AN EVALUATION OF THE PERFORMANCE OF MOVING AVERAGE AND TRADING VOLUME TECHNICAL INDICATORS IN THE U.S. EQUITY MARKET

A Senior Scholars Thesis

by

BETHANY KRAKOSKY

Submitted to Honors and Undergraduate Research
Texas A&M University
in partial fulfillment of the requirements for the designation as

UNDERGRADUATE RESEARCH SCHOLAR

May 2012

Major: Economics

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ABSTRACT

An Evaluation of the Performance of Moving Average and Trading Volume Technical Indicators in the U.S. Equity Market. (May 2012)

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This paper examines the profitability of several simple technical trading rules by using the S&P 500 index. The purpose of this research is to test the assumption that markets are efficient and therefore do not allow for the exploitation of predictable price patterns. Returns generated from using the trading rules in the market are compared to returns from a buy-and-hold investing strategy to determine the success of technical indicators. Further investigation into technical analysis is done through several regression models in an attempt to capture the "true" model of the market. The models give insight into why the trading rules may work. Results from the regression models are compared to the returns generated by the trading rules to examine whether the models chosen are a good representation of the dynamics that are happening in the market. The results present evidence that the trading rules do consistently generate excess returns over the buy-and-hold method of investing. This suggests that the movements of the market may not be an unpredictable random walk, but rather can be captured by an autoregressive econometric model.

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NOMENCLATURE

40WMA	40 Week Moving Average
10WMA	10 Week Moving Average
DMA	Difference in Moving Averages
VMA	Volume Moving Average
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroskedasticity
GARCH	Generalized Autoregressive Conditional Heteroskedasticity

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CHAPTER I

INTRODUCTION

Many economists, especially those in academia, believe asset markets are instantaneously efficient, or nearly so. If stock markets are efficient, the stock market price history would contain no information about future returns, and short run changes in stock prices cannot be predicted using past prices. According to this theory, it would not be possible for an investor (without inside information) to consistently beat the market. This is known as the efficient market theory. In contrast, many of the investment strategies put into practice on Wall Street diverge from the ideas of the efficient market theory. A large number of firms and brokerages employ a variety of technical analysis techniques in an attempt to take advantage of predictable movements in stock prices that lead to profitable opportunities for market timing.

Technical analysis is the practice of trying to forecast future prices by studying historical movements of common stock prices, trading volume, and numerous other asset market properties that can potentially reveal predictable price patterns. Technical analysts believe that markets are not efficient, and they attempt to exploit the inefficiencies through use of various trend indicators based on signals such as those arising from price and volume data. The existence of market inefficiencies has a variety of explanations, including a possible sluggishness of the price response to new information and the

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This thesis follows the style of *The Quarterly Review of Economics and Finance*.

hypotheses that the emotional nature of humans causes fluctuations in the market price based on alternating waves of optimism and pessimism. These are but two of a range of potential explanations for market inefficiency, but regardless of the explanation, the end result is that stock prices exhibit patterns that can be predicted using technical indicators based on past data.

Due to the large number of technical indicators and the different sources of stock data, the literature on technical analysis varies greatly from one study to the next. Brock et al. (1992) carried out a study to test moving average and trading range break strategies against several null (efficient markets theory) models using a bootstrap methodology. They found that returns during buy periods are larger and less volatile than returns during sell periods, where buy and sell periods are defined by various technical strategies. Their results provide strong support for the profitability of a set of technical strategies. Kwon and Kish (2002) extended the research done by Brock et al. (1992), adding consideration of indicators based on moving averages of trading volume. They hypothesized that volume and price changes are positively correlated, so including a volume indicator could help confirm a buy or sell signal. Their results show that these technical trading rules displayed higher profitability than a buy-and-hold strategy, but also that the profit potential appeared to be weakening over time, possibly due to technological innovation. A different view is presented by Ready (2002), who conjectured that the apparent profitability of technical trading rules resulted from data snooping. He found support for this hypothesis and concluded that authors who found persistent patterns in the historical data did not necessarily find patterns that would persist into the future.

