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http://hdl.handle.net/11728/7193

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Annals of Management Science
Vol. 4, No. 1, July 2015, 67-88

Back to the Future. A Behavioural Perspective on Technical Analysis into PIGS Countries

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Abstract

In this paper, we investigate the possible presence of the behavioural phenomenon in the stock markets of some members of the European Union who are historically known as PIGS (Portugal, Italy, Greece and Spain). We used technical analyses methods and rules to explain behavioural phenomenon in the examined stoch markets. We use different types of moving average technical rules. We perform some further analyses and tests. In our further analyses, we apply standard t-tests in combination with bootstrap methodology under the GARCH (1,1) null model. Overall, the results obtained in the paper show that our technical strategies (buy and hold) "win" the market and that there is a presence of European phenomenon in the PIGS stock markets. In addition, we document significant excess returns for moving average trading strategies and reject the weak-form efficient market hypothesis of Fama (1965).

Keywords: *Behavioural Finance, GARCH(1,1) Technical Analysis, Bootstrap, Matlab, PIGS.*

1. Introduction

During the economic recession that started in 2008, some members of the European Union, namely: Portugal, Italy, Greece and Spain, were grouped together and given the acronym PIGS. The reason why these countries were grouped together is due to the great weakness and instability of their economies which became a very big and open problem in 2009. Several members of PIGS were in serious financial trouble due to their external or sovereign debt. Their debt became very risky due to their weak economy.

Accurately predicting the future is a difficult thing in any academic discipline, particularly in a discipline that involves limitless human interactions. For a discipline like behavioural finance, which focuses on the study of worldly human behavior, there is too much timeless abstraction and too little scrutiny of real-world events. The typical economics theory (Efficient Market Theory – EMH) starts with the study of how rational agents interact in frictionless markets, producing an outcome that is best for everyone. In the early 1990s, several financial economists conducted studies in the field of behavioural finance. Behavioural finance is“finance from a broader social science perspective including psychology and sociology" (Shiller 2003).

Technical analysis is the study of prices of stocks, with charts as the primary tool, to make better investments. In other words, technical analysis is a methodology for forecasting the direction of stock prices through the study of past market data, primarily price and volume (Kirkpatrick & Dahlquist 2006). The basic idea of technical analysis is to forecast the equity prices based on past prices.

In behavioral theories, investors suffer from cognitive biases and cannot process available information rationally (Thaler 1993). Consistent with the experimental results that motivate behavioral finance, the background assumption in most behavioral theories is that investors act irrationally. In contrast, "Efficient Market Theory" states that security prices represent everything that is known about the security at a given moment. This theory concludes the notion that it is impossible to forecast prices, since prices already reflect everything that is currently known about the security. In behavioural finance, it is observed that there are rational and irrational expectations about returns. The same applies to technical analysis.

In behavioral economics and quantitative analysis, the same tools of technical analysis are mostly used (Mizrach & Weerts 2009; Azzopardi 2010). Shiller (1981) attributed financial anomalies to irrationality, using the evidence that stock prices move too much relative to news about future dividends. Lakonishok et al. (1994) presented evidence to show that excess returns earned by portfolios based on publicly available accounting and price data are consistent with excessive extrapolation of past performance into the future. Hong & Stein (1999) also studied overreaction and underreaction, modelling the interactions of traders who follow price trends. Brav & Heaton (2002) showed that rational uncertainty and behavioral biases can deliver similar price patterns. In behavioural models, noise traders buy when prices rise and sell when prices fall, the same as technical analysis.

Several studies tried to incorporate the Behavioural phenomenon into Technical Analysis. Behavioural models suggest that technical trading profits may be available even in the long run if technical trading strategies are based on noise or other models and not on information such as news or fundamental factors (Shleifer & Summers, 1990). According to some articles from the psychological literature (Mussweiler 2003; Mussweiler & Strack 1999b; Tversky & Kahneman 1974), investment decisions are likely to be influenced by past prices as depicted in charts. They suggested that investors’ expectations about future stock prices are assimilated to a salient high or low on the chart. **In other words, inspectors expect a stock with a salient high a chart to perform better, and vice versa.** In fact, it has been demonstrated that past stock prices do influence forecasts of stock prices (De Bondt, 1993) and buying and selling behavior (Andreassen 1988; Schachter et al., 1987).

In this paper we will conduct a study on the possible presence of the behavioural phenomenon in the stock markets of some members of the European

Union which are known as PIGS (Portugal, Italy, Greece and Spain). So, the paper will essentially delve into testing the presence of behavioural phenomenon in PIGS by applying technical analysis methods and analyses of stock indices (see Vasiliou et al., 2008). As investors generally want to know when to either dispose or maintain their assets in a stock, a study that assist in predicting the returns of asset will be found useful and will be appreciated by investors. Although this study is directly relevant to investors in PIGS, there are lessons to be learnt from it by other investors from other countries. Another objective of our study is to enlighten investors on how financial markets work and to help them to understand why practitioners should apply technical tools in making investment decisions. The study introduces human characteristics as parts of important factors to be considered in making investment decisions. The technical analysis methods used will be further enriched by using it together with bootstrap methodology under GARCH(1,1) model (see Efron, 1979; Efron & Tibshirani, 1986). The technical analysis methods used are compared with buy and hold strategy. In our analyses, we will consider the changes in the returns to the Brock et al. (1992) on Ibex35 Index (Sranish Stock market), FtseMib Index (Italian Stock market), PSI-20 Index (Portugal Stock market), General Index (Greek Stock market) over the 2003–2014 period. Furthermore, we will explore various types of the moving averages technical rules.

