2012

Finding Profitability of Technical Trading Rules in Emerging Market Exchange Traded Funds

Austin P. Hallett
Claremont McKenna College

CLAREMONT MCKENNA COLLEGE

FINDING PROFITABILITY OF TECHNICAL TRADING RULES IN EMERGING MARKET EXCHANGE TRADED FUNDS

SUBMITTED TO

PROFESSOR DARREN FILSON

AND

DEAN GREGORY HESS

BY

AUSTIN HALLETT

FOR

SENIOR THESIS

SPRING 2012

APRIL 23, 2012

Table of Contents

Acknowledgements

This thesis is the capstone of my undergraduate experience in financial economics. I thank the Financial Economics Institute for support in writing this thesis, and for instilling a passion within me for finance. I would like to thank my reader, Professor Darren Filson, who has worked extensively with me on this project. I would also like to thank Dean Gregory Hess for his guidance. Lastly, I am grateful for the opportunity to attain an education from Claremont McKenna College. This opportunity stemmed from the support and encouragement of my parents.

Abstract

This thesis further investigates the effectiveness of 15 variable moving average strategies that mimic the trading rules used in the study by Brock, Lakonishok, and LeBaron (1992). Instead of applying these strategies to developed markets, unique characteristics of emerging markets offer opportunity to investors that warrant further research. Before transaction costs, all 15 variable moving average strategies outperform the naïve benchmark strategy of buying and holding different emerging market ETF's over the volatile period of 858 trading days. However, the variable moving averages perform poorly in the "bubble" market cycle. In fact, sell signals become more unprofitable than buy signals are profitable. Furthermore, variations of 4 of 5 variable moving average strategies demonstrate significant prospects of returning consistent abnormal returns after adjusting for transaction costs and risk.

I. Introduction

Technical analysis is a broad title that encompasses the use of a variety of trading strategies in global markets. The strategy that technical analysts exercise derives its strength from the concept that future stock prices are predictable through the study of past stock prices. Furthermore, technical analysts detect the ebb and flow of supply and demand from a specialized conception of stock charts and intraday market action. These beliefs violate the random walk hypothesis – that market prices move independently of their past movements and trends.

A related theory known as the efficient market hypothesis (EMH) states that investors cannot anticipate to generate abnormal profits by relying on information contained within past prices if the market is at least weak form efficient. EMH identifies the concept that sources of predictable patterns that offer significant returns are immediately exploited by investors. By exploiting these patterns in the market, investors quickly and efficiently eliminate any predictability in the market.

There exist stark contrasts in successful investment strategies that boil down to differing conceptions of the EMH. Investors who accept EMH attempt to construct portfolios that mimic the market or optimally diversify risk. On the other hand, successful investors such as Warren Buffet attempt to consistently beat the market by uncovering inefficiencies in market structure. Essentially, this paper will be concerned with the determination of whether certain asset markets are at least weak form efficient and therefore restrict the abilities of investors to generate abnormal profits.

Prior to the proliferation and extensive use of financial information, technical analysis was considered to be the primary tool for investment analysis. In a study conducted by Taylor and Allen (1992) a questionnaire survey revealed that among chief foreign exchange dealers based in London, at least 90 percent of respondents place some weight on this form of non-fundamental analysis. Additionally, there is a skew towards a reliance on technical analysis, rather than fundamental, when considering shorter horizons of investing. Technical analysis techniques vary from basic mathematical concepts to complex multi-faceted programs. Despite the variance within technical analysis, the idea remains the same; to find the optimal entry and exit point in a dynamic market.

Technical analysis, although considered by some as purely conjecture, is still widely accepted as supplemental information to major brokerage firms. There exist two explanations for the success of technical analysis and why its profitability is still debated: (1) stock return predictability stems from prices wandering apart from their fundamental valuations, and (2) stock return predictability forms from efficient markets that can be analyzed by time-varying equilibrium returns. Essentially, both explanations depict some sort of overall market inefficiency in which investors are able to exploit.

Many studies have focused on the use of technical trading strategies in equity, futures and commodity markets. However, research analyzing the use of technical analysis in emerging markets is scant. For this reason, this thesis will focus on the profitability of technical trading strategies in emerging markets. The profitability of these strategies within developing markets will be compared to the profitability of similar strategies from past studies of globally developed and undeveloped markets. Additionally, to observe excess market returns of the following technical analysis trading strategies, this thesis will also analyze the profitability of a "buy-and-hold" strategy over the same time constraints. These strategies will be evaluated solely on their ability to forecast future prices and to provide optimal entry and exit points.

The inclusion of emerging markets data will provide an opportunity to determine remaining excess return and profitability from markets that may not be considered entirely “efficient” or “developed.” These emerging markets may not be considered as deep or liquid as other global markets. Characteristics of emerging markets this thesis will be primarily interested in examining will be the high risks and volatility, the regulatory constraints, and the relatively low volume, which all contribute to possible profitable conditions for technical trading strategies.

This thesis will attempt to examine the entirety of what is considered to be the emerging market today. Moreover, country specific data will uncover any dramatic differences in trading strategy profitability between countries. Using exchange-traded-funds (ETF’s) the results will portray any superior predictability among the technical trading strategies implemented within emerging market data. Based upon previous academic research on technical trading strategies, this study will carefully avoid data collection biases and report results from the variety of technical trading strategies conducted.

II. Literature Review

Primarily, early academic literature on technical analysis focused upon the profitability of simple technical trading rules such as moving averages and trading range breaks (Fama and Blume, 1966). However, a large portion of academic literature on technical analysis tested profitability from charting patterns, genetic programming methods, dozens of other technical trading methods. Recently, after many technical analysis academic studies branched off to look at commodity, foreign exchange, and futures markets, academics have returned to examine new data on simple trading rules in equity markets (Brock et al., 1992; Bessembinder and Chan, 1995; Ito, 1999; Coutts and Cheung, 2000; Gunasekarage and Power, 2001; Loh, 2005). These empirical studies suggest that technical trading rules offer some predictive power; however, the abnormal returns obtained by investors would be dramatically reduced after accounting for transaction costs.

Furthermore, academic studies have begun to test EMH in a variety of emerging and developed markets with the use of simple technical trading rules. Bessembinder and Chan (1995), Ito (1999) and Chang et al. (2004) all demonstrate an increased profitability of technical analysis trading rules in emerging markets relative to developed markets. Research conducted by Kwon and Kish (2002) and Hudson et al. (1996) indicate that gains obtained by investors from technical trading are squandered as technological advancements improve informational and general efficiency of equity markets. Thus, this paper will expand upon the results found that demonstrate how informational and general market efficiency impact the profitability of technical analysis trading rules.

Early empirical studies by Fama and Blume (1966) and Van Horne and Parker (1967) presented evidence supporting weak form market efficiency and the random walk theory. Fama and Blume studied 30 individual stocks listed on the Dow Jones Industrial Average (DJIA) over a six-year period. Fama and Blume found, after commissions, that only 4 of 30 securities had positive average returns. Furthermore, the rules they applied proved inferior to the buy and hold strategy before commissions for all but two securities. Van Horne and Parker analyzed 30 stocks listed on the New York Stock Exchange

(NYSE) over a similar six-year period and found that no trading rule that was applied earned a return greater than the buy and hold strategy on the same index. Additionally, Jensen and Benington (1970) analyzed alternative technical trading rules over a period from 1931-1965 on NYSE stocks and found further confirmation that technical trading rules do not outperform the buy and hold strategy.

Despite this, an extensive study performed by Alexander (1961) found information that supports the use of technical analysis. Alexander's study prompted a series of studies attempting to disprove his results, and thus initiate the argument over the success of technical analysis in financial markets. Alexander researched the stock returns of the Standard and Poor Industrials and the Dow Jones Industrials from 1897-1959 and 11 filter rules from 5.0% to 50%. Although transaction costs were not accounted for in the study, all the profits found were not likely to be eliminated by commissions. As a result, the debate on whether technical analysis is a viable investment tool to find excess stock returns began in the 1960's, and the debate continues today. The benefits of using technical analysis are still debated within equity markets, but many empirical studies suggest consistent excess profitability of technical analysis above the buy and hold strategy within commodity and futures markets. Lukac, Brorsen and Irwin (1988) look at 12 futures from various exchanges including interest rates, agricultures, and currencies during the 1970's and 1980's. The study found evidence that suggested certain trading systems produced significant net returns in these markets.

More recently research has taken several precautions to eliminate or diminish issues that were relevant for early empirical studies. These issues included, but were not limited to: data snooping and the non-allocation of transaction costs. In an effort to mitigate these issues Brock, Lakonishok, and LeBaron (1992) used a large data series (1897-1986) and reported results for all rules that were evaluated. The Brock et. al. study indicated that some technical trading rules have an ability to forecast price changes in the DJIA. For statistical inferences, Brock et. al. performed their tests using a statistical bootstrapping methodology inspired by Efron (1979) and Jensen and Bennington (1970). Stock prices are studied frequently in financial research, and are therefore susceptible to data snooping.

Brock et. al. opened the door for further arguments in support of technical analysis as a powerful forecasting tool, especially in markets that may be considered less "efficient." Bessembinder and Chan (1995), Ito (1999), and Ratner and Leal (1999) researched similar technical trading strategies as Brock et. al. in a variety of foreign markets in Latin America and Asia. The studies each found significantly higher profits using technical trading strategies than using the buy and hold strategy in countries such as Malaysia, Thailand, Taiwan, Indonesia, Mexico, and the Philippines. In fact, Ratner and Leal found forecasting ability from 82 out of the 100 trading rules evaluated when statistical significance was ignored.

Sullivan, Timmerman and White (1999), or STW from hereon, dug further into technical analysis by utilizing certain strategies to address the issue of data-snooping. Data-snooping occurs when data sets are reused for inference or model selection. Given this, the success of the results obtained may be due to chance rather than the merit of the actual strategy. STW (1999) employed White's Reality Check bootstrap methodology to filter the data in a way not previously done. Jensen and Bennington (1970) refer to the impacts of data-snooping as a "selection bias." STW (1999) explain it in this way:

> "data-snooping need not be a consequence of a particular researcher's efforts… as time progresses, the rules that happen to perform well historically receive more attention, and are considered serious contenders by the investment community, and unsuccessful trading rules tend to be forgotten…If enough trading rules are considered over time, some rules are bound by pure luck to produce superior performance[1]."

STW (1999) implemented over 8000 technical trading strategies to the same data set used by Brock et. al. (1992). STW sought to find that certain trading strategies outperform the benchmark buy-and-hold strategy after controlling for data-snooping. Although the Reality Check bootstrap methodology allowed for STW to differentiate themselves from previous researchers, the bootstrap methodology is not unique to technical analysis academic literature. Data snooping is a concern for all financial empirical studies, especially those that consider stock-market returns as addressed in Lo and MacKinlay (1990).

Perhaps one of the most recognized studies on the subject of technical analysis was the work conducted by Andrew Lo and Craig MacKinlay beginning in 1988 and spanning until they compiled their work into the book *A Non-Random Walk down Wall Street* in 1999. The research and book argued against famous research by Fama (1970) that dictated that prices fully reflect all available information. Lo and MacKinlay produced arguments for the creation of the concept of relative efficiency. Relative efficiency dictates that instead of comparing markets and their inefficiencies to a "frictionless-ideal[2]" market, professionals should consider the varying degrees of efficiencies that currently exist within markets.

---

[1] Sullivan, Ryan, Allan Timmermann, and Halbert White. "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap." *American Finance Association* 54.5 (1999): 1651. Print.

[2] "Contents for Lo & MacKinlay: A Non-Random Walk Down Wall Street." Web. Feb. 2012.