Many studies have analyzed the profitability of technical trading rules using various techniques, but more recent research in the field is shifting toward an interest in explaining the origin of profitability. Gencay (1999), Nam et al. (2001), Sarantis (2001), and Nam et al. (2005) examine the asymmetric properties of return dynamics and determine that predictable patterns are better explained by nonlinear models than the linear framework used to study trading rule profitability in the previous literature. Research holds that technical trading rules can increase profitability; however the origin and persistence of the technical trading rule advantage has not been conclusively analyzed.

One of the major motivations for this research is to combine various aspects of the prior literature in order to develop a comprehensive examination of technical analysis. Early research on the topic strongly supports the efficient market hypothesis, whereas more recent research has developed models and procedures that produce significant support for using trading rules for increased profitability in the market. Price moving average trading rules examined by Brock et al. (1992) and price-volume moving average trading rules tested by Kwon et al. (2002) are applied to the S&P 500 index to generate buy and hold signals. Using the S&P 500 index allows for a wider view of the market than the Dow Jones Industrial Average (DJIA) used in Brock's research. Returns made by implementing these rules are then examined through simple statistical testing across several time periods, which will test the reliability of the results generated by these trading rules. Advanced statistical testing of the rules is done through nonlinear autoregressive models and GARCH models. The nonlinear autoregressive models used are an extension of the models developed in Nam et al.'s (2005) study of the asymmetric dynamic process of stock returns. They developed five models that allow that constant term and the serial correlation coefficient to change based on a previous positive or negative return. These nonlinear autoregressive models are structured in such a way that artificially divides the market into patterns of positive and negative returns. To further develop those models, this paper combines the dynamic pattern of the market into one model that includes dummy interaction terms for both positive and negative previous return patterns. Rather than separating the market into two separate models based on positive or negative returns, this model lets the serial correlation coefficient vary with the actual asymmetric dynamic process of returns that Nam et al. (2005) described.

The generalized autoregressive conditional heteroskedasticity models (GARCH) are developed directly from the trading rules used in preliminary testing. Financial time-series of data are heteroskedastic, having changing variance across time and therefore an ordinary least squares model is not appropriate for measuring changes in the equities market. This study implements GARCH models to examine the reliability of the trading rules in order to account for the varying volatility in the data and provide a measure of risk. Brock et. Al (1992), Kwon and Kish (2002), and a majority of recent financial literature assert the usefulness of ARCH/GARCH models in assessing financial data. The remainder of this paper is organized as follows: Chapter II presents the various trading rules tested and explains the reasoning behind and the structure of the nonlinear autoregressive models and the GARCH models that are implemented to generate results. Chapters III and IV contain the empirical results of all the methods used and each are discussed in terms of their reliability in producing excess returns in the market. A brief summary of the results and a concluding discussion are provided in Chapter V.

CHAPTER II

METHODOLOGY

Data description

The data series used in this study is the S&P 500 Index, including the weekly closing price for the weeks of January 7th 1957 through November 28th 2011, employing almost 54 years of data (obtained from yahoo.finance.com). This series was chosen because it is widely used and considered to be one of the best measures of the U.S. equities market, covering about 75% of all U.S. equities. In addition to the entire sample, results are also calculated for two subsamples to evaluate the persistence of returns across time. The subsamples are 1/7/1957-5/21/1984 and 5/29/1984-11/28/2011. Three month T-Bill rates are used as a cash equivalent. During times of a “sell” signal, the investor would have their money in treasury bills rather than the equities market. The weekly rates on treasury bills were obtained from the FRED database.

Trading rule selection and testing

Defining the investing strategies

This study evaluates three types of different investing strategies, each with several variations. The first strategy is the buy and hold method of investing, in which an investor “buys the index” (in this case the S&P 500). This strategy assumes that the index is bought on the last day of the initial trading week and is held until the last day of the trading week at the end of the specified holding period, when it is sold at the closing price for that week.