Section 2 of the paper presents the literature review. Section 3 describes the data and the methodology used. In section 4 we present the outcomes and findings of the research. Finally, in Section 5, we present summaries, conclusions and recommendations

2. Literature Review

Deng & Zheng (2006) stated that technical analysis constitutes the real cornerstone of the financial investment theories. Pruden et al. (2004) showed that behavioral science models which explain the stock market behavior provide solid scientific foundations based on the principles and practices of technical market analysis.

Nebesnijs (2012) examined a broad range of literature on market efficiency, behavioral finance and technical analysis. It was shown that price action followed by the breakouts exhibits a non-random price behaviour which in some currency pairs can help to systematically generate alpha. Caginalp et al. (1998) provided evidence that traders are influenced by price behavior. To the best of their knowledge, theirs is the first scientific test to provide strong evidence in favor of any trading rule or pattern on a large unrestricted scale.

Ben-Zion et al. (2003) stated that market efficiency is higher in developed financial markets than in an emerging capital market, such as the Tel-Aviv Stock Exchange. Lachhwani et al. (2013) found strong evidence of profitability by using Relative Strength Index (RSI) compared to other trading strategies like buy and hold strategy (B&H) in both long run and short run.

Lento & Gradojevic (2007) tested the Dow Jones Industrial Average, Toronto Stock Exchange, and Canadian/U.S. Exchange Rate using the Combined

Signal Approach (CSA). The CSA was found to enhance the profitability of technical trading rules. The study suggested that "testing the robustness of the combined signal approach is a priority". Raval et al. (2013a) investigated agreement in stock selection by following Fundamental and Technical Analysis on Nifty Stocks. Their study showed that stock pickers reported Fundamental and Technical style as independent of each other, with only moderate measure of agreement. Raval et al. (2013b) found that there is no significant effect on emotional state change when stock traders books loss on his loss making position.

Haug & Hirschey (2006) finding brought new perspective to the tax-loss selling hypothesis and suggests that behavioral explanations are relevant to the January effect. After a generation of intensive study, the January effect continues to present a serious challenge to the efficient market hypothesis. Scott et al. (2003) found that price momentum and trading volume appear to predict subsequent stock returns in the U.S. market and that they seem to do so in a nonlinear fashion.

Sias (2007) suggested that window dressing by institutional investors and tax-loss selling contributes to stock return momentum. Investors using a momentum strategy should focus on quarter-ending months and securities with high levels of institutional trading. Malliaris & Malliaris (2013) analyzed the movements of the S&P 500 Index using several methodologies such as technical analysis, econometric modeling, time series techniques and theories from behavioral finance. They showed that certain conditional forecasts outperform the unconditional random walk model.

Ebert & Hilpert (2013) showed that technical analysis may be attractive to investors who are less than fully rational. Vasiliou et al. (2008), tried to apply Technical Analysis methodology to investigate the Behavior Theory for the large capitalization firms of the Athens Stock Exchange. Their results support a strong increase in trading rules performance over time. Hence we believe there is existence of the behavioral phenomenon in the large capitalization firms of the Athens Stock Exchange. Vasileiou (2014) documented that behavioral finance theories may provide some useful and alternative explanations regarding some of the reasons that contribute to the Greek stock market's inefficient environment.

3. Data and Methodology

The data used is for this research consists of 3,984 observations covering the period from 11/4/2003 to 10/1/2014 for the PIGS Stock Exchanges. So we use four indices [General Index (Greek Market), PSI-20-20 Index (Portugal Market), FTSEMIB Index (Italian Market), IBEX35 Index (Spanish Market)].

The Athens Stock Exchange General Index is a major stock market index which tracks the performance of Greek stocks listed on the Athens Stock Exchange (ASE). It is a capitalization-weighted index on 60 stocks quoted on the ASE. The ASE General Index has a base value of 100 as of December 31, 1980.

The Portuguese Stock Index PSI-20 is a benchmark stock market index which tracks the performance of 20 companies with the largest market capitalization and share turnover in the Euronext Lisbon Stock Exchange. It is a free-float, capitalization weighted index. The PSI-20 Index has a base value of 3000 as of December 31, 1992.

The FTSE MIB (Milano Italia Borsa) is the benchmark stock market index for the Borsa Italiana, the Italian national stock exchange, which superseded the MIB-30 in September 2004. The index consists of the 40 most-traded stock classes on the exchange. The index was administered by Standard & Poor's from its inception until June 2009, when this responsibility was passed to FTSE Group, which is 100% owned by the Borsa Italiana's parent company London Stock Exchange Group.

The IBEX 35 is the official index of the Spanish Continuous Market. The index comprises the 35 most liquid stocks traded on the Continuous market. It is calculated, supervised and published by the Sociedad de Bolsas. The equities use free float shares in the index calculation. The index was created with a base level of 3000 as of December 29, 1989.