Recently, academic literature on technical analysis has ventured to include examinations of behavioral finance in an effort to derail EMH further. West (1988) examined theories that there exist disparate differences in the volatility of stock prices as compared to volatility of fundamentals or expected returns. West suggests that it may be necessary to consider non-standard models focusing on sociological or psychological mechanisms such as momentum in stock prices. Momentum and concepts behind herd mentality are prominent in many tools used by technical analysts including moving averages and trading range breakouts. Scharfstein and Stein (1990) summarize arguments for the presence of momentum in equity markets:

> The consensus among professional money managers was that price levels were too high – the market was, in their opinion, more likely to go down than up. However, few money managers were eager to sell their equity holdings. If the market did continue to go up, they were afraid of being perceived as lone fools for missing out on the ride. On the other hand, in the more likely event of a market decline, there would be comfort in numbers – how bad could they look if everybody else had suffered the same fate?

Money managers that use momentum strategies to invest are evidence that bolster arguments inconsistent with EMH because these strategies challenge the validity of the random walk hypothesis. Lakonishok, Shliefer, and Vishny (1992) find evidence of pension fund managers either buying or selling in herds, with slightly stronger evidence that they herd around small stocks. Stock market efficiency, in essence, demonstrates that the price of a stock should at all times reflect the collective market beliefs about the value of its underlying assets. Any change in value should immediately be portrayed in the stock price of the asset via new information. If this informational efficiency is in place then any historical changes in price cannot be used to predict future changes in the price. This thesis will test the productivity of information transmission in emerging markets by testing for superior predictability of technical trading strategies.

To properly test for superior predictability this thesis will mimic past studies through the use of separate sample periods in order to test whether the a certain trading strategy contains inherent superior capabilities across time periods or if it gained superior capabilities by chance. Lukac, Brorsen, and Irwin (1988) were some of the first researchers to implement such a strategy with technical analysis. The use of both in-samples and out-of-sample data will be constructed to deliver more meaningful results in this thesis.

Tending to the concept behind less efficient markets, this study intends to examine "less efficient" capital markets in hopes of finding conclusive evidence regarding superior predictability within these markets. Emerging capital markets (hereon ECM) attract many investors particularly during times of financial instability in developed markets. Additionally, investors seeking to diversify their portfolios often find ECM attractive. Since the early 1990's many countries currently considered as ECM have undergone immense financial liberalization processes. Also, characteristics such as higher sample average returns and low correlations to developed markets have led to substantial increases in capital flows (Bekaert and Harvey, 1997). Despite this dramatic increase of capital flows, little research has analyzed the profitability of technical trading rules in these markets.

Bekaert and Harvey (1997) suggest ECM's exhibit both higher volatility and higher persistence in stock returns as compared with developed markets. This evidence pokes holes in EMH and demonstrates the possibility of at least some market inefficiency that could offer opportunities for abnormal returns to investors. ECM's are arguably more likely to demonstrate these characteristics given their low level of liquidity. Nonsynchronous trading biases and general market thinness provide significant evidence of the possibility for market inefficiencies. Other research such as Barkoulas et. al. (2000) suggests that investors in ECM's react slower and more gradually to information as compared with developed markets. This "learning effect" is important in our analysis among other non-normal, non-linear, and long-range dependence effects of ECM's suggested by Bekaert and Harvey (1997).

ECM's exhibit unique characteristics that help investors implement diversification within their portfolio. Standard statistical tests may not fully uncover the potential for abnormal profits to be achieved in emerging markets due to certain unique characteristics. To further develop the research on technical analysis in emerging markets there is a need to further explore the momentum-based trading rules that Brock et. al. used. Secondly, research must attempt or acknowledge that results may be suspect due to data-snooping biases, and take necessary precautions to eliminate this bias within the data. Additionally, research applying technical analysis to emerging markets has not fully developed or made use of a large data set similar to what Brock et. al. used for U.S. equity markets. Lastly, emerging market research needs to control for transaction costs and explore deeper into recent developments of emerging markets by including new countries and data points. This thesis will implement data from emerging market ETF's in order to differentiate from previous studies and to produce a more comprehensive data set of ECM.

III. Theory

Technical Trading Systems

Technical trading systems are composed of sets of trading rules that govern when it is appropriate for a trading to buy or sell their position within an asset. The simple trading strategies that will be discussed in this thesis generally have one or two parameters that offer optimal trade timing through generated buy and sell signals. This study will replicate some of the moving average strategies that are part of the 26 technical trading systems examined by Brock, Lakonishok, and LeBaron (1992) to avoid compounding the dangers of data snooping. These 26 technical trading systems consist of variable moving averages (VMA), fixed moving averages (FMA), and trading range breaks (TRB). The following sections will illustrate the technical trading strategies that are commonly used in studies with a specific focus on the strategies that will be implemented in this thesis.

Moving Averages

Perhaps the most simple and popular trend-following system used by money managers within technical analysis is the moving average. Gartley (1935) was one of the first to study moving averages. Moving average rules are designed to offer buy and sell signals depending upon the movement and relationship between a long and short-period moving average. Gartley (1935) explains how moving average systems generate signals:

> In an uptrend, long commitments are retained as long as the price trend remains above the moving average. Thus, when the price trend reaches a top, and turns downward, the downside penetration of the moving average is regarded as a sell signal… Similarly, in a downtrend, short positions are held as long as the price trend remains below the moving average. Thus, when the price trend reaches a bottom, and turns upward, the upside

penetration of the moving average is regarded as a buy signal.[3]

Figures 1 and 2 display moving average trading signals and the differences that occur in the signal generated depending upon the length of the long-period moving average. There exists thousands of trading rule variations that can be performed just within shifting long and short-period moving averages. Moving average systems can take multiple forms depending upon the method used to average the stock prices. For example, simple moving averages are calculated by giving equal weight to each day in the sample. On the other hand, exponential or variable moving averages give greater weight to more recent days so that the investor is able to keep a closer eye on quickly developing underlying trends. Some researchers, such as Brock, Lakonishok, and LeBaron use variable moving averages, but treat them as simple moving averages. For consistency, this thesis will mimic the terminology used by Brock et. al., but will use variable moving averages by giving each day an equal weight in the calculation of the moving average. Essentially, both moving averages attempt to smooth out price actions of the stock and avoid false signals.

Moving averages work efficiently in markets that are coming out of sideways price action. In other words, moving averages perform well in scenarios where strong trends develop. When the market is "congested[4]" moving averages will tend to give investors something known as "whipsawing." Whipsawing occurs when buy and sell signals are generated, but by the time the investor enters the market, the trend has depreciated and significant profits are no longer obtainable. One solution to whipsawing is the

---

[3] Gartley, H.M. *Profits in the Stock Market*. 1935. 256.
[4] Park, Cheol-Ho, and Scott H. Irwin. "The Profitability of Technical Analysis: A Review." *Social Science Research Network* (2004): 1-106. SSRN, Oct. 2004.

development of a band surrounding the moving averages that attempts to eliminate less than profitable trend signals. These filters are imposed on the moving average rules so that a buy signal is generated only when the short moving average rises above the long moving average by a fixed amount, b. These trading strategies allow the investor to sit out of the market during periods where the market lacks direction. This price band is demonstrated in the trading strategies used in Brock et. al. (1992) and will be implemented within this study. If the short moving band is inside of the band, no signal will be generated. Trading strategies without a band will classify all days as either buys or sells. The following depicts the mathematical calculation of moving averages:

$$Ma_t = 1/N \sum P_{t-i} \qquad (1)$$

Where ma_t is the moving average for ETF over a period of days N. In this paper a day is considered to generate a buy signal when:

$$\sum^S R_{i,t} / S > \sum^L R_{i,t-1} / L = \text{Buy} \qquad (2)$$

Where $R_{i,t}$ is the daily return in the short-period (1, 2, or 5 days), and $R_{i,t-1}$ is the return used in the long-period. This calculation is repeated every day in order to take into account a constant shifting moving average of the previous N days[5]. The variables S and L dictate the number of days used in the short-period and long-period moving averages, respectively. For VMA rules, this position is held until an imminent sell signal is indicated by the following equation:

$$\sum^S R_{i,t} / S < \sum^L R_{i,t-1} / L = \text{Sell} \qquad (3)$$

---

[5] Moving averages for certain days are calculated as the arithmetic mean of prices over the previous *n* days, including the current day. Thus, short-period moving averages have smaller values of *n* than long-period moving averages.

On the other hand, the FMA rules Brock et. al. examined are discussed shortly.

The VMA rules analyzed by Brock et. al. are as follows: 1-50, 1-150, 5-150, 1-200, 2-200, where 1, 2, and 5 represent the number of preceding days used to calculate the short-period moving average, and 50, 150, and 200 represent the number of preceding days used to calculate the long-period moving averages. Each moving average rule is evaluated with price bands of zero and 1%, which brings the total number of VMA technical trading rules to ten. In addition to VMA rules, this study will briefly examine theories behind FMA rules. FMA rules generate similar signals, however, after a buy or sell signal is generated the position is held for only ten trading days. The theory behind FMA strategies is that after significant momentum produces a buy signal, it is important to limit the amount of time spent in the market because the majority of the price adjustment will occur quickly.

For the use of this study both VMA and FMA trading rules can be classified as "double crossover methods[6]." This implies that both strategies make use of two moving averages – one short and one long period. Technically, the strategies that use a one-day moving average for the short period look at the profitability from the price moving above the 50, 150, or 200 day moving average.

Trading Range Breaks

Trading range breaks (TRB), also known as support and resistance or price channels, are used intensely within technical trading. The use of price channels to help investment decisions date back to the early 1900's with Wyckoff (1910). Essentially, the

[6] Murphy, John. "Technical Analysis of the Financial Markets [Hardback]." *Technical Analysis of the Financial Markets (Book) by John Murphy*. Web.

underlying concept of price channel trading strategies is that markets that move to new highs or lows suggest continued trends in the established direction. A buy signal is generated in a price channel strategy when the price pierces the resistance level. For price channels the resistance level is defined as the level of the local maximum price. A sell signal is generated, on the other hand, when the price pierces below the support level. Intuitively, the support level is the level of the local minimum price. Technical analysts use these strategies under the belief that traders are willing to sell (buy) at the peak (trough). Therefore, if the price surpasses the extremity of the local maximum (minimum) then it will signal a continuing movement to a new maximum (minimum) that is significant.

Brock et. al. (1992) implemented a simple ten day holding strategy following a buy or sell signal within the price channel strategy. Similarly to the moving average strategies, price channel strategies generate trading signals based upon a comparison of today's price level with the price levels achieved over some number of days in the past. There are several different types of price channel strategies, but this study will look at Outside Price Channel strategies. Outside Price Channel strategies compare the closing price to a previous number of days of price action. For the sake of this study we will analyze price channels over the same time periods as the long-period moving averages (50, 150, and 200). Lastly, price bands will be considered just as they will be considered in our test of moving averages. These zero and 1% bands will be applied to each time period (50, 150, and 200) to let us determine any superior profitability.

Other Trading Strategies to Consider

Although moving average strategies will be the only technical trading systems tested in this study, it is worth briefly noting the extent other technical trading oscillators and recommend tests for future studies.

Other prominent technical trading rules used by money managers include the relative strength index, momentum oscillators, and volume-based trading rules. As with many other technical trading strategies, these strategies gain credibility on their ability to accurately quantify the degree of momentum or velocity that exists within prices. The relative strength index (RSI) measures the speed and change of price movements. The index allows for the oscillator to range between values of 0 and 100. Practitioners, consider values above 70 to be overbought and value below 30 to be oversold. However, divergences, failure swings and centerline crossovers can also generate trading signals. RSI is calculated by the ratio of average gains to average losses over a specified period of time. In addition to RSI, momentum and volume based oscillators help capture similar concepts behind price movements. Ultimately, these rules have proven to be powerful in certain markets. Nonetheless, the potential strength of using these trading strategies together must be noted. There exists little research on technical trading strategies that implement dual confirmation from several oscillators. Perhaps as markets become more efficient it will be necessary to test technical analysis trading strategies that, for example, require signals from both a moving average and relative strength index.

