significant negative returns, and similarly to the other two strategies, strictly following the rule generates losses in returns.

Then, we distinguished between buy and sells positions in each strategy for all stocks, and we found that neither of the buy or sell positions in any of the strategies for each stock generate returns statistically significant higher that the unconditional mean. Finally, we found that for only CORFICOL, the long positions are better than short positions in both SMV 10-40 and SMV 20-50 strategies.

6. ANNEXES

Annex 1. Summary statistics for the sample (Index and stocks)

Variable	Obs	Mean	Std. Dev.	Min	Max
colcap	1,951	1450.054	312.0453	686.64	1942.37
corficol	1,942	25009.07	9159.199	7873.19	38076.64
exito	1,945	22803.81	7615.338	7660	37040
isa	1,950	9775.031	2214.246	5420	14980
ecopetl	1,951	3307.957	1185.958	1090	5850
isagen	1,947	2479.861	393.4999	1615	3400
bvc	1,812	28.32052	7.644325	15.7	47.1
pfbcolo	1,951	24327.08	5615.734	9600	31820
prec	1,471	35981.1	15024.93	2765	67260
gruposur	1,951	30765.4	8235.235	11100	44300
cemargos	1,943	7157.961	2266.393	2782.94	12100
fabri	1,421	39.75447	26.02191	8	94
cnec	1,323	12341.56	7478.106	3040	33000
etb	1,752	629.0285	220.7935	370	1280
pfdavvnd	1,277	23894.17	3013.412	16129	32400
tablema	1,382	7.971737	2.277915	3.38	13.1
nutresa	1,933	22109.38	4072.763	11918.58	29500
pfaval	1,131	1262.697	81.12606	1020	1455
eeb	1,489	1425.894	233.5324	700	1870

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