Moving averages are one of the oldest and most popular technical analysis tools. A moving average is an indicator that shows the average value of a security's price over a period of time. When calculating a moving average, you specify the time span to calculate the average price. According to the moving average rule, buy and sell signals are generated by two moving averages of the level of the index: a long-period average and a short-period average. A typical moving average trading rule prescribes a buy (sell) when the short-period moving average crosses the long-period moving average from below (above). Simple moving averages apply equal weight to the prices. We evaluate the following popular moving average rules: 1-9, 1-15, 1-30, 1-60, 1-90 and 1-120 where the first number in each pair indicates the days in the short period and the second number shows the days in the long period.

All transactions assume 0.09% (of the investing capital) commission as entry (buy) fees and 0.09% as exit (sell) fee.

We follow similar methodology with Brock et al. (1992) adding transaction costs. The investigation of these technical strategies will be achieved by comparing the returns given by the buy signals of the moving averages with the returns of the buy and hold method (benchmark). Furthermore, the returns given by the buy signals of the moving averages minus the returns of the sell signals of the moving average with the returns of the buy and hold method will be compared. The hypothesis that the returns of the buy and hold method are different from the returns of the moving average will be examined using the t-test methodology. The moving averages give buy signal when the short term moving average crosses over the long-term moving average. In the other way round, we have a sell signal when the long term moving average crosses over the short-term moving average.

As we said earlier in this paper, the methodology that is going to be used for the analysis of the data is t-test, which was used in the past in many studies in which technical rules are investigated (Neftci 1991; Levich & Thomas 1993; Vasiliou et al., 2006a; Vasiliou et al., 2008; Gençay 1998; Fernandez-Rodriguez et al., 1997; Brown & Jenning 1989; Balsara et al., 1996; Papathanasiou & Samitas 2010; Vasiliou et al., 2006b).

The t-test is used test difference of The t-statistic is given by the formulas:

$$\frac{\mu_{buys(sells)} - \mu_{buy\&hold}}{\sqrt{\left(\frac{\sigma^2}{\mathrm{N}_{obser}} + \frac{\sigma^2}{\mathrm{N}_{buys(sells)}}\right)}} \tag{1}$$

and

$$\frac{\mu_{buys} - \mu_{sells}}{\sqrt{\left(\frac{\sigma^2}{\mathrm{N}_{buys}} + \frac{\sigma^2}{\mathrm{N}_{sells}}\right)}} \tag{2}$$

where σ^2 is the variance of the returns, $\mu_{buys(sells)}$ is the mean return for the buys (sells), $\mu_{(sells)}$ is the mean returns for the sells, $\mu_{buy\&hold}$ is the mean return for buy and hold method, N_{obser} is the number of the observations, $\mathrm{N}_{buys(sells)}$ is the number of signals for the buys (sell), N_{sells} is the number of signals for the sells.

Using t-test will compare the mean returns of the unconditional buy methodology with the returns of the buy signals given by the moving averages and the returns of the unconditional buy methodology with the returns of the buy signals minus the returns of the sell signals given by the moving averages (3). The results of the t-test will help to either accept the null hypothesis (there is no actual difference between the mean returns -buys, sells- or reject it (there is an actual difference between the mean returns). The hypothesis to be tested is:

$$\begin{aligned} &Ho: \overline{R_1} - \overline{R_2} = 0 \quad \text{versus} \\ &H_1: \overline{R_1} - \overline{R_2} \neq 0 \end{aligned} \tag{3}$$

where $\overline{\mathrm{R}}_1$ is the mean daily returns of the index of case 1 (buy), and $\overline{\mathrm{R}}_2$ is the mean daily returns of the index of case 2 (sell).

The t-test assume independent, stationary and asymptotically normal distributions. Many times these assumptions certainly do not characterize the returns from the Banking Index of the Athens Stock Exchange series. Following Brock et al. (1992), this problem can be solved using bootstrap methods. Bootstrapping is a method, introduced by Efron (1979) for estimating the distributions of statistics that are otherwise difficult or impossible to determine. The general idea behind the bootstrap is to use resampling to estimate an empirical distribution for the statistic. The values from the Banking Index series will be compared with empirical distributions from a GARCH(1,1) model for stock returns. In the bootstrap procedure, we input the original series into our model to obtain estimated parameters and residuals. We standardize the residuals using the residual standard error. The estimated residuals are then redrawn with replacement to form a scrambled residuals series, which is then used with the estimated parameters to form a new representative series for the given GARCH(1,1) model. Each of the simulation is based on 5,000 replications of the GARCH(1,1) model. We believe that this should provide a good approximation of the return distribution under the GARCH(1,1) model. The null hypothesis is rejected at a percent level if returns obtained from the actual Banking Index data are greater than the a percent cutoff of the simulated returns under the GARCH(1,1) model. We fit a GARCH(1,1) model which is given by:

$$\begin{aligned} r_t &= \delta + \rho r_{t-1} + e_t \\ h_t &= w + a e^2_{t-1} + b h_{t-1} \\ e_t &= h^{1/2}_t z_t, \quad z_t \sim N(0, 1) \end{aligned} \tag{4}$$

where:
$e_{t:}$ is an independent, identically distributed normal random variable
$r_{t:}$ is the conditional variance
h_t: is a linear function of the square of the last periods's errors and of the last period's
conditional variance.