Autocorrelation and EMH

The profitability attached to the trading rules examined in this study of emerging markets could be related with the autocorrelation in these markets. Research conducted by Harvey (1995) suggests that autocorrelation is much higher in emerging markets than in developed markets. This is most likely due to the unique characteristics of emerging markets that were discussed earlier. One influential characteristic of emerging markets on autocorrelation is the low level of volume also known as nonsynchronous trading. Campbell, Grossman, and Wang (1993) find that first-order autocorrelation in daily stock returns is higher when volume is low. Other research, including Harvey (1995), finds that the level of autocorrelation is directly affiliated with the degree of concentration of investors in the market.

The level of autocorrelation is relevant to our study because substantial autocorrelation may suggest patterns in the stock price data. These patterns are exactly what technical trading strategies attempt to employ in order to sustain profitability from predictability. The potential for weak form market inefficiency is potentially greater with a larger magnitude of autocorrelation. In fact, Ratner and Leal (1999) suggest that trading signals in moving average strategies follow large movements in stock price and assume that autocorrelation bias in the time series trend will apply pressure on the stock price to continue in the same direction. This concept seems applicable to a wide variety of momentum-based indicators including price channels. Thus, Ratner and Leal display arguments for a connection between significant levels of autocorrelation and the profitability of technical analysis in markets.

Nonsynchronous trading is observed when low liquidity or low volume levels are exhibited in markets. Trading takes place less frequently and therefore prices are unable to adjust quickly to incorporate newfound value in the asset. The following equations demonstrate how nonsynchronous trading and first-order autocorrelation may be contributors to any predictability found in this study of emerging markets:

$$\ln P_t = \ln P_{t-1} + e_t \qquad (4)$$

and rearranging equation three gives us:

$$\ln P_t - \ln P_{t-1} = e_t \qquad (5)$$

Returns here are calculated as log differences. The log differences of the series are equal to the shocks to log prices. If future returns are somewhat dependent upon past returns, the error term e is not independently random drawn as in a random walk. Instead, the error term is predictable much like Lo and MacKinlay (1990) suggest.

The theory behind the efficient market hypothesis holds that investors use all publicly available information to inform themselves and their trading strategies. When new information is dispersed into the market, some investors may overreact while other investors under react to the information. However, the reactions are random and follow a normal distribution, which allows for the net effect on the market to be fairly valued. There are three common forms of EMH; the weak form state, the semi-strong-form state, and the strong form state. This paper is primarily concerned with whether or not ECM's are considered at least weak-form efficient. If this is so, technical analysis strategies will not provide excess returns to investors. In weak-form efficiency, stock prices do not exhibit serial dependencies, which allow patterns to form within the market. Thus, this study intends to suggest whether or not profits can be systematically obtained from markets that are not classified as weak-form efficient.

IV. Data

This study will obtain daily data from the Center for Research in Security Prices (CRSP) through the Wharton Research Data Services (WRDS) and Yahoo Finance Database. Data will be pulled from this resource for the ETF's Vanguard MSCI Emerging Markets (NYSE: VWO) and iShares MSCI Emerging Markets Index (NYSE:

EEM). VWO seeks to track the performance of the Morgan Stanley Composite Index (MSCI) for 21 emerging markets. Refer to Table 1 for a list of specific countries that the MSCI Index tracks. MSCI tracks the return of stocks issued by companies located in these 21 emerging market countries. EEM is a fund that seeks investment results that correspond to the performance of publicly traded equity securities in emerging markets. MSCI is designed to measure equity market performance in the global emerging markets. Lastly, MSCI seeks to capture 85 percent of the total market capitalization.

Data is collected daily from March 10, 2005 to December 30, 2011 for the ETF's VWO and EEM. Together, the data consists of nearly 3500 price observations from which moving averages will be constructed to determine superior predictability of technical trading strategies.

V. Methodology

A study conducted by David Leinweber, the managing director of First Quadrant in Pasadena, sought to determine from a large list of variables which variable was the best predictor of performance in the Standard and Poor's 500 Index. It was discovered that the single best predictor was butter production in Bangladesh[7]. This is relevant to this thesis because the research performed attempts to determine if technical trading strategies have true predictive power or if they vaguely suggest patterns in markets that do not significantly improve trading performance. This section will strive to motivate the purpose of this paper, and to demonstrate the methods that will help determine whether technical trading strategies have inherent predictive abilities in emerging market ETF's.

---

[7] Sullivan, Ryan, Allan Timmermann, and Halbert White. "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap." *American Finance Association* 54.5 (1999): 1647-691. Print.

This thesis will be primarily focused on whether simple technical trading strategies suggest profitability above the benchmark of buying and holding ETF's in the emerging markets. Previous research has shown evidence of the profitability of technical trading rules in certain emerging markets. This study is interested in encompassing a greater field of countries that are currently considered as ECM. Also, although risk needs to be considered, it may be useful to determine if any advantages to investing in emerging markets exist.

Variable moving average strategies used by Brock et. al. (1992) will be implemented in similar fashions to Ratner and Leal (1999). Brock et. al. chose to use zero and 1% percent price bands surrounding the moving averages in order to eliminate effects of "whipsawing." However, this study will implement moving average strategies that Brock et. al. used with zero, 0.5, and 1 standard deviation price bands surrounding the moving averages. These standard deviation price bands are constructed based upon the standard deviation of each trading rule ratio on the data of each ETF.

In total 30 trading strategies will be analyzed (15 for each ETF) and they will comprise of 15 VMA strategies. Using the statistical Software called STATA, smoothed moving averages of 1, 2, 5, 50, 150, and 200 days will be constructed to implement the trading rules. Each strategy will be imposed upon the data, and the results of each strategy will be discussed in order to mitigate data-snooping effects. Furthermore, displaying trading strategy results from both in-sample and out-of-sample periods will mitigate data snooping. Brock et. al. note than there is no complete remedy for data snooping biases, but certain precautions will be executed in order to mitigate the problem. By reporting in-sample and out-of-sample periods the success of each strategy is further bolstered due to its inherent superior characteristics rather than from chance. In essence, the two periods will allow us to examine the inherent predictability of each technical trading strategy in varying types of markets. Given that the period breaks on the date August 6, 2008, the data will allow us to examine the profitability of each VMA strategy in both a "bubble" market and a volatile trending market. This further differentiates this study by examining the profitability of technical analysis in specific market cycles.

Each trading strategy will generate buy and sell signals that will attempt to outperform the benchmark strategy. A few key assumptions will be necessary to successfully understand the potential profitability of these technical trading rules. First, whenever a buy signal is generated, the price of the stock will be irrelevant because the trading strategies will assume equal weighting of investments into each strategy. In other words, only percentage returns will be analyzed. The trading strategies will not consider heavier weighting on some buy signals than other buy signals.

Secondly, whenever a sell signal is generated, the investment will take a short position in the ETF. For strategies that have a price band around the moving average, the strategy will liquidate a buy or sell signal when it is generated and an investment will be made into risk-free treasury rate. Assumptions of the treasury rate during the period 2005-2011 need to be considered. Therefore, whenever a trading strategy has not signaled a buy signal, the investor will be considered to be acquiring a conservative 3 percent from United States Treasury Bills[8]. Lastly, the construction of the moving average rules in STATA only signal buy or sell trades if the ratio of the moving averages

[8] Information is gathered from United States Department of Treasury at www.treasury.gov

exceed the value. Due to this, if the ratio of the moving averages based upon the closing price is ever exactly equal to the value needed to generate a signal (such as zero) then the signal generated will be an investment in treasuries. Returns are calculated for each trading rule once a signal has been generated. Returns begin accumulating in that position based upon the adjusted closing price one day forward divided by the current day adjusted closing price minus one. This way, returns are not biased to include any significant move in prices that occurred prior to the signal generated by the closing price.

In Table 2, the mean daily returns and standard errors for 5 VMA strategies on the Vanguard Emerging Market ETF (VWO) and the MSCI Emerging Market ETF (EEM) are displayed in log percentages. In order to determine the significance of the results found, the profitability of each trading strategy is compared to the profitability of the benchmark strategy of buying and holding the given ETF. Statistical significance is determined using a standard student t-test and distribution offered from the statistical Software STATA. Prior to calculating a difference of means two-sample t-test, the variance of the benchmark strategy is compared to the variance from a specified trading rule. Using the F-test for equality of two variances, the two variances are deemed as either equal or unequal to one another before accurately calculating statistical significance in a t-test.[9] After determining equality of variances the calculation of the test statistic for equal variances is as follows:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{S_{X_1X_2} \cdot \sqrt{\frac{2}{n}}} \tag{6}$$

Where X_1 and X_2 represent the mean daily returns in log percentages for the trading rule

---

[9] The F-test is calculated as the (explained variance)/(unexplained variance).

and benchmark. N_1 and N_2 represent the number of days each position for the strategy was held, and Sx_1x_2 represent an estimator of the common standard deviation of the two samples. Intuitively, all variance tests for columns labeled combined within the zero standard deviation price band tests returned confirmations of equal variance between the trading rule and the benchmark. Nonetheless, several strategies under both ½ and 1 standard deviation price band rules had statistically significant unequal variances from the benchmark strategy. For these scenarios, a t-test assuming unequal variances was calculated as follows:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{S_{X_1X_2} \cdot \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \qquad (7)$$

Where,

$$S_{X_1X_2} = \sqrt{\frac{(n_1 - 1)S_{X_1}^2 + (n_2 - 1)S_{X_2}^2}{n_1 + n_2 - 2}}. \qquad (8)$$

Tables 2 through 10 display the results obtained using these calculations. Variances were determined as either equal or unequal depending upon whether the F-test was significant at the 5 percent level.

The following sections will exemplify all trading strategies that were imposed upon the data in this study. The purpose of the study is to determine whether modified trading rules used by Brock et. al. contain any predictive ability in emerging markets. Due to the unique characteristics of emerging capital markets, the hypothesis of this study is that certain trading rules provide evidence of superior predictive ability in emerging market ETF's. However, any results are suspect to biases that exist from the use of stock return data and critical assumptions that have been made in the process of the study.

VI. Empirical Findings

The analysis conducted in this thesis demonstrates contrasts when technical trading strategies are distributed into both in-sample and out-of-sample results. In Tables 2 through 4, the data suggests that significant abnormal returns may be obtainable by investors while using Brock et. al. variable moving average strategies for exchange traded funds in the emerging markets. However, results exhibited in this thesis are suspect due to the inability to control for data snooping biases, the inherent risk attached to emerging market funds, any profits obtained during the Great Recession, and the effects of transaction costs on trading rule profits.

Overall, 7 out of 15 technical trading strategies analyzed over a period from March 10, 2005 to December 31, 20011 were more profitable than the benchmark when averaging the returns across the two ETF's. Despite this, after adjusting for statistical significance this number is greatly reduced. No variable moving average strategies (including individual buy and sell strategies) were statistically significant during this period. This is displayed in Table 2 through Table 4. On average, buy signals generated by the moving average rules with zero and ½ standard deviation price bands outperformed the benchmark strategy during this period for the ETF VWO. Buy signals for EEM were slightly less efficient and profitable than they were for VWO[10].