The second strategy involves moving averages based on the index price. This strategy compares a short run moving average of price to a long run moving average of price in order to generate buy and sell signals. The 40WMA indicator is one variation of this strategy. If the weekly stock market closing price is above the 40WMA, the investor will hold the index. If the weekly closing price is below the 40 week moving average, the investor will hold cash, i.e. treasury bills. Here the 3 month T-bill rate is used as a cash equivalent. While the investor holds "cash" he earns an interest rate equivalent to that of the three month T-Bill. This technical strategy allows the investor to quickly exit the equity market during periods of falling price in order to stop overall losses.

Another variation of the price moving average strategy uses both the 10 week moving average and the 40 week moving average. A buy signal is generated when the 10WMA closes above the 40WMA for the week, and a sell signal is generated when the 10WMA closes below the 40WMA. This strategy keeps the investor holding the index during rising prices and holding cash during other times. In contrast to the simple 40WMA strategy, the investor would not be protected from a sharp decline, but this strategy triggers transactions more slowly and therefore avoids the "whiplash" and consequent large numbers of trades and accompanying high transactions costs caused by frequent price movements.

The Difference in Moving Averages (DMA) trading rule, an additional variation to the price moving average strategy, is a momentum indicator. It has a quick response to changes in trends, but is therefore more likely to generate "false alarms." The DMA strategy variation takes a seven week moving average between the difference of the 10WMA and the 40WMA. The idea behind this strategy is to permit the investor to profit from short term trends.

The third and final strategy combines the price moving average indicators with a trading volume indicator. Because volume and the absolute value of price changes are positively correlated, the general rule is that a buy signal is generated when the moving average for both price and volume is rising, and a sell signal is generated with the moving average for price is falling, regardless of the direction of volume. This strategy helps confirm the buy or sell signals that are produced by simple price moving average strategies. Several variations of this strategy use different lengths for the short and long run moving averages of price, and different lengths for the short and long run moving averages of volume. This study uses 1, 5, 10, and 40 week moving averages for price and 1, 5, and 10 week moving averages for volume.

Decision rules

Price moving average decision rules

In the analysis, three different price moving average indicators were used and developed into investing strategies to be compared with a buy and hold strategy. The ten week (10WMA) and the forty week (40WMA) simple moving averages were calculated by:

$$40WMA_i = \frac{1}{40}\sum_{j=i-39}^{i} CLOSE_i \qquad (1)$$

$$10WMA_i = \frac{1}{10}\sum_{j=i-9}^{i} CLOSE_i \quad (2)$$

where *i* is the closing price of the current week. The 10WMA and the 40WMA are derived from the widely used 50 and 200 days moving average indicators adapted for the use of weekly data. The decision rule for the 40WMA strategy is shown below:

$$If\ CLOSE_i > 40WMA_i \Rightarrow BUY_i \quad (3)$$

$$If\ CLOSE_i < 40WMA_i \Rightarrow SELL_i$$

The decision rule for the 10-40WMA strategy is as follows:

$$If\ 10WMA_i > 40WMA_i \Rightarrow BUY_i \quad (4)$$

$$If\ 10WMA_i < 40WMA_i \Rightarrow SELL_i$$

The third indicator used is known as the Difference in Moving Averages (DMA). It measures the difference between two different moving average indicators (10WMA and 40WMA in this study) and is a measure of trend momentum. Prices are increasing in momentum as the indicator increases, and decreasing in momentum and the indicator decreases. DMA is measured by:

$$DMA_i = 10WMA_i - 40WMA_i \quad (5)$$

A short moving average of the DMA indicator is then used to generate buy and sell signals. This study used the 7 week average of the DMA as the trigger. The decision rule is produced by the following formulas:

$$DMA7_i = \frac{1}{7}\sum_{j=i-6}^{i} DMA_j \quad (6)$$

$$If\ DMA_i > DMA7_i \Rightarrow BUY_i \quad (7)$$

$$If\ DMA < DMA7_i \Rightarrow SELL_i$$

Volume moving average decision rules

Trading volume is often used in combination with price moving average indicators in order to confirm the buy or sell signal. This study used 1, 5, 10, and 40 week price moving averages and 1, 5, and 10 week volume moving averages. The trading rule is expressed as:

$$If\ CLOSE_i > \frac{1}{L_1}\sum_{j=0}^{L_1-1} CLOSE_j\ \ and\ VOLUME_n > \frac{1}{L_2}\sum_{m=0}^{L_2-1} VOLUME_m\ \Rightarrow BUY \quad (8)$$

$$If\ CLOSE_i < \frac{1}{L_1}\sum_{j=0}^{L_1-1} CLOSE_j\ and\ VOLUME_n < \frac{1}{L_2}\sum_{m=0}^{L_2-1} VOLUME_m\ \Rightarrow SELL$$

L_1 and L_2 refer to the length of the indicators, where L_1 is the length of the price indicator (1, 5, 10 or 40 weeks) and L_2 is the length of the volume indicator (1, 5, or 10 weeks).

Buy and sell signals were generated using a spreadsheet program. Following a buy signal, an investor would earn the index returns in the following period. This can be thought of as an investor who observes the buy signal as market close on Friday of week t, buys the index, and hence earns the index return in the following week. The investor would then remain in the market until a sell signal, after which he would shift his holdings from stocks to T-Bills. An investor observing a sell signal at the end of week t would sell at the market price at that time, and invest in treasury bills, so that in the following week he would earn the treasury bill rate. Weekly returns were calculated by the formula:

$$RET_i = \frac{CLOSE_i - CLOSE_{i-1}}{CLOSE_{i-1}} \tag{9}$$

The weekly returns were calculated under the assumption that index was bought at the closing price and held until the weekly close at the end of each holding period.

Autoregressive models

As an extension of the work of Nam et al. (2005), this paper observes several nonlinear autoregressive models to encompass the possibility of an asymmetric pattern in stock returns. Nam's works shows the existence of an asymmetric dynamic process of returns, but uses models that separate the market into periods of positive and negative returns. In contrast, we combine the models of positive and negative returns into one autoregressive model in an attempt to capture the overall movements of the index. We also use weekly rather than daily data. Weekly data allows consideration of the performance of technical trading rules for investors who are not constantly 'in' the market, and has the practical advantage of aggregating over data irregularities such as holidays and other non-trading days in the midst of the week, as well as day-of-the-week effects and weekend effects. Two autoregressive models are tested in this paper:

$$R_t = (c_0 + \alpha_1 R_{t-1}) + (c_1 + \beta_1 R_{t-1}) \times p_t + (c_2 + \gamma_1 R_{t-1}) \times n_t + \varepsilon_t \tag{10}$$

$$R_t = (c_0 + \sum_{i=1}^{2} \alpha_i R_{t-i}) + (c_1 + \sum_{i=1}^{2} \beta_i R_{t-i}) \times p_t + (c_2 + \sum_{i=1}^{2} \gamma_i R_{t-i}) \times n_t + \varepsilon_t \tag{11}$$