Our model is fitted and the standardized residuals and estimated parameters are used to generate simulated GARCH(1,1) series. We use Matlab to estimate the parameters for the models via maximum likelihood and OLS and then resample the standardized residuals with replacement to create 5,000 replications of the GARCH(1,1) model. The bootstrap methodology requires high computer power and computer programming.

To test the significance of the trading rule excess returns, the following hypothesis was tested.

$$\begin{aligned} &H_0: XR \leq \overline{XR}^* \quad \text{versus} \\ &H_1: XR > \overline{XR}^* \end{aligned} \tag{5}$$

The null hypothesis states that the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\overline{XR}^*$). The p-values from the bootstrap procedure were used to determine whether the trading rule excess returns are significantly greater than the average trading rule return given that the GARCH(1,1) model.

4. Findings

4.1. Standard Statistical Results

Tables 1-4 reports some summary statistics for daily returns of the PIGS Stock Exchanges [table 1: General Index (Greek Market), table 2: PSI-20 Index (Portugal Market), table 3: FTSEMIB Index (Italian Market), table 4: IBEX35 Index (Spanish Market)].

As can be seen in Table 1 [General Index (Greek Market)], Table 2 [PSI-20 Index (Portugal Market)], Table 3 [FTSEMIB Index (Italian Market)], and Table 4 [IBEX35 Index (Spanish Market)], the returns exhibit excessive kurtosis and non-normality. Besides, Jarque-Bera p-value for table 1-4 rejects normality. We will use the bootstrap methodology under the GARCH (1,1) model to address this problem of non-normality.

As we can see in Tables 5-8, the buy-sell differences are positive for all rules and for all the PIGS. The t-tests for these differences are highly significant at 5% significance level, using two-tailed test. Thus the null hypothesis that the differences are zero is rejected. [At 5% significance level, the upper (lower) critical values of the t-test are +(-) 1.960].

The mean buy-sell returns (Table 5) for General Index (Greek Market) are all positive with an average daily return of 0.004834 which is about 121% at an annual rate (250 trading days x 0.14%). The t-statistics rejected the null hypothesis that the means of the returns are not different from the means of the unconditional returns.

The means of the buy returns for PSI-20 Index (Portugal Market) (Table 6) are all positive with an average daily return of 0.00056 which is about 14% annual rate (250 trading days x 0.00056). The t-statistics reject the null hypothesis that the means of these buy returns are equal to the means of the unconditional returns. That is, all the tests reject the null hypothesis that the means of the buy returns are equal to the means of the unconditional returns at the 5% significance level using a two-tailed test.

The mean of buy-sell returns for FTSEMIB Index (Italian Market) (see Table 7) are all positive with an average daily return of 0.00009 which is about 2.35% annual rate (250 trading days x 0.00009). The t-statistics reject the null hypothesis that the means of buy-sell returns are equal to the means of the unconditional returns.

The means of buy-sell returns for IBEX35 Index (Spanish Market) (see Table 8) are all positive with an average daily return of 0.000183 which is about 4.58% annual rate (250 trading days x 0.000183). The t-statistics reject the null hypothesis that the means of the buy-sell returns are equal to the means of unconditional returns.

Overall, our technical strategies “beat” all the market [General Index (Greek Market), PSI-20 Index (Portugal Market), FTSEMIB Index (Italian Market), IBEX35 Index (Spanish Market)] strategies. In particular, buy-hold strategy (Tables 1-4) gives us about:

- -4.66% per year (-0.01864% x 250 days) for the General Index (Greek Market while moving averages strategy gives 121% per year for buy-sell method (250 trading days x 0.004834) at an annual rate.
- -0.97% per year (-0.00388% x 250 days) for the PSI-20 Index (Portugal Market) while moving averages strategy gives us an annual rate of 14% (250 trading days x 0.00056) for buy-sell method.
- -2.05% per year (-0.000082% x 250 days) for the FTSEMIB Index (Italian Market) while moving averages strategy gives us an annual rate of 2.35 % (250 trading days x 0.00009) for buy-sell method.
- 2.44 per year (0.0000976% x 250 days) while moving averages strategy gives us an annual rate of 4.58 % (250 trading days x 0.000183) for buy-sell method.

So we notice abnormal returns over the General Index (Greek Market), the PSI-20 Index (Portugal Market), the FTSEMIB Index (Italian Market) and the IBEX35 Index (Spanish Market) benchmarks.