In Table 2 the (1, 150; 5, 150; 1, 200; 2, 200) strategies with zero standard deviation price bands outperformed the benchmark strategy in both combined and buy signals for each ETF[11]. In Table 3 the (5, 150; 1, 200; 2, 200) strategies were also more

[10] Efficiency describes the change in mean daily return, while profitability describes changes in the holding period return.
[11] Analyzed over the period March 10, 2005 – December 31, 2011.

profitable than the benchmark with ½ standard deviation price bands for VWO over the same period. In fact, buy signals were more than 20 percent more efficient for both ETF's when using ½ standard deviation price bands instead of zero standard deviation price bands. This resulted in strategies (1, 50; 1, 200; 2, 200) becoming more profitable in the combined strategy using ½ standard deviation price bands.

The VMA strategy (5, 150) was consistently the most profitable for all periods and ETF's. This VMA strategy garnered a holding period return of 122 log percent for the ETF VWO and 110 log percent for the ETF EEM using zero standard deviation price bands over the entire period. Using this trading rule over the 82 month period produced double the returns of the benchmark strategy and topped an annual rate of 16 percent. This mean daily return is calculated by classifying every daily return experienced in the ETF as a buy, sell, or holding return. For sell returns, the negative of the mean daily return in the ETF is used to signify profits for the trading rule. Thus, if we were to summarize the returns of the benchmark strategy when a trading rule signified a buy return, the mean daily return for the benchmark would match the mean daily return for the trading rule in the buy column. Essentially, the trading rules attempt to select the most profitable days in the market for either a long position or a short position. Holding return days signal an investment to be made into treasuries because the market does not appear to be significantly profitable in either a long or short position. For this reason, the variance of each trading rule diminishes as more days are classified as "holding" days.

If an investor was interested in solely using the buy signals to construct a trading strategy, the columns labeled buy would dictate the performance of these strategies. For example, in Table 9 the buy signal was extremely profitable to the investor. On days that a buy signal was generated for the ETF VWO, the investor would obtain profits of 0.122 log percent. However, only 35 percent (303/858) of the total days in the period where characterized by a buy signal. On average, buy signals for VWO in Table 9 produced an annual return to investors over 10 log percent while the benchmark strategy failed to break even annually. On the other hand, the trading rule (1, 50, 1) in Table 10 demonstrates a significant reduction in profitable buy signals with only -0.003 log percent on the ETF VWO. Yet, only 131 trading days were classified as buy signals under this strategy. The benchmark strategies of buying and holding the ETF's achieved mean daily returns of 0.032 and 0.034 log percent for EEM and VWO respectively. Interestingly, both ETF's experienced a higher return during the "bubble" market period than for the entire period.

The least statistically significant profitable strategy used on the ETF's was consistently the strategy using the ratio of the one-day moving average to the fifty-day moving average. On average, the strategy (1, 50) produced positive mean daily returns to the investor in only five out of nine instances.

Contrary to what the beta's of the two ETF's display, the standard deviations for the trading rules on EEM were slightly higher than the standard deviations for the trading rules on VWO. The running three year beta for EEM is 1.09 while the running three year beta for VWO is 1.12 given a beta of 1.00 for the Standard and Poor's 500 Index[12]. Furthermore, the calculated three year Sharpe ratio for EEM is 0.92 and 0.98 for VWO[13]. Standard deviations of the trading rules diminish as price bands grow to ½ standard

---

[12] *Yahoo! Finance*. Web. Jan. 2012. <http://finance.yahoo.com/>.
[13] *Yahoo! Finance*. Web. Jan. 2012. <http://finance.yahoo.com/>.

deviations. Despite this, standard deviation of the trading rules increase when moving to using 1 standard deviation price bands. This demonstrates that volatility is diminished by the exclusion of a certain amount of "whipsaw" price action.

Many past studies have examined the profitability of technical trading strategies using moving averages based upon the cross of one moving average over another. In addition to this strategy, this thesis examines and displays the profitability of technical trading strategies that incorporate price bands of both one-half and one standard deviation around moving averages. Interestingly, of the ten trading rules (five for each ETF) for the whole period, eight of the ten trading rules found the most efficient profitability above the benchmark with the use of one-half or one standard deviation price bands. This demonstrates and suggests that eliminating a certain amount of "whipsaw" price action can be profitable to the investor.

Two sample periods were constructed within the period analyzed in order to determine profitability of technical trading strategies in different types of markets, and to determine if the trading strategies hold any inherent predictive ability. In essence, by constructing two separate and distinct periods in the data, this thesis strives to mitigate data snooping biases. The second constructed period demonstrates the volatility present due to The Great Recession in late 2008 and early 2009. Following this downward trending market, poor news out of Europe and a significant likelihood of default of many European countries caused further erratic sell-offs. Along with this volatile risk, the technical trading strategies during the volatile period possessed a higher daily mean return than in the bubble period or the entire period. In Tables 2 through 10 data is collected in the combined columns that portray this relationship. This demonstrates the theory behind the CAPM model in finance; that higher risk brings a higher reward.

There exists a contrast in the significance of the profitability of the trading strategies when examined in two separate smaller periods. The trading rules displayed unequal variances when compared to the variance of the benchmark more often during the "bubble" market period from March 10, 2005 to August 5, 2008 than during the volatile period from August 6, 2008 to December 31, 2011. In other words, the statistical t-test assuming unequal variances was conducted more often during the "bubble" market period than in the other two periods. This difference is mostly due to an increased amount of "holding" days for each of the strategies. These days lower volatility for the trading strategies and create a larger margin between the variance in the trading strategies and the benchmark strategy. Given that the market is less volatile in the "bubble" period, it is likely that fewer signals (either buy or sell) will be generated because the price action is less erratic.

Also noteworthy are the returns of the varying strategies when broken out into separate time periods. The Tables suggest that creating sample periods did not change the order of which the strategies achieve the highest profits. Apart from the consistently least profitable strategy (1, 50) and the most profitable strategy (5, 150) the remaining three strategies hold similar satisfactory returns throughout the three periods. Of the remaining three strategies, one strategy is not consistently more profitable than the others. However, (1, 200 and 2, 200) consistently provide more efficient profitability from buy signals, while the strategy (1, 150) provides consistently more efficient profitability from sell signals. Aside from this exception, the trading rules suggest that they contain some inherent predictive ability in these markets to the extent that the achieved significance in the t-statistics dictates.

Interestingly, the most profitable period for the trading rules was the whole period. Nevertheless, when returns are annualized, the trading rules performed better in the volatile market cycle than in either of the other market periods. Comparing the average combined columns in Tables 2, 5, and 8, then Tables 3, 6, and 9, and then Tables 4, 7, and 10, we understand that the trading rules were still very profitable after separating the whole period into two sample periods. Specifically, the trading rule buy signals for (5, 150 and 1, 200) returned to investors an annualized rate of 10.5 log percent and 12.3 log percent respectively[14]. Despite this success, the trading rules performed remarkably poor during the "bubble" period due to the lack of success of optimally generating sell signals. In fact, the sell signals were more unprofitable during the "bubble" period than any buy signals were profitable during any period. As a result, the sell signals during this period would have been more successful as buying opportunities than the buying opportunities were. In essence, during "bubble" market cycles, like the period during 2005 – 2008, any significant dip in an asset's price could be a very profitable signal to buy, not sell.

At an annualized rate, sell signals for (1, 50) during the "bubble" period were -15 log percent. On average, all sell signals during the "bubble" period were significantly different than the benchmark strategy at the 10 percent level. Further, on average, the combined effect of the buy and sell signals generated by the trading rules using a one standard deviation price band during the "bubble" period were significantly different from the benchmark at the 10 percent level. Table 7 demonstrates how negatively profitable both the buy and sell signals were at the 5 and 10 percent level of statistical

[14] Using zero standard deviation price bands during the "bubble" period.

significance. In essence, if the momentum of price swings of the ETF's pushed the moving averages apart more than one standard deviation from one another, this was an excellent signal to purchase if in a downtrend and sell if in an uptrend. Technical trading rules used in "bubble" markets may be more useful in ways opposite to their common use.

In the volatile period, trading rules (5, 150 and 1, 150) consistently generated the most profits to the investor. The holding period return using zero standard deviations were 29 and 24.5 percent at an annualized rate for rules (5, 150 and 1, 150) respectively. Although nearly 50 percent of this profitability came from short positions during the six-month decline that was the Great Recession, the trading rules still offered a consistent advantage in buy signals. Using zero and ½ standard deviation price bands, four of five trading rules offered annualized returns over 10 percent from buy signals. Interestingly, unlike "bubble" markets, volatile markets allow moving average strategies to correctly identify momentum-based trends in ways that moving averages are commonly used.

In support of past research conducted by Brock et. al. (1992), this thesis suggests that the volatility of sell signals is greater than the volatility of the buy signals. This could suggest that sell-offs within this emerging market index are often erratic. In fact, the standard deviations of the sell signals were more than double the standard deviations of the buy signals during the volatile sample period. In this thesis, sell signals were often not optimally placed to reward the investor. Instead, in many cases the sell signals offered better buying opportunities. The success of the consistently most profitable strategy, (5, 150), was due to its ability to better identify more profitable selling signals than the other strategies.

Strategies (5, 150; 1, 150; 1, 200 and 2, 200) suggest some predictive abilities by optimally identifying investing opportunities. Variations of these strategies, such as only using buy signals with one-half standard deviation price bands, could provide consistent profitability above the benchmark strategy over longer horizons that encompass multiple market cycles. However, significant risk is undertaken by employing these strategies as seen by the results during "bubble" markets. Finally, arbitrage opportunities may be available to the investor who is able to consistently identify market cycles and employ basic moving average strategies to emerging markets.

VII. Conclusion

This thesis strives to determine whether technical trading rules exhibit any inherent predictive abilities in emerging market exchange traded funds. The results suggest that profits are attainable by investors above the buy and hold benchmark before accounting for transaction costs and risk. Although transaction costs will have a significant impact on the results, it seems unlikely that certain trading rule variations will be less profitable than the benchmark even after adjustments have been made. Furthermore, data snooping biases were mitigated by the inclusion of two sample periods.

Averaging across trading rules, Tables 5 through 10 demonstrate the degree to which buy and sell signals optimally identify price trends in differing market cycles. Sell signals consistently underperform in both types of markets when accounting for the profits obtained from the 2008-2009 crash. In fact, sell signals underperform to the extent that they offer better buy signals than the actual buy signals in "bubble" markets. Despite this, buy signals generated by the trading rules consistently return positive profits to the investor while using both zero and ½ standard deviation price bands in all investment periods. Furthermore, buy signals generated by a select few trading rules (1, 200; 2, 200; 1, 150 and 5, 150) while using both zero and ½ standard deviation price bands outperform the benchmark strategy. In some instances, (1, 200 and 2, 200), the success of these buy signals offers interesting evidence that they may consistently outperform the benchmark. This is attributable to a lowered amount of necessary portfolio adjustments due to the use of longer moving averages (see comparison of Figures 1 and 2).