In these models, p_t and n_t are dummy variables that account for different cases of prior returns. To remain consistent with the patterns tested by Nam et al. (2005), several different specifications are tested for each model, defined by prior holding week returns and prior consecutive week returns. For model 1, the dummy variables are defined as:

$$p_t = 1\ if\ R_{t-1} > 0\ and\ p_t = 0\ if\ R_{t-1} < 0 \tag{12}$$

$$n_t = 1\ if\ R_{t-1} < 0\ and\ n_t = 0\ if\ R_{t-1} > 0$$

For model 2, the prior holding week return is positive if the returns earned in the previous two weeks combine to be a positive return. The prior consecutive week return is positive if the previous two weeks each had a positive return. Therefore, the dummy variables for the holding period are defined as:

$$p_t = 1\ if\ R_{t-1} + R_{t-2} > 0, otherwise\ p_t = 0 \tag{13}$$

$$n_t = 1\ if\ R_{t-1} + R_{t-2} < 0, otherwise\ n_t = 0$$

The dummy variables for the prior consecutive week returns are defined as:

$$p_t = 1\ if\ R_{t-1} > 0\ and\ R_{t-2} > 0, otherwise\ p_t = 0 \tag{14}$$

$$n_t = 1\ if\ R_{t-1} < 0\ and\ R_{t-2} < 0, otherwise\ n_t = 0$$

Each of these models is tested individually by running least squares regressions of autoregressive models in the statistical program STATA. Robust standard errors are used to account for the heteroskedasticity in the data.

GARCH models

The GARCH models are tested by running ARCH/GARCH regressions in the statistical program STATA. The models are developed directly from the price moving average and volume moving average trading rules for various week moving average lengths. The regressions contained two periods of lagged returns and a one lag of the short moving average and one lag of the long moving average. The price moving average models are:

$$Ret_t = c_0 + \gamma_1 D + \beta_1 ret_{t-1} + \beta_2 ret_{t-2} + \beta_3 MA_{S(t-1)} + \beta_4 MA_{L(t-1)} \tag{15}$$

where MA_S is the short run moving average of index price and MA_L is the long run moving average of price. The variable D represents a dummy variable that allows the constant term in the model to change in response to the buy or sell signal generated by the trading rule. In this model, D=1 if the short run moving average is greater than the long run moving average; otherwise, D=0. The volume moving average models are:

$$Ret_t = c_0 + \gamma_1 D + \beta_1 ret_{t-1} + \beta_2 ret_{t-2} + \beta_3 MA_{S(t-1)} + \beta_4 MA_{L(t-1)} \tag{16}$$
$$+\beta_5 VMA_{S(t-1)} + \beta_6 VMA_{L(t-1)}$$

where VMA_S is the short run moving average of trading volume and VMA_L is the long run moving average of volume. In this model, D=1 if the short run moving average is greater than the long run moving average for both price and volume; otherwise, D=0. For each of these models, 1, 5, 10, and 40 weeks were used for the price moving averages and 1, 5, and 10 weeks were used for the volume moving averages. These moving average lengths were adapted to weekly values from popular day trading rules.

CHAPTER III

TRADING RULE EMPIRICAL RESULTS

This chapter analyzes the results of implementing the trading strategies on the S&P 500 index from January 1954-November 2011. The returns generated from variants of the price moving average strategy and the volume moving average strategy are compared to returns that would be gained by an investor using the buy and hold method of investing. Any returns gained from using the trading rules that exceed the returns of buy and hold are considered to be excess returns, which would indicate a potentially profitable active trading rule following the principles of technical analysis. Key statistics examined in the results include index returns following a buy signal, index returns following a sell signal, average weekly return, annualized return, standard deviation of the annualized return, and the Sharpe Ratio. The Sharpe Ratio, developed by William Forsyth Sharpe in 1966, is a reward-to-risk ratio that measures the ability of the return that is earned to compensate for the risk taken on by the investor (Sharpe 1966). The ratio is calculated as:

$$Sharpe\ Ratio = (Return - Risk\ Free\ Return) \div STDEV(Return) \qquad (17)$$

The annualized return, the average 3-month T-Bill return, and the standard deviation of the annualized return are used to calculate the Sharpe Ratio in this study. A higher Sharpe Ratio indicates a higher expected return per unit of risk, and hence a more desirable portfolio.