Table 1. Statistics for daily returns for General Index (Greek Market)

max:	0.111185825	skewness:	0.25368085
min:	-0.094575522	kurtosis:	6.584661477
num:	3,985	jarquebera:	1499,14137578
std:	0.019084267	jbpval:	0.00
Buy-Hold mean return -0.0001864 = -4.66% yearly			

Table 2. Statistics for daily returns for PSI-20 Index (Portugal Market)

max:	0.068945050	skewness:	-0.055419
min:	-0.096405033	kurtosis:	9.33123491
num:	3,983	jarquebera:	3349,605404
std:	0.0123438239	jbpval:	0.00
Buy-Hold mean return -0.0000388 = - 0.97% yearly			

Table 3. Statistics for daily returns for FTSEMIB Index (Italian Market)

max:	0.0596050403	skewness:	0.1285645665
min:	-0.089499393	kurtosis:	4.4040404497
num:	3,976	jarquebera:	2705,449494
std:	0.0144040404	jbpval:	0.00
Buy-Hold mean return -0.00000082 = - 2.05% yearly			

Table 4. Statistics for daily returns for IBEX35 Index (Spanish Market)

max:	0.5345949191	skewness:	0.105605045
min:	-0.075050552	kurtosis:	5.233030331
num:	3,983	jarquebera:	2540,3033303
std:	0.019084267	jbpval:	0.00
Buy-Hold mean return 0.000000976 = 2.44% yearly			

If technical analysis does not have the ability to forecast price movements, then we should observe the returns on days when the rules indicate buy signals do not differ appreciably from the returns on days when the rules indicate sell signals.

In Tables 5-8, we present the results from simple moving average trading strategies. The rules differ by the length of the short and long period. For example (1,15) indicates that the short period is one day, the long period is 15 days. We present the results for the 6 rules that we examined. In columns 3 and 4 of Table 5 of each table, we report the number of buy "N(Buy)" and sell "N(Sell)" signals generated during the period. The (daily) mean buy and sell returns are reported separately in columns 6 and 7 of each table. The last column of each table, column 8, shows the differences, "Buy-Sell", between the mean daily buy and sell returns. The t statistics for the Buy and Sell are computed using Brock et al. (1992) methodology.

In columns 6, 7 and 8 of each table, the number in parentheses are standard t-statistics testing the difference between the mean buy return and the unconditional mean return, the mean sell return and the unconditional mean return, and buy-sell and zero, respectively. The last row each table reports averages across all 6 rules. The upper (lower) critical values of the t-test values are +/-1.96 at 5% level.

Table 5. Standard results for moving averages (2003-2014 period) General Index (Greek Market)

(1) Period	(2) Test	(3) N(buy)	(4) N(Sell)	(5) Sum	(6) Buy	(7) Sell	(8) Buy-Sell
11/4/2003 to 10/1/2014	(1,9)	148	148	296	0.00321 (4.84789)	0.000997 (-2.50246)	0.002213 (4.98635)
	(1,15)	116	116	232	0.002821 (4.3957)	0.0075 (-2.11981)	-0.004679 -441.353
	(1,30)	89	89	178	0.002686 (3.49822)	0.000849 (-1.54533)	0.001837 (3.44118)
	(1,60)	64	64	128	0.002334 (3.49194)	0.000621 (-1.60028)	0.001713 (4.9509)
	(1,90)	43	43	86	0.002575 (3.00933)	0.000793 (-1.33952)	0.001782 (2.97219)
	(1,120)	33	33	66	0.002798 (2.77301)	0.00083 (-1.09812)	0.001968 (2.63154)
Average					0.016424	0.01159	0.004834

Table 6. Standard results for moving averages (2003-2014 period) PSI-20 Index (Portugal Market)

(1) Period	(2) Test	(3) N(buy)	(4) N(Sell)	(5) Sum	(6) Buy	(7) Sell	(8) Buy-Sell
11/4/2003 to 10/1/2014	(1,9)	27	27	54	0.001909 (4.1723)	0.000604 (-2.98761)	0.001305 (4.58247)
	(1,15)	23	23	46	0.001266 (4.00287)	0.000724 (-2.66951)	0,000542 (4.11489)
	(1,30)	19	19	38	0.001089 (3.290765)	0.000558 (-1.97599)	0.000531 (3.14552)
	(1,60)	13	13	26	0.000934 (3.072335)	0,000863 (-1.632105)	0.000071 (3.12955)
	(1,90)	14	14	28	0.00074 (2.97678)	0.000573 (-1.39357)	-0.001313 (2.53321)
	(1,120)	10	10	20	-0,00021 (2.55098)	0.000363 (-1.14588)	-0.000576 -(2.63495)
Average					0.004245	0.003685	0.00056

Table 7. Standard results for moving averages (2003-2014 period) FTSEMB Index (Italian Market)

(1)	(2)	(3)	(4)	(5)	6	7	8
Period	Test	N(buy)	N(sell)	Sum	Buy	Sell	Buy/Sell
11/4/2003 To 10/1/2014	(1,9)	34	34	68	0.000943	0.000299	0.000644
					(4.00563)	(-2.66667)	(4.267779)
	(1,15)	31	31	62	0.000759	0.000336	0.000423
					(3.95557)	(-2.33467)	(4.19623)
	(1,30)	18	18	36	0.000622	0.000327	0.000295
					(3.282445)	(-1.78995)	(3.44913)
	(,60)	18	19	37	-0.00055	0.000421	-0.000968
					(2.49777)	(-1.46989)	(2.804495)
	(1,90)	7	8	15	0.00074	0.000805	-6.5E-05
					(3.105212)	(-1.26328)	(2.99456)
	(1,120)	4	5	9	0.000685	0.00092	-0.000235
					(2.11467)	(-1.01678)	(2.236657)
Average					0.003202	0.003108	0.00009