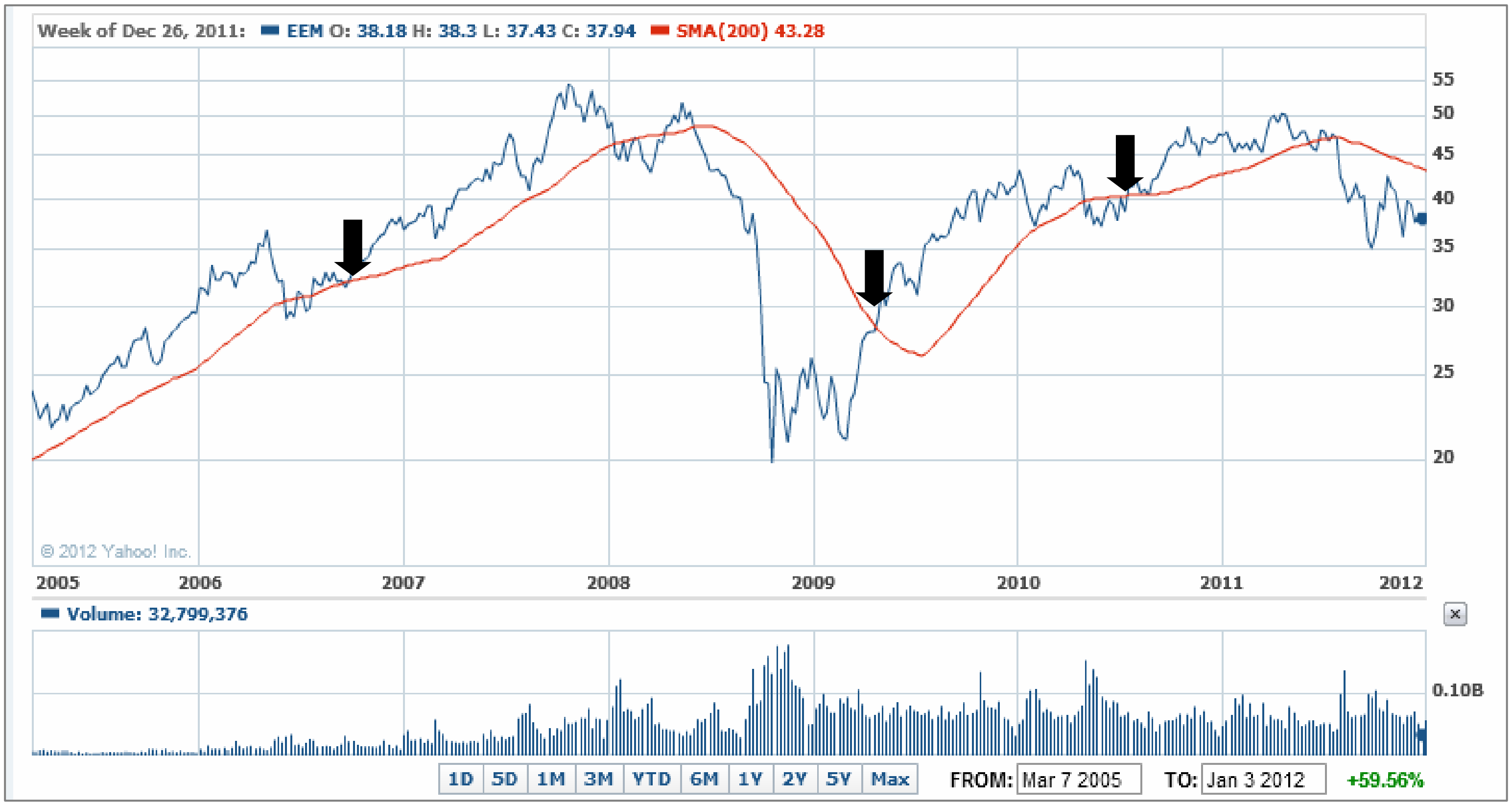
As a risk adverse investor, it is important to determine trading portfolios and strategies that maximize return while minimizing risk. For this typical investor, the trading rule results in this thesis are valuable. In analyzing the profitability of the trading rules during each type of market, key measures of variance are discovered that offer investing suggestions. For example, during periods of market instability it may be prudent for the risk adverse investor to only make trades based upon buy signals. This way the investor is not exposed to the erratic behavior of price action during sell signals. The buy signals still generate statistically significant profits above the buy and hold strategy while maintaining daily standard deviations of less than 2 percent. In fact, during volatile market periods the daily standard deviation of the return is greater than all other trading rule standard deviations of the return. On the other hand, during periods of market stability or "bubble" type markets, the adverse investor may choose to undertake the benchmark strategy because of its efficiency of returns and lack of volatility.

This thesis explores technical trading in new realms of study. To further the results found in this thesis, research should be conducted on the profitability of technical trading strategies in individual country ETF's in the emerging markets. Additionally, as all markets continue to develop in efficiency it may be necessary to test new types of technical trading strategies. These new trading strategies may include multiple confirmations from several indicators or oscillators in hopes of still uncovering hidden inefficiencies in markets. Lastly, the remaining technical trading strategies performed by Brock et. al. should be applied to the same dataset used in this thesis in order to avoid further data snooping biases.

Due to unique characteristics of emerging markets, investors may be able to consistently obtain abnormal profits from technical trading strategies in ECM. Research (Bessembinder and Chan, and Ratner and Leal) suggests that abnormal profits may be consistently obtained through the use of technical trading rules. Variable moving average trading rules in this thesis are inspired from the study by Brock, Lakonishok, and LeBaron (1992). These rules attempt to optimally generate buy and sell signals for the investor to employ in order to outperform the market. In essence, the success of these trading rules depends upon whether certain "emerging market" countries can be considered at least weak-form efficient.

In this thesis, certain trading rule variations (5, 150; 1, 150; 1, 200 and 2, 200) exhibit extraordinary predictive abilities that suggest profits are consistently attainable to the investor above the buy and hold strategy before transaction costs. Furthermore, it seems unlikely that adjusting for transaction costs will completely mitigate all abnormal profits available to the investor while employing these strategies. However, depending upon the willingness of the investor to take on more risk by investing in emerging markets, the combination of risk and transaction cost adjustment may be powerful enough to completely mitigate any abnormal returns attainable by the investor.

Figure 1: MSCI Emerging Market ETF with Labeled Buy Signals



Notes:
a) Smoothed red line represents the 200 day moving average for EEM
b) Underlying blue line represents price movements based on closing price of EEM
c) Examples of buy signals of the (1, 200, 0) trading rule are depicted by black arrows
d) Courtesy of Yahoo Finance

Figure 2: Vanguard Emerging Market ETF with Labeled Sell Signals

Notes:

a) Smoothed red line represents the 50 day moving average for VWO

b) Underlying blue line represents price movements of closing prices for VWO

c) Examples of sell signals of the (1, 50, 0) trading rule are depicted by black arrows

d) Courtesy of Yahoo Finance

Table 1: Emerging Market Indices of the MSCI Index

Americas	Europe, Middle East & Africa	Asia
Brazil	Czech Republic	China
Chile	Egypt	India
Colombia	Hungary	Indonesia
Mexico	Morocco	Korea
Peru	Poland	Malaysia
	Russia	Philippines
	South Africa	Taiwan
	Turkey	Thailand

Table 2: Summary Statistics for Variable Moving Average Rules Using 0 Standard Deviation Price Bands (Whole Period, daily log % returns)

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	**Buy**	**Sell**	**Combined**	**Buy**	**Sell**	**Combined**	**Buy**	**Sell**
1,50,0	mean	0.013%	0.038%	-0.027%	-0.006%	0.021%	-0.049%	0.003%	0.030%	-0.038%
	sum	22.208%	40.130%	-17.934%	-10.398%	22.417%	-32.851%	5.905%	31.273%	-25.392%
	sd	2.303%	1.596%	3.130%	2.447%	1.656%	3.336%	2.375%	1.626%	3.233%
	N	1716	1061	654	1716	1047	666	1716	1054	660
	t-stat	0.2235	-0.0545	0.4553	0.3841	0.1416	0.5755	0.3038	0.04355	0.5154
1,150,0	mean	0.045%	0.062%	0.016%	0.042%	0.058%	0.012%	0.044%	0.060%	0.014%
	sum	77.777%	67.915%	9.851%	71.617%	63.945%	7.660%	74.697%	65.930%	8.755%
	sd	2.303%	1.607%	3.194%	2.448%	1.664%	3.421%	2.375%	1.636%	3.307%
	N	1716	1101	614	1716	1095	620	1716	1098	617
	t-stat	-0.1252	-0.3784	0.1264	-0.0933	-0.3341	0.1346	-0.10925	-0.35625	0.1305
5,150,0	mean	0.071%	0.083%	0.050%	0.064%	0.077%	0.040%	0.067%	0.080%	0.045%
	sum	121.994%	91.411%	30.548%	109.507%	84.525%	24.947%	115.751%	87.968%	27.747%
	sd	2.302%	1.628%	3.176%	2.446%	1.678%	3.412%	2.374%	1.653%	3.294%
	N	1716	1100	613	1716	1095	618	1716	1097.5	615.5
	t-stat	-0.4073	-0.6649	-0.1148	-0.3171	-0.5742	-0.0528	-0.3622	-0.61955	-0.0838
1,200,0	mean	0.047%	0.061%	0.020%	0.032%	0.049%	-0.002%	0.039%	0.055%	0.009%
	sum	80.813%	69.432%	11.368%	54.549%	55.411%	-0.874%	67.681%	62.422%	5.247%
	sd	2.303%	1.607%	3.290%	2.448%	1.664%	3.511%	2.375%	1.635%	3.400%
	N	1716	1147	568	1716	1135	580	1716	1141	574
	t-stat	-0.1458	-0.366	0.0925	0.007	-0.2122	0.2161	-0.0694	-0.2891	0.1543
2,200,0	mean	0.050%	0.063%	0.024%	0.018%	0.039%	-0.022%	0.034%	0.051%	0.001%
	sum	85.666%	72.158%	13.484%	31.355%	44.180%	-12.848%	58.510%	58.169%	0.318%
	sd	2.303%	1.618%	3.277%	2.448%	1.671%	3.505%	2.375%	1.644%	3.391%
	N	1716	1145	569	1716	1134	580	1716	1139.5	574.5
	t-stat	-0.1772	-0.3987	0.068	0.1445	-0.084	0.3478	-0.01635	-0.24135	0.2079
Benchmark	mean	0.034%			0.032%					
	sum	57.971%			55.731%					
	sd	2.303%			2.448%					
	N	1716			1716					
Average	mean	0.045%	0.061%	0.016%	0.030%	0.049%	-0.004%			
	sum	77.692%	68.209%	9.463%	51.326%	54.095%	-2.793%			
	sd	2.303%	1.611%	3.213%	2.447%	1.666%	3.437%			
	N	1716	1110.8	603.6	1716	1101.2	612.8			
	t-stat	-0.1264	-0.3725	0.12548	0.02504	-0.21258	0.24424			

Rules

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Whole Period is March 10, 2005 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 3: Summary Statistics for Variable Moving Average Rules Using 1/2 Standard Deviation Price Bands (Whole Period, daily log % returns)