Following the analysis of the statistics discussed above, a transaction penalty is applied to the returns following any trades. This is especially important when evaluating technical trading rules. The use of trading rules as a method of investing often results in frequent trading in and out of the market, especially when compared to a buy and hold strategy. This frequent trading results in costs incurred from brokerage and transactions fees that have potential to offset any excess profits earned by using the trading rules. The average number of transactions per year is calculated for each rule, to which a transaction penalty is then applied.

Table 1 lists the results of a buy and hold method of investing to be used for comparison for the trading rule results.

Table 1
Buy and hold results.

	S&P 500 Index 1954-2011
Observations	2865
Average weekly return	0.138%
Annualized return	7.434%
Standard deviation	11.757%
Sharpe ratio	0.407

Returns following a buy signal and returns following a sell signal are not applicable to the buy and hold method of investing.

Price moving average trading results

Table 2 lists the performance results of the price moving average trading rules, including 40WMA, 10/40WMA, and DMA for the entire sample period. Tables 3a and 3b show the outcomes for these trading rules divided into two sub periods to evaluate the robustness of the results. As seen on the following page in Table 2, the price moving average trading rules generated significantly higher returns than the buy and hold method of investing. The annualized percentage of weekly returns is calculated for a more intuitive comparison across the trading strategies. In addition to the higher returns,

Table 2
Price moving average trading results.

S&P 500 Index 1954-2011	40WMA	10/40WMA	DMA
Observations	2846	2846	2846
Average weekly returns following a buy signal	0.271%	0.206%	0.180%
Average weekly returns following a sell signal	-0.006%	0.003%	0.005%
Average weekly return	0.182%	0.170%	0.153%
Annualized return	9.917%	9.234%	8.275%
Standard deviation	11.130%	10.689%	11.948%
Sharpe ratio	0.653	0.616	0.471

each of the price moving average strategies exhibit a higher Shape Ratio than buy and hold. This shows evidence that following these technical trading rules based on moving averages of price may reward investors with a higher risk to reward ratio. The 40WMA rule has the highest Sharpe Ratio, indicating that this rule provides the highest return per unit of risk. Tables 3a and 3b show the same statistics for the price moving average strategies divided into two sub periods to evaluate if the excess returns are persistent over time, or if the trading rule success can only be attributed to an anomaly in the data over one short period of time. These results show that two of the three price moving average rules performed better in the first sub period compared to the second. However all three consistently outperformed the buy and hold strategy in each sub period and overall.

Table 3a
Price moving average trading results sub period a.

S&P 500 Index 1/7/54-4/16/84	**40WMA**	**10/40WMA**	**DMA**
Observations	1425	1425	1425
Average weekly returns following a buy signal	0.275%	0.229%	0.171%
Average weekly returns following a sell signal	-0.0003%	0.002%	-0.0005%
Average weekly return	0.190%	0.198%	0.142%
Annualized return	10.374%	10.833%	7.659%
Standard deviation	11.815%	14.632%	8.390%
Sharpe ratio	0.654	0.600	0.598

Table 3b
Price moving average trading results sub period b.

S&P 500 Index 4/23/84-7/11/11	**40WMA**	**10/40WMA**	**DMA**
Observations	1420	1420	1420
Average weekly returns following a buy signal	0.199%	0.179%	0.193%
Average weekly returns following a sell signal	0.003%	-0.0001%	0.0006%
Average weekly return	0.158%	0.144%	0.153%
Annualized return	8.556%	7.770%	8.274%
Standard deviation	10.374%	9.077%	10.234%
Sharpe ratio	0.570	0.565	0.550

The better performance on average during the first sub period compared to the second may be explained by periods of high volatility in the second sub period such as the Dot Com bubble in 2000 or the Housing Bubble and Financial Crisis in 2007. This may also be due to rising interest rates during the first sub period; therefore an investor would have earned a higher return when out of the equity market in the first sub period compared to the second sub period. Regardless, all of the rules in the price moving average category generate returns in excess of buy and hold across the entire sample and in both sub periods.