Table 8. Standard results for moving averages for IBEX35 Index (Spanish) for the period 2003-2014

(1) Period	(2) Test	(3) N(buy)	(4) N(Sell)	(5) Sum	(6) Buy	(7) Sell	(8) Buy-Sell
11/4/2003 to 10/1/2014	(1,9)	32	33	65	0.000812 (4.39574)	0.000292 (-2.50246)	0.00052 (4.98635)
	(1,15)	22	23	45	0.002115 (4.39574)	0.000348 (-2.11981)	0.001767 (4.41353)
	(1,30)	21	21	42	0.000401 (3.49822)	0.000305 (-1.54533)	0.000096 (3.44118)
	(1,60)	16	17	33	-0.00137 (3.49194)	0.000342 (-1.60028)	-0.001707 (4.9509)
	(1,90)	16	17	33	0.001429 (3.00933)	0.000244 (-1.33952)	0.001185 (2.97219)
	(1,120)	14	15	29	-0.0014 (2.77301)	0.00028 (-1.09812)	-0.001678 (2.63154)
Average					0.001994	0.001811	0.000183

4.2. Bootstrap Results

Applying the approach used by Brock et al. (1992), we obtained 5,000 bootstrap samples, each consisting of 3,984 observations using sampling with replacement from the original return series. In the bootstrap procedure our, objective is to fit the original series to obtain estimated parameters and residuals. We standardize the residuals using the residual standard error. The estimated residuals are then redrawn with replacement to form scrambled residuals series, which is then used with the estimated parameters to form a new representative series for the given GARCH(1,1) model.

Each of the simulation is based on 5,000 replication of the GARCH(1,1) model. This should provide a good approximation of the return distribution under the GARCH(1,1) model. The null hypothesis is rejected if returns obtained from the actual General Index (Greek Market), the PSI-20 Index (Portugal Market), the FTSEMIB Index (Italian Market), and the IBEX35 Index (Spanish Market) data are greater than the returns of the simulated returns under the econometric model [GARCH(1,1)].

Table 9. Parameter estimates for GARCH(1,1) model for the General Index (Greek Market) for the period 2003-2014.

δ	ρ	ω	a	b
0.00046369	0.20372	9.0779e-006	0.15669	0.82531
(1.6497)	(10.3268)	(6.1913)	(14.3335)	(77.8410)

GARCH (1,1) model: $r_t = 0.00046369 + 0.20372r_{t-1}+e_t$

$h_t = 9.0779e\text{-}006 + 0.15669e^2_{t-1} + 0.82531h_{t-1}$ $\quad e_t = h^{1/2}t\, z_t,\ z_t \sim N(0, 1)$

where e_t, r_t, *and* h_t *are as defined earlier in section 3.*

Numbers in parentheses are t-ratios.

Table 10. Parameter estimates for GARCH(1,1) model for the PSI-2o Index (Portugal Market) for the period 2003-2014.

δ	ρ	ω	a	b
0.00038453445	0.222332	8.0953e-006	0.14234	0.79454
(1.334)	(9.3455)	(5.8664)	(13.2234)	(59.645)

GARCH (1,1) model: $r_t = 0.00038453445 + 0.222332r_{t-1}+e_t$

$h_t = 8.0953e\text{-}006 + 0.14234e^2_{t-1} + 0.79454h_{t-1}$ $\quad e_t = h^{1/2}t\, z_t,\ z_t \sim N(0, 1)$

where e_t, r_t, *and* h_t *are as defined earlier.*

Numbers in parentheses are t-ratios.

Table 11. Parameter estimates for GARCH(1,1) model for FTSEMIB Index (Italian Market) for the period 2003-2014.

δ	ρ	ω	a	b
0.000459593	0.212343	7.9754e-006	0.16345	0.83434
(1.597)	(9.5054)	(5.3741)	(12.8745)	(66.4543)

GARCH (1,1) model: $r_t = 0.000459593 + 0.212343r_{t-1}+e_t$

$h_t = 7.9754e\text{-}006 + 0.16345e^2_{t-1} + 0.8343\, h_{t-1}$ $\quad e_t = h^{1/2}t\, z_t,\ z_t \sim N(0, 1)$

e_t, r_t, *and* h_t *are as defined earlier.*

Numbers in parentheses are t-ratios.

Table 12. Parameter estimates for GARCH(1,1) model for IBEX35 Index (Spanish Market) for the period 2003-2014.

δ	ρ	ω	a	b
0.00056734	0.1934333	8.5123e-006	0.14535	0.74434
(1.6865)	(9.45341)	(5.1422)	(15.5645)	(56.987)

GARCH (1,1) model: $r_t = 0.00056734 + 0.1934333r_{t-1}+e_t$

$h_t = 8.5123e\text{-}006 + 0.14535e^2_{t-1} + 0.74434h_{t-1}$ $\quad e_t = h^{1/2}t\, z_t,\ z_t \sim N(0, 1)$

e_t, r_t, *and* h_t *are as earlier defined.*

Numbers in parentheses are t-ratios.