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,0.5	mean	0.017%	0.064%	-0.027%	0.001%	0.044%	-0.049%	0.009%	0.054%	-0.038%
	sum	28.346%	41.327%	-17.934%	0.914%	29.063%	-32.851%	14.630%	35.195%	-25.392%
	sd	2.175%	1.629%	3.130%	2.329%	1.703%	3.336%	2.252%	1.666%	3.233%
	N	1716	646	654	1716	655	666	1716	650.5	660
	t-stat	0.2258	-0.3558	0.4553	0.3917	-0.1336	0.5755	0.30875	-0.2447	0.5154
1,150,0.5	mean	0.036%	0.065%	0.016%	0.024%	0.038%	0.012%	0.030%	0.052%	0.014%
	sum	61.820%	47.517%	9.851%	40.331%	28.433%	7.660%	51.075%	37.975%	8.755%
	sd	2.176%	1.602%	3.194%	2.328%	1.666%	3.421%	2.252%	1.634%	3.307%
	N	1716	728	614	1716	740	620	1716	734	617
	t-stat	-0.0293	-0.3871	0.1264	0.11	-0.0698	0.1346	0.04035	-0.22845	0.1305
5,150,0.5	mean	0.058%	0.089%	0.050%	0.048%	0.071%	0.040%	0.053%	0.080%	0.045%
	sum	100.016%	65.087%	30.548%	81.561%	52.352%	24.947%	90.788%	58.720%	27.747%
	sd	2.181%	1.643%	3.176%	2.331%	1.701%	3.412%	2.256%	1.672%	3.294%
	N	1716	735	613	1716	740	618	1716	737.5	615.5
	t-stat	-0.32	-0.6659	-0.1148	-0.1845	-0.4449	-0.0528	-0.25225	-0.5554	-0.0838
1,200,0.5	mean	0.054%	0.104%	0.020%	0.037%	0.080%	-0.002%	0.046%	0.092%	0.009%
	sum	93.003%	76.801%	11.368%	63.579%	59.869%	-0.874%	78.291%	68.335%	5.247%
	sd	2.164%	1.598%	3.290%	2.312%	1.644%	3.511%	2.238%	1.621%	3.400%
	N	1716	742	568	1716	751	580	1716	746.5	574
	t-stat	-0.2676	-0.8627	0.0925	-0.0563	-0.5611	0.2161	-0.16195	-0.7119	0.1543
2,200,0.5	mean	0.053%	0.097%	0.024%	0.027%	0.072%	-0.022%	0.040%	0.084%	0.001%
	sum	90.373%	72.091%	13.484%	45.940%	54.240%	-12.848%	68.156%	63.166%	0.318%
	sd	2.166%	1.617%	3.277%	2.314%	1.658%	3.505%	2.240%	1.638%	3.391%
	N	1716	744	569	1716	754	580	1716	749	574.5
	t-stat	-0.2474	-0.7765	0.068	0.0702	-0.467	0.3478	-0.0886	-0.62175	0.2079
Benchmark	mean	0.034%			0.032%					
	sum	57.971%			55.731%					
	sd	2.303%			2.448%					
	N	1716			1716					
Average	mean	0.044%	0.084%	0.016%	0.027%	0.061%	-0.004%			
	sum	74.712%	60.565%	9.463%	46.465%	44.791%	-2.793%			
	sd	2.172%	1.618%	3.213%	2.323%	1.674%	3.437%			
	N	1716	719	603.6	1716	728	612.8			
	t-stat	-0.1277	-0.6096	0.12548	0.06622	-0.33528	0.24424			

Rules

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Whole Period is March 10, 2005 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 4: Summary Statistics for Variable Moving Average Rules Using 1 Standard Deviation Price Bands (Whole Period, daily log % returns)

Rules

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,1	mean	-0.007%	-0.020%	-0.027%	-0.020%	-0.052%	-0.049%	-0.014%	-0.036%	-0.038%
	sum	-12.459%	-4.466%	-17.934%	-34.576%	-11.583%	-32.851%	-23.518%	-8.024%	-25.392%
	sd	2.049%	1.884%	3.130%	2.200%	2.016%	3.336%	2.125%	1.950%	3.233%
	N	1716	227	654	1716	222	666	1716	224.5	660
	t-stat	0.5515	0.3905	0.4553	0.6624	0.5733	0.5755	0.60695	0.4819	0.5154
1,150,1	mean	0.024%	0.075%	0.016%	0.006%	-0.022%	0.012%	0.015%	0.027%	0.014%
	sum	41.375%	21.858%	9.851%	10.072%	-6.909%	7.660%	25.724%	7.474%	8.755%
	sd	2.047%	1.792%	3.194%	2.195%	1.809%	3.421%	2.121%	1.801%	3.307%
	N	1716	290	614	1716	313	620	1716	301.5	617
	t-stat	0.13	-0.3494	0.1264	0.3352	0.4619	0.1346	0.2326	0.05625	0.1305
5,150,1	mean	0.034%	0.066%	0.050%	0.012%	-0.044%	0.040%	0.023%	0.011%	0.045%
	sum	59.129%	18.831%	30.548%	20.474%	-13.795%	24.947%	39.801%	2.518%	27.747%
	sd	2.045%	1.877%	3.176%	2.198%	1.876%	3.412%	2.122%	1.877%	3.294%
	N	1716	284	613	1716	315	618	1716	299.5	615.5
	t-stat	-0.0091	-0.2613	-0.1148	0.2587	0.6298	-0.0528	0.1248	0.18425	-0.0838
1,200,1	mean	0.025%	0.070%	0.020%	0.009%	0.022%	-0.002%	0.017%	0.046%	0.009%
	sum	42.852%	21.496%	11.368%	15.925%	7.144%	-0.874%	29.389%	14.320%	5.247%
	sd	2.033%	1.754%	3.290%	2.187%	1.813%	3.511%	2.110%	1.784%	3.400%
	N	1716	309	568	1716	325	580	1716	317	574
	t-stat	0.1188	-0.3133	0.0925	0.2928	0.09	0.2161	0.2058	-0.11165	0.1543
2,200,1	mean	0.025%	0.066%	0.024%	0.006%	0.043%	-0.022%	0.016%	0.054%	0.001%
	sum	43.529%	20.021%	13.484%	10.401%	13.499%	-12.848%	26.965%	16.760%	0.318%
	sd	2.033%	1.805%	3.277%	2.181%	1.817%	3.505%	2.107%	1.811%	3.391%
	N	1716	305	569	1716	317	580	1716	311	574.5
	t-stat	0.1135	-0.2714	0.068	0.3338	-0.0856	0.3478	0.22365	-0.1785	0.2079
Benchmark	mean	0.034%			0.032%					
	sum	57.971%			55.731%					
	sd	2.303%			2.448%					
	N	1716			1716					
Average	mean	0.020%	0.051%	0.016%	0.003%	-0.011%	-0.004%			
	sum	34.885%	15.548%	9.463%	4.459%	-2.329%	-2.793%			
	sd	2.041%	1.823%	3.213%	2.192%	1.866%	3.437%			
	N	1716	283	603.6	1716	298.4	612.8			
	t-stat	0.18094	-0.16098	0.12548	0.37658	0.33388	0.24424			

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Whole Period is March 10, 2005 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 5: Summary Statistics for Variable Moving Average Rules Using 0 Standard Deviation Price Bands ("Bubble" Period, daily log % returns)

Rules	ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
			Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
Rules	1,50,0	mean	-0.016%	0.042%	-0.140% *	-0.040%	0.021%	-0.175% *	-0.028%	0.031%	-0.157% *
		sum	-13.441%	24.369%	-37.822%	-37.565%	11.810%	-49.387%	-25.503%	18.090%	-43.604%
		sd	1.704%	1.363%	2.275%	1.801%	1.445%	2.359%	1.753%	1.404%	2.317%
		N	858	586	271	858	575	282	858	580.5	276.5
		t-stat	1.0086	0.3804	1.4138	1.2386	0.5831	1.6035	1.1236	0.48175	1.50865
	1,150,0	mean	-0.009%	0.043%	-0.153% *	-0.006%	0.044%	-0.149% *	-0.008%	0.044%	-0.151% *
		sum	-8.031%	27.074%	-35.117%	-5.131%	28.027%	-33.170%	-6.581%	27.550%	-34.144%
		sd	1.705%	1.565%	2.037%	1.798%	1.636%	2.197%	1.751%	1.601%	2.117%
		N	858	627	230	858	634	223	858	630.5	226.5
		t-stat	1.1348	0.3421	1.538	1.0025	0.2962	1.3768	1.06865	0.31915	1.4574
	5,150,0	mean	0.028%	0.072%	-0.088%	0.012%	0.058%	-0.126%	0.020%	0.065%	-0.107%
		sum	24.296%	44.625%	-20.365%	10.174%	37.314%	-27.175%	17.235%	40.970%	-23.770%
		sd	1.703%	1.606%	1.948%	1.796%	1.664%	2.151%	1.749%	1.635%	2.049%
		N	858	623	232	858	640	215	858	631.5	223.5
		t-stat	0.6372	0.0086	1.1402	0.7997	0.1377	1.2396	0.71845	0.07315	1.1899
	1,200,0	mean	0.022%	0.063%	-0.100%	0.002%	0.049%	-0.136% *	0.012%	0.056%	-0.118%
		sum	18.469%	40.324%	-21.867%	1.926%	31.556%	-29.641%	10.198%	35.940%	-25.754%
		sd	1.704%	1.617%	1.941%	1.798%	1.687%	2.092%	1.751%	1.652%	2.016%
		N	858	639	218	858	639	218	858	639	218
		t-stat	0.7617	0.1064	1.2014	0.9506	0.235	1.3385	0.85615	0.1707	1.26995
	2,200,0	mean	0.010%	0.056%	-0.124% *	-0.014%	0.039%	-0.171% *	-0.002%	0.048%	-0.147% *
		sum	8.597%	35.687%	-27.114%	-11.691%	25.112%	-36.827%	-1.547%	30.400%	-31.971%
		sd	1.704%	1.633%	1.903%	1.801%	1.701%	2.064%	1.753%	1.667%	1.983%
		N	858	637	219	858	640	216	858	638.5	217.5
		t-stat	0.9501	0.1857	1.3904	1.1913	0.3427	1.5739	1.0707	0.2642	1.48215
	Benchmark	mean	0.072%			0.071%					
		sum	62.098%			60.643%					
		sd	1.703%			1.797%					
		N	858			858					
	Average	mean	0.007%	0.055%	-0.121% *	-0.009%	0.042%	-0.151% *			
		sum	5.978%	34.416%	-28.457%	-8.457%	26.764%	-35.240%			
		sd	1.704%	1.557%	2.021%	1.799%	1.626%	2.172%			
		N	858	622.4	234	858	625.6	230.8			
		t-stat	0.89848	0.20464	1.33676	1.03654	0.31894	1.42646			

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Bubble Period is March 10, 2005 - August 5, 2008

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 6: Summary Statistics for Variable Moving Average Rules Using 1/2 Standard Deviation Price Bands ("Bubble" Period, daily log % returns)

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,0.5	mean	-0.018%	0.055%	-0.140% *	-0.047% *	0.019%	-0.175% *	-0.032% *	0.037%	-0.157% *
	sum	-15.681%	19.308%	-37.822%	-40.006%	6.750%	-49.387%	-27.843%	13.029%	-43.604%
	sd	1.540%	1.346%	2.275%	1.626%	1.400%	2.359%	1.583%	1.373%	2.317%
	N	858	349	271	858	355	282	858	352	276.5
	t-stat	1.1563	0.1843	1.4138	1.418	0.5362	1.6035	1.28715	0.36025	1.50865
1,150,0.5	mean	-0.027% *	0.023%	-0.153% *	-0.039% *	-0.005%	-0.149% *	-0.033% *	0.009%	-0.151% *
	sum	-22.903%	9.821%	-35.117%	-33.131%	-2.319%	-33.170%	-28.017%	3.751%	-34.144%
	sd	1.489%	1.489%	2.037%	1.595%	1.592%	2.197%	1.542%	1.540%	2.117%
	N	858	427	230	858	437	223	858	432	226.5
	t-stat	1.283	0.5334	1.538	1.3324	0.777	1.3768	1.3077	0.6552	1.4574
5,150,0.5	mean	0.010%	0.061%	-0.088%	-0.006%	0.045%	-0.126%	0.002%	0.053%	-0.107%
	sum	8.468%	26.547%	-20.365%	-5.088%	19.659%	-27.175%	1.690%	23.103%	-23.770%
	sd	1.495%	1.547%	1.948%	1.587%	1.630%	2.151%	1.541%	1.589%	2.049%
	N	858	434	232	858	439	215	858	436.5	223.5
	t-stat	0.8079	0.1188	1.1402	0.9361	0.2614	1.2396	0.872	0.1901	1.1899
1,200,0.5	mean	0.013%	0.070%	-0.100%	-0.012%	0.039%	-0.136% *	0.001%	0.055%	-0.118%
	sum	10.992%	30.395%	-21.867%	-10.018%	17.278%	-29.641%	0.487%	23.837%	-25.754%
	sd	1.473%	1.549%	1.941%	1.564%	1.607%	2.092%	1.518%	1.578%	2.016%
	N	858	433	218	858	443	218	858	438	218
	t-stat	0.7749	0.0231	1.2014	1.0126	0.3234	1.3385	0.89375	0.17325	1.26995
2,200,0.5	mean	0.007%	0.071%	-0.124% *	-0.024%	0.032%	-0.171% *	-0.008%	0.051%	-0.147% *
	sum	6.186%	30.895%	-27.114%	-20.456%	14.026%	-36.827%	-7.135%	22.461%	-31.971%
	sd	1.481%	1.578%	1.903%	1.563%	1.625%	2.064%	1.522%	1.602%	1.983%
	N	858	437	219	858	445	216	858	441	217.5
	t-stat	0.8457	0.0176	1.3904	1.1624	0.3976	1.5739	1.00405	0.2076	1.48215
Benchmark	mean	0.072%			0.071%					
	sum	62.098%			60.643%					
	sd	1.703%			1.797%					
	N	858			858					
Average	mean	-0.003%	0.056%	-0.121% *	-0.025%	0.026%	-0.151% *			
	sum	-2.587%	23.393%	-28.457%	-21.740%	11.079%	-35.240%			
	sd	1.496%	1.502%	2.021%	1.587%	1.571%	2.172%			
	N	858	416	234	858	423.8	230.8			
	t-stat	0.97356	0.17544	1.33676	1.1723	0.45912	1.42646			

Rules

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Bubble Period is March 10, 2005 - August 5, 2008

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 7: Summary Statistics for Variable Moving Average Rules Using 1 Standard Deviation Price Bands ("Bubble" Period, daily log % returns)

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,1	mean	-0.042% *	-0.043%	-0.140% *	-0.060% **	-0.087%	-0.175% *	-0.051% *	-0.065%	-0.157% *
	sum	-36.103%	-4.127%	-37.822%	-51.437%	-7.836%	-49.387%	-43.770%	-5.982%	-43.604%
	sd	1.368%	1.458%	2.275%	1.442%	1.541%	2.359%	1.405%	1.499%	2.317%
	N	858	96	271	858	90	282	858	93	276.5
	t-stat	1.5349	0.722	1.4138	1.6609	0.9088	1.6035	1.5979	0.8154	1.50865
1,150,1	mean	-0.031% *	0.022%	-0.153% *	-0.053% *	-0.124%	-0.149% *	-0.042% *	-0.051%	-0.151% *
	sum	-26.444%	2.626%	-35.117%	-45.248%	-17.924%	-33.170%	-35.846%	-7.649%	-34.144%
	sd	1.214%	1.609%	2.037%	1.308%	1.650%	2.197%	1.261%	1.630%	2.117%
	N	858	120	230	858	144	223	858	132	226.5
	t-stat	1.4455	0.3063	1.538	1.6266	1.2196	1.3768	1.53605	0.76295	1.4574
5,150,1	mean	-0.028% *	-0.084%	-0.088%	0.057% **	-0.194% *	-0.126%	0.014% *	-0.139%	-0.107%
	sum	-23.823%	-9.554%	-20.365%	-48.587%	-27.388%	-27.175%	-36.205%	-18.471%	-23.770%
	sd	1.211%	1.829%	1.948%	1.307%	1.829%	2.151%	1.259%	1.829%	2.049%
	N	858	114	232	858	141	215	858	127.5	223.5
	t-stat	1.4038	0.9118	1.1402	1.6782	1.6183	1.2396	1.541	1.26505	1.1899
1,200,1	mean	-0.017%	0.012%	-0.100%	-0.036% *	-0.045%	-0.136% *	-0.026% *	-0.017%	-0.118%
	sum	-14.245%	1.610%	-21.867%	-30.562%	-6.754%	-29.641%	-22.403%	-2.572%	-25.754%
	sd	1.165%	1.600%	1.941%	1.268%	1.690%	2.092%	1.217%	1.645%	2.016%
	N	858	135	218	858	150	218	858	142.5	218
	t-stat	1.2632	0.3864	1.2014	1.4157	0.7339	1.3385	1.33945	0.56015	1.26995
2,200,1	mean	-0.034% *	-0.063%	-0.124% *	-0.042% *	-0.033%	-0.171% *	-0.038% *	-0.048%	-0.147% *
	sum	-29.563%	-8.449%	-27.114%	-35.855%	-4.920%	-36.827%	-32.709%	-6.685%	-31.971%
	sd	1.169%	1.684%	1.903%	1.255%	1.714%	2.064%	1.212%	1.699%	1.983%
	N	858	135	219	858	147	216	858	141	217.5
	t-stat	1.5147	0.8572	1.3904	1.5031	0.6536	1.5739	1.5089	0.7554	1.48215
Benchmark	mean	0.072%			0.071%					
	sum	62.098%			60.643%					
	sd	1.703%			1.797%					
	N	858			858					
Average	mean	-0.030% *	-0.031%	-0.121% *	-0.027% *	-0.097%	-0.151% *			
	sum	-26.036%	-3.579%	-28.457%	-42.338%	-12.965%	-35.240%			
	sd	1.225%	1.636%	2.021%	1.316%	1.685%	2.172%			
	N	858	120	234	858	134.4	230.8			
	t-stat	1.43242	0.63674	1.33676	1.5769	1.02684	1.42646			

Rules

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Bubble Period is March 10, 2005 - August 5, 2008

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 8: Summary Statistics for Variable Moving Average Rules Using 0 Standard Deviation Price Bands (Volatile Period, daily log % returns)

Rules

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,0	mean	0.042%	0.033%	0.052%	0.032%	0.022%	0.043%	0.037%	0.028%	0.047%
	sum	35.649%	15.761%	19.888%	27.166%	10.607%	16.536%	31.407%	13.184%	18.212%
	sd	2.777%	1.845%	3.616%	2.958%	1.883%	3.902%	2.868%	1.864%	3.759%
	N	858	475	383	858	472	384	858	473.5	383.5
	t-stat	-0.2813	-0.2989	-0.2732	-0.2099	-0.2118	-0.2185	-0.2456	-0.25535	-0.24585
1,150,0	mean	0.100%	0.086%	0.117%	0.089%	0.078%	0.103%	0.095%	0.082%	0.110%
	sum	85.809%	40.841%	44.968%	76.748%	35.918%	40.830%	81.278%	38.379%	42.899%
	sd	2.775%	1.663%	3.718%	2.958%	1.703%	3.945%	2.867%	1.683%	3.832%
	N	858	474	384	858	461	397	858	467.5	390.5
	t-stat	-0.6176	-0.7472	-0.5748	-0.5196	-0.651	-0.4884	-0.5686	-0.6991	-0.5316
5,150,0	mean	0.114%	0.098%	0.134%	0.116%	0.104%	0.129%	0.115%	0.101%	0.131%
	sum	97.699%	46.786%	50.913%	99.333%	47.211%	52.122%	98.516%	46.998%	51.518%
	sd	2.775%	1.659%	3.730%	2.957%	1.700%	3.922%	2.866%	1.679%	3.826%
	N	858	477	381	858	455	403	858	466	392
	t-stat	-0.6995	-0.8469	-0.6489	-0.6623	-0.8508	-0.6141	-0.6809	-0.84885	-0.6315
1,200,0	mean	0.073%	0.057%	0.095%	0.061%	0.048%	0.079%	0.067%	0.053%	0.087%
	sum	62.344%	29.108%	33.235%	52.622%	23.855%	28.767%	57.483%	26.482%	31.001%
	sd	2.776%	1.596%	3.902%	2.959%	1.635%	4.137%	2.867%	1.615%	4.020%
	N	858	508	350	858	496	362	858	502	356
	t-stat	-0.4556	-0.5249	-0.4355	-0.3657	-0.431	-0.3553	-0.41065	-0.47795	-0.3954
2,200,0	mean	0.090%	0.072%	0.116%	0.050%	0.039%	0.066%	0.070%	0.055%	0.091%
	sum	77.068%	36.471%	40.598%	43.046%	19.067%	23.979%	60.057%	27.769%	32.288%
	sd	2.776%	1.601%	3.898%	2.959%	1.633%	4.129%	2.867%	1.617%	4.014%
	N	858	508	350	858	494	364	858	501	357
	t-stat	-0.557	-0.6466	-0.5277	-0.3046	-0.3548	-0.2998	-0.4308	-0.5007	-0.41375
Benchmark	mean	-0.005%			-0.006%					
	sum	-4.127%			-4.912%					
	sd	2.777%			2.959%					
	N	858			858					
Average	mean	0.084%	0.069%	0.103%	0.070%	0.058%	0.084%			
	sum	71.714%	33.793%	37.920%	59.783%	27.332%	32.447%			
	sd	2.776%	1.673%	3.773%	2.958%	1.711%	4.007%			
	N	858	488.4	369.6	858	475.6	382			
	t-stat	-0.5222	-0.6129	-0.49202	-0.41242	-0.49988	-0.39522			

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Volatile Period is August 6, 2008 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 9: Summary Statistics for Variable Moving Average Rules Using 1/2 Standard Deviation Price Bands (Volatile Period, daily log % returns)

Rules

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	Buy	Sell	Combined	Buy	Sell	Combined	Buy	Sell
1,50,0.5	mean	0.051%	0.074%	0.052%	0.048%	0.074%	0.043%	0.050%	0.074%	0.047%
	sum	44.027%	22.020%	19.888%	40.920%	22.313%	16.536%	42.473%	22.166%	18.212%
	sd	2.663%	1.912%	3.616%	2.865%	2.005%	3.902%	2.764%	1.958%	3.759%
	N	858	297	383	858	300	384	858	298.5	383.5
	t-stat	-0.3361	-0.541	-0.2732	-0.2969	-0.5213	-0.2185	-0.3165	-0.53115	-0.24585
1,150,0.5	mean	0.099%	0.125%	0.117%	0.086%	0.101%	0.103%	0.092%	0.113%	0.110%
	sum	84.723%	37.696%	44.968%	73.462%	30.752%	40.830%	79.093%	34.224%	42.899%
	sd	2.693%	1.751%	3.718%	2.880%	1.768%	3.945%	2.787%	1.760%	3.832%
	N	858	301	384	858	303	397	858	302	390.5
	t-stat	-0.6046	-0.9392	-0.5748	-0.4948	-0.7483	-0.4884	-0.5497	-0.84375	-0.5316
5,150,0.5	mean	0.107%	0.128%	0.134%	0.101%	0.109%	0.129%	0.104%	0.118%	0.131%
	sum	91.548%	38.540%	50.913%	86.649%	32.693%	52.122%	89.098%	35.616%	51.518%
	sd	2.697%	1.774%	3.730%	2.890%	1.801%	3.922%	2.794%	1.788%	3.826%
	N	858	301	381	858	301	403	858	301	392
	t-stat	-0.6516	-0.9526	-0.6489	-0.5777	-0.7893	-0.6141	-0.61465	-0.87095	-0.6315
1,200,0.5	mean	0.096%	0.150%	0.095%	0.086%	0.138%	0.079%	0.091%	0.144%	0.087%
	sum	82.011%	46.406%	33.235%	73.597%	42.591%	28.767%	77.804%	44.499%	31.001%
	sd	2.683%	1.665%	3.902%	2.871%	1.695%	4.137%	2.777%	1.680%	4.020%
	N	858	309	350	858	308	362	858	308.5	356
	t-stat	-0.5845	-1.1564	-0.4355	-0.4947	-1.0302	-0.3553	-0.5396	-1.0933	-0.3954
2,200,0.5	mean	0.098%	0.134%	0.116%	0.077%	0.130%	0.066%	0.088%	0.132%	0.091%
	sum	84.187%	41.196%	40.598%	66.396%	40.214%	23.979%	75.291%	40.705%	32.288%
	sd	2.682%	1.674%	3.898%	2.876%	1.705%	4.129%	2.779%	1.690%	4.014%
	N	858	307	350	858	309	364	858	308	357
	t-stat	-0.5997	-1.0327	-0.5277	-0.4492	-0.9699	-0.2998	-0.52445	-1.0013	-0.41375
Benchmark	mean	-0.005%			-0.006%					
	sum	-4.127%			-4.912%					
	sd	2.777%			2.959%					
	N	858			858					
Average	mean	0.090%	0.122%	0.103%	0.079%	0.111%	0.084%			
	sum	77.299%	37.172%	37.920%	68.205%	33.713%	32.447%			
	sd	2.683%	1.755%	3.773%	2.876%	1.795%	4.007%			
	N	858	303	369.6	858	304.2	382			
	t-stat	-0.5553	-0.92438	-0.49202	-0.46266	-0.8118	-0.39522			