General Index (Greek Market) data are greater than the returns of the simulated returns under the null model. PSI-20 Index (Portugal Market) data are greater than the returns of the simulated returns under the null model as well. FTSEMIB Index (Italian Market) data are greater than the returns of the simulated returns under the null models and IBEX35 Index (Spanish Market) data are greater than the returns of the simulated returns under the null models. Tables 9-12 contains estimation results for the GARCH(1,1) model which will be used for comparison with the actual General Index (Greek Market – Table 9), PSI-20 Index (Portugal Market- Table 10), FTSEMIB Index (Italian Market - Table 11), and IBEX35 Index (Spanish Market - Table 12) series.

In Tables 13-16 we present the results of GARCH(1,1) simulations using simple moving average trading strategies via bootstrap methodology. For the simulations, we create 5,000 bootstrap samples, each consisting of 3,984 observations by resampling the standardized residuals of the GARCH (1,1) models with replacement.

The rules differ by the length of the short and long period. We present results for the 6 rules that we examined. All the numbers presented in columns (4), (5), (6) of the tables are the fractions of the simulated result which are larger than the results for the original indices [General Index (Greek Market – Table 13), the PSI-20 Index (Portugal Market – Table 14), the FTSEMIB Index (Italian Market – Table 15), and the IBEX35 Index (Spanish Market – Table 16)]. The mean buy and sell returns are reported separately in columns (4) and (5) of the Tables. The results presented in columns (4), (5) and (6) of each table (excluding the ones in parentheses) are p-values. The numbers in parentheses under Buy, Sell, and Buy-sell in columns (4), (5), and (6) of each table show how many series from 5,000 replications are greater than the original returns.

The p-values from the bootstrap procedure are then used to determine whether the trading rule excess returns (simple moving averages) are significantly greater than the average trading rule return given from original series. The numbers in parenthesis in clumns (4), (5), and (6)of the tables show how many series from 5,000 replications are greater than the series from the original returns. More specifically, the number in the column labelled Buy (Table 13), which is (5000), shows that 500 of the simulated GARCH(1,1)s generated a mean buy return as large as that from the original examined indices. As can be seen from the values in columns (4) (5) and (6) of each table, most of the simulated GARCH(1,1)s are greater than those from the examined indices [General Index (Greek Market – Table 13), the PSI-20 Index (Portugal Market – Table 14), the FTSEMIB Index (Italian Market – Table 15), and the IBEX35 Index (Spanish Market – Table 16)]. All the buy, sell and buy-sell are highly significant, leading to the acceptance of the null hypothesis. Under the null hypothesis, the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\overline{XR}*$). At 0.05 significant level, the p-value is greater than 0.05 (p-value>0.05). Therefore we accept H_0: $XR \leq \overline{XR}*$ and reject H_1: $XR > \overline{XR}*$. Finally, we found that various forms of moving averages contain significant forecast power for General Index (Greek

Market), the PSI-20 Index (Portugal Market), the FTSEMIB Index (Italian Market), and the IBEX35 Index (Spanish Market)].

Table 13. Simulations Test (5000 replications) for GARCH(1,1) for General Index (Greek Market) for the period 2003-2014.

			GARCH(1,1)		
(1) Period	(2) Test	(3) Results	(4) Buy	(5) Sell	(6) Buy-Sell
11/04/2003 to 10/01/2014	(1,9)	Fraction> General Index	1 (5000)	0.906 (4530)	1 (5000)
	(1,15)	Fraction> General Index	1 (5000)	0.802 (4010)	1 (5000)
	(1,30)	Fraction> General Index	0.994 (4970)	0.63 (3150)	0.994 (4970)
	(1,60)	Fraction> General Index	0.992 (4960)	0.466 (2330)	0.982 (4910)
	(1,90)	Fraction> General Index	0.986 (4930)	0.354 (1770)	0.938 (4690)
	(1,120)	Fraction> General Index	0.988 (4940)	0.316 (1580)	0.946 (4730)
	Average		**0.9933**	**0.579**	**0.9766**

Table 14. Simulations Test (5000 replications) for GARCH(1,1) for PSI-20 Index (Portugal Market) for the period 2003-2014.

			GARCH(1,1)		
(1) Period	(2) Test	(3) Results	(4) Buy	(5) Sell	(6) Buy-Sell
11/04/2003 to 10/01/2014	(1,9)	Fraction> PSI-20 Index	0.842 (4210)	0.116 (580)	0.566 (2830)
	(1,15)	Fraction> PSI-20 Index	0.856 (4280)	0.13 (650)	0.566 (2830)
	(1,30)	Fraction> PSI-20 Index	0.856 (4280)	0.126 (630)	0.572 (2860)
	(1,60)	Fraction> PSI-20 Index	0.864 (4320)	0.158 (790)	0.62 (3100)
	(1,90)	Fraction> PSI-20 Index	0.866 (4330)	0.146 (730)	0.664 (3320)
	(1,120)	Fraction> PSI-20 Index	0.87 (4350)	0.176 (880)	0.674 (3370)
	Average		**0.859**	**0.142**	**0.6103**

Table 15. Simulations Test (5000 replications) for GARCH(1,1) for FTSEMIB Index (Italian Market) for the period 2003-2014.