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Volatile Period is August 6, 2008 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

Table 10: Summary Statistics for Variable Moving Average Rules Using 1 Standard Deviation Price Bands (Volatile Period, daily log % returns)

ETF Name		VWO	VWO	VWO	EEM	EEM	EEM	Average	Average	Average
		Combined	**Buy**	**Sell**	**Combined**	**Buy**	**Sell**	**Combined**	**Buy**	**Sell**
1,50,1	mean	0.028%	-0.003%	0.052%	0.016%	-0.028%	0.043%	0.022%	-0.015%	0.047%
	sum	23.644%	-0.339%	19.888%	16.861%	-3.746%	16.536%	20.253%	-2.043%	18.212%
	sd	2.555%	2.149%	3.616%	2.758%	2.290%	3.902%	2.656%	2.220%	3.759%
	N	858	131	383	858	132	384	858	131.5	383.5
	t-stat	-0.2512	-0.0106	-0.2732	-0.1837	0.1014	-0.2185	-0.21745	0.0454	-0.24585
1,150,1	mean	0.079%	0.113%	0.117%	0.064%	0.065%	0.103%	0.072%	0.089%	0.110%
	sum	67.819%	19.232%	44.968%	55.321%	11.015%	40.830%	61.570%	15.124%	42.899%
	sd	2.627%	1.915%	3.718%	2.816%	1.934%	3.945%	2.721%	1.925%	3.832%
	N	858	170	384	858	169	397	858	169.5	390.5
	t-stat	-0.4862	-0.6746	-0.5748	-0.3779	-0.3942	-0.4884	-0.43205	-0.5344	-0.5316
5,150,1	mean	0.097%	0.167%	0.134%	0.080%	0.078%	0.129%	0.089%	0.123%	0.131%
	sum	82.952%	28.385%	50.913%	69.061%	13.594%	52.122%	76.007%	20.989%	51.518%
	sd	2.625%	1.907%	3.730%	2.819%	1.910%	3.922%	2.722%	1.908%	3.826%
	N	858	170	381	858	174	403	858	172	392
	t-stat	-0.7779	-0.9854	-0.6489	-0.4635	-0.4749	-0.6141	-0.6207	-0.73015	-0.6315
1,200,1	mean	0.067%	0.114%	0.095%	0.054%	0.079%	0.079%	0.060%	0.097%	0.087%
	sum	57.097%	19.886%	33.235%	46.487%	13.898%	28.767%	51.792%	16.892%	31.001%
	sd	2.628%	1.869%	3.902%	2.820%	1.915%	4.137%	2.724%	1.892%	4.020%
	N	858	174	350	858	175	362	858	174.5	356
	t-stat	-0.413	-0.6987	-0.4355	-0.3223	-0.4823	-0.3553	-0.36765	-0.5905	-0.3954
2,200,1	mean	0.085%	0.167%	0.116%	0.054%	0.108%	0.066%	0.070%	0.138%	0.091%
	sum	73.092%	28.470%	40.598%	46.256%	18.420%	23.979%	59.674%	23.445%	32.288%
	sd	2.627%	1.895%	3.898%	2.818%	1.905%	4.129%	2.722%	1.900%	4.014%
	N	858	170	350	858	170	364	858	170	357
	t-stat	-0.5213	-0.9928	-0.5277	0.3205	-0.6422	-0.2998	-0.1004	-0.8175	-0.41375
Benchmark	mean	-0.005%			-0.006%					
	sum	-4.127%			-4.912%					
	sd	2.777%			2.959%					
	N	858			858					
Average	mean	0.071%	0.112%	0.103%	0.054%	0.061%	0.084%			
	sum	60.921%	19.127%	37.920%	46.797%	10.636%	32.447%			
	sd	2.612%	1.947%	3.773%	2.806%	1.991%	4.007%			
	N	858	163	369.6	858	164	382			
	t-stat	-0.48992	-0.67242	-0.49202	-0.20538	-0.37844	-0.39522			

Rules

Notes

*** 1% significance, ** 5% signficance, * 10% significance

a) Volatile Period is August 6, 2008 - December 31, 2011

b) Rules are stated (short MA, long MA, standard deviation price band)

c) Mean rows display daily mean returns in log percent

d) Sum rows display holding period return in log percent. (i.e. mean*N=sum)

e) Sd rows display standard deviation of rules in log percent

f) N rows display the number of days in each position

g) T-stat rows display significance above the benchmark strategy using a two-sample student t-test

h) Combined columns display total profitability from buy and sell signals for each ETF

i) Buy columns display profitability of trading rules when a buy trading signal is generated

j) Sell columns display profitability of trading rules when a sell trading signal is generated

k) Cells in percentages are rounded to 3 decimal places

l) t-tests are conducted (benchmark mean) - (trading rule mean), one-sided

References

Alexander, Sidney S., 1961, Price Movements in Speculative Markets: Trends or Random Walks, Industrial Management Review, 2 (2), 7-26.

Bekaert, G. and Harvey, C. Research in Emerging Markets Finance: Looking to the Future. NBER, 2002.

Bessembinder, Hendrik, and Kalok Chan. *Market Efficiency and the Returns to Technical Analysis*. Publication. Arizona State University, Dec. 1997. Web. <http://home.ust.hk/~kachan/research/tech.pdf>.

Bessembinder, Hendrik, and Kalok Chan. "The Profitability of Technical Trading Rules in the Asian Stock Markets." *Pacific-Basin Finance Journal* 3.2-3 (1995): 257-84. *ScienceDirect*. Web. <http://sciencedirect.com>.

Brock, William, Josef Lakonishok, and Blake LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *Journal of Finance* 47.5 (1992): 1731-764. Print.

Campbell, John Y., Grossman, Sanford J., and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, Quarterly Journal of Economics, 108, 905-939.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok. "Momentum Strategies." *Journal of Finance* (1996). Web.

Chang, Eui J., Eduardo J. Lima, and Benjamin Tabak. "Testing for Predictability in Emerging Equity Markets." *Emerging Markets Review* 5.3 (2004): 295-318. *Science Direct*. Web. <http://sciencedirect.com>.

Cheung, Y.W., Chinn, M.D., 2001. Currency traders and exchange rate dynamics: a survey of the US market. Journal of International Money and Finance 20(4), 439-471.

"Contents for Lo & MacKinlay: A Non-Random Walk Down Wall Street." Web. Feb. 2012. <http://press.princeton.edu/books/lo/>.

CRSP. Wharton Research Data Services. Web. <https://wrds-web.wharton.upenn.edu/wrds/>.

Efron, B. 1979. Bootstrap Methods: Another Look at the Jackknife. The Annals of Statistics 7 (1) : 1-26.

Fama, E.F. and M. Blume, 1966. Filter Rules and Stock Market Trading Profits. Journal of Business, 226-241.

Gartley, H.M. Profits in the Stock Market. New York, NY: H.M. Gartley Inc., 1935.

Hatgioannides, John, and Spyros Mesomeris. "On the Returns Generating Process and the Profitability of Trading Rule in Emerging Capital Markets." *Journal of International Money and Finance* 26.6 (2007): 948-73. Web. <http://sciencedirect.com>.

Hudson, R., Dempsey, M., Keasey, K., 1996. A note on weak form efficiency of capital markets: The application of simple technical trading rules to UK prices 1935-1994. Journal of Banking and Finance 20, 1121-1132.

"iShares MSCI Emerging Market Index." *Yahoo! Finance*. Web. Jan. 2012. <http://finance.yahoo.com/>.

Ito, A., 1999. Profits on Technical Trading Rules and Time-Varying Expected Returns: Evidence from Pacific-Basin Equity Markets, Pacific-Basin Finance Journal 7(3-4), 283-330.

Jensen, Michael C. and George A. Benington Random Walks and Technical Theories: Some Additional Evidence.

Karz, Gary. "Investor Home - Technical Anomalies." *Investor Home*. Web. <http://investorhome.com/anomtec.htm>.

Kwon, K-Y, Kish, R., 2002. A Comparative Study of Technical Trading Strategies and Return Predictability: An Extension of Brock, Lakonishok, and LeBaron (1992) Using NYSE and NASDAQ Indices, Quarterly Review of Economics and Finance 42(3), 611-631.

Lakonishok, J., Shleifer, A., and Vishny, R. The impact of institutional trading on stock prices. Journal of Financial Economics 32 (1992) 23-43.

LeBaron, Blake. "Technical Trading Rules and Regime Shifts in Foreign Exchange." Technical Analysis, May 1991. Web. Jan. 2012. <http://technicalanalysis.org.uk/moving-averages/LeBa91.pdf>.

LeBaron, Blake. *The Stability of Moving Average Technical Trading Rules on the Dow Jones Index*. Thesis. Brandeis University, 1999. Print.

Lukac, L. P., B. W. Brorsen and S. H. Irwin. “A Test of Futures Market Disequilibrium Using Twelve Different Technical Trading Systems.” Applied Economics, 20(1988):623-639.

Malkiel, Burton Gordon. *A Random Walk down Wall Street: The Time-tested Strategy for Successful Investing*. New York: W.W. Norton, 2003. Print.

Murphy, John. "Technical Analysis of the Financial Markets [Hardback]." *Technical Analysis of the Financial Markets (Book) by John Murphy*. Web. <http://books.global-investor.com/books/10044/John-Murphy/Technical-Analysis-of-the-Financial-Markets/>.

Park, Cheol-Ho, and Scott H. Irwin. "The Profitability of Technical Analysis: A Review." *Social Science Research Network* (2004): 1-106. SSRN, Oct. 2004. Web. Jan. 2012. <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=603481>.

Park, Cheol-Ho, and Scott H. Irwin. "The Profitability of Technical Trading Rules in US Futures Markets: A Data Snooping Free Test." *Social Science Research Network* (2005): 1-106. SSRN, May 2005. Web. Jan. 2012.

Ratner, Mitchell, and Ricardo Leal. "Tests of Technical Trading Strategies in the." (1998): 1-15. *TechnicalAnalysis.org.uk*. Web. Feb. 2012. <http://www.technicalanalysis.org.uk/moving-averages/RaLe98.pdf>.

Scharfstein, David S. and Jeremy C. Stein, 1990, Herd behavior and investment. American Economic Review 80, 465-479.

Sullivan, Ryan, Allan Timmermann, and Halbert White. "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap." *American Finance Association* 54.5 (1999): 1647-691. Print.

Taylor, Mark P., and Helen Allen, 1992. The Use of Technical Analysis in the Foreign Exchange Market. Journal of International Money and Finance,11 (3), 304–314.

The Journal of Finance , Vol. 25, No. 2, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969 (May, 1970), pp. 469-482.

"Vanguard Emerging Market Index." *Yahoo! Finance*. Web. Jan. 2012. <http://finance.yahoo.com/>.

Van Horne, James, C. and George G.C. Parker. Technical Trading Rules: A Comment. Financial Analysts Journal , Vol. 24, No. 4 (Jul. - Aug., 1968), pp. 128-132.