			GARCH(1,1)		
(1) Period	(2) Test	(3) Results	(4) Buy	(5) Sell	(6) Buy-Sell
11/04/2003 to 10/01/2014	(1,9)	Fraction> FTSEMIB Index	0.860 (4300)	0.766 (3830)	0.860 (4300)
	(1,15)	Fraction> FTSEMIB Index	0.830 (4150)	0.790 (3950)	0.840 (4200)
	(1,30)	Fraction> FTSEMIB Index	0.802 (4010)	0.754 (3770)	0.810 (4050)
	(1,60)	Fraction> FTSEMIB Index	0.842 (4210)	0.764 (3820)	0.858 (4290)
	(1,90)	Fraction> FTSEMIB Index	0.834 (4170)	0.732 (3660)	0.842 (4210)
	(1,120)	Fraction> FTSEMIB Index	0.854 (4270)	0.740 (3700)	0.866 (4330)
	Average		**0.837**	**0.758**	**0.846**

Table 16. Simulations Test (5000 replications) for GARCH(1,1) for IBEX35 Index (Spanish Market) for the period 2003-2014.

			GARCH(1,1)		
(1) Period	(2) Test	(3) Results	(4) Buy	(5) Sell	(6) Buy-Sell
11/04/2003 to 10/01/2014	(1,9)	Fraction> IBEX35 Index	0.844 (4220)	0.740 (3700)	0.844 (4220
	(1,15)	Fraction> IBEX35 Index	0.810 (4050)	0.730 (3650)	0.814 (4070)
	(1,30)	Fraction> IBEX35 Index	0.794 (3970)	0.708 (3540)	0.800 (4000)
	(1,60)	Fraction> IBEX35 Index	0.816 (4080)	0.720 (3600)	0.828 (4140)
	(1,90)	Fraction> IBEX35 Index	0.802 (4010)	0.742 (3710)	0.810 (4050)
	(1,120)	Fraction> IBEX35 Index	0.776 (3880)	0.722 (3610)	0.780 (3900)
	Average		**0.807**	**0.727**	**0.813**

5. Summaries and Conclusions

5.1. Summaries

In this paper we conducted a study on the presence of the behavioural phenomenon in PIGS (Portugal, Italy, Greece and Spain), a group of countries in European Union. We used technical analysis rules to explain behavioural phenomenon in the examined stock markets (the General Index (Greek Market), the PSI-20 Index (Portugal Market), the FTSEMIB Index (Italian Market), and the IBEX35 Index (Spanish Market)) over the years 2003–2014 period. Furthermore. we used various types of moving averages technical rules. We evaluated the following popular moving averages rules: 1-9, 1-15, 1-30, 1-60, 1-90, and 1-120 where the first number in each pair indicates the days in the short period and the second number shows the days in the long period. Moving averages are used in this paper because they are the most commonly used by the chartists-technical analysts

We did further analyses and tests. In our further analyses, we used standard t-tests in combination with bootstrap methodology under the GARCH (1,1) null model.. In all transactions, we assume 0.09% (of the investing capital) commission as entry (buy) fees and 0.09% as exit (sell) fee.

Overall the results obtained from the study show that our technical strategies (buy-hold strategies). “win” the market. In particular:

i. buy-hold strategy gave us -4.66% per year (-0.01864% x 250 days) for the General Index (Greek Market) (see Table 1) while moving averages strategy 121% (250 trading days x 0.004834) per year for buy-sell method.
ii. buy-hold strategy gave -0.97% per year (-0.00388% x 250 days) for the PSI-20 Index (Portugal Market) (see Table 2) while moving averages strategy gave us 14% per year (250 trading days x 0.00056) for the buy-sell method.
iii. buy-hold strategy gave us -2.05% per year (-0.000082% x 250 days) for the FTSEMIB Index (Italian Market) (see Table 3) while moving averages strategy gave us 2.35 % per year for buy-sell method (250 trading days x 0.00009).
iv. buy-hold strategy gave us 2.44 per year (0.0000976% x 250 days) while (see Table 4) moving averages strategy gave us 4.58 % per year (250 trading days x 0.000183) for buy-sell method.

So, we noticed abnormal returns over the General Index (Greek Market), the PSI-20 Index (Portugal Market), the FTSEMIB Index (Italian Market), and the IBEX35 Index (Spanish Market) benchmark. Hence, Technical Analysis and Behavioral Finance Theory seem to exist in the examined stock markets.

In addition, we document significant excess returns for moving average trading strategies and reject the weak-form efficient market hypothesis of Fama (1965).

5.2. Conclusions

These results obtained in this research seem to contradict the Efficient Market Hypothesis, as investors can gain abnormal returns investing in the effects of the market.

Our results here seem to agree with previous results in literature (De Long et al. 1991; Shleifer & Summers. 1990; Deng & Zhen 2006; Pruden et al. 2004; Nebesnijs 2012; Ben-Zion 2003; Lachhwani et al. 2013; Lento 2007; Raval & Vyas 2013a; Raval & Vyas 2013b; Papathanasiou & Siati 2014; Haug & Hirschey 2006; Scott et al 2003; Sias 2007; Malliaris et al 2013; Papakonstantinidis 2012; Christopoulos et al 2014; Ebert & Hilpert 2013; Vasiliou et al. 2008, Vasileiou 2014 etc).

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