Volume moving average trading results

Table 4 lists the performance results of the volume moving average trading rules, including the six variations of short and long price and volume moving averages for the entire sample period. Tables 5a and 5b show the outcomes for these trading rules divided into two sub periods to evaluate the robustness of the results. As seen in Table 4, the volume moving average trading rules generated significantly higher returns than the buy and hold method of investing. As with the price moving average rules, each of the volume trading strategies had a higher Sharpe Ratio than buy and hold.

The excess returns over the buy and hold strategy across all of the trading rules show substantial evidence that there are indeed patterns or dynamics in the stock index that can be captured and exploited through the use of technical analysis. The rule VMA

P10V10 had the highest Sharpe Ratio, and higher than the rules using only price moving averages.

Table 4
Volume moving average trading results.

S&P 500 Index 1954-2011	**VMA P40V5**	**VMA P40V10**	**VMA P10V5**	**VMA P10V10**	**VMA P5V5**	**VMA P5V10**
Observations	2825	2825	2825	2825	2825	2825
Average weekly returns following a buy signal	0.521%	0.461%	0.512%	0.515%	0.473%	0.482%
Average weekly returns following a sell signal	0.071%	0.081%	0.046%	0.042%	0.045%	0.050%
Average weekly return	0.163%	0.159%	0.180%	0.186%	0.179%	0.176%
Annualized return	8.838%	8.612%	9.803%	10.145%	9.746%	9.575%
Standard deviation	10.426%	10.661%	10.174%	10.237%	11.093%	10.465%
Sharpe ratio	0.594	0.559	0.704	0.732	0.640	0.662

As with the price moving average trading rules, the results are evaluated over two sub periods to examine the consistency of excess returns. The sub period results are shown in Tables 5a and 5b on the following page. These results show that four of the six volume moving average rules performed better in the first sub period, however all six did consistently outperform the buy and hold strategy. In addition to the reasons discussed in the price moving average section, a possible explanation for lower performance on average in the second sub period may be explained by advanced in technology. Kwon and Kish (2002) hypothesize that the profit potential of trading rules may be weakening over time, possibly due to technological innovation that allows for almost instantaneous dissemination of information in the market that allows prices to quickly respond to

Table 5a
Volume moving average trading results sub period a.

S&P 500 Index 1/7/54- 4/16/84	**VMA P40V5**	**VMA P40V10**	**VMA P10V5**	**VMA P10V10**	**VMA P5V5**	**VMA P5V10**
Observations	1424	1424	1425	1424	1424	1424
Average weekly returns following a buy signal	0.809%	0.534%	0.360%	0.652%	0.257%	0.692%
Average weekly returns following a sell signal	0.099%	0.013%	0.022%	0.008%	0.049%	0.006%
Average weekly return	0.187%	0.178%	0.168%	0.198%	0.156%	0.206%
Annualized return	10.203%	8.556%	9.121%	10.833%	8.443%	11.295%
Standard deviation	12.202%	9.976%	9.447%	11.043%	9.284%	12.713%
Sharpe ratio	0.619	0.592	0.685	0.741	0.624	0.680

Table 5b
Volume moving average trading results sub period b.

S&P 500 Index 4/23/84- 7/11/11	**VMA P40V5**	**VMA P40V10**	**VMA P10V5**	**VMA P10V10**	**VMA P5V5**	**VMA P5V10**
Observations	1420	1420	1420	1420	1420	1420
Average weekly returns following a buy signal	0.362%	0.420%	0.739%	0.426%	0.794%	0.317%
Average weekly returns following a sell signal	0.040%	0.025%	0.006%	-0.0004%	0.041%	0.004%
Average weekly return	0.142%	0.148%	0.201%	0.167%	0.222%	0.163%
Annualized return	7.658%	7.994%	11.006%	9.064%	12.222%	8.838%
Standard deviation	9.957%	10.037%	11.676%	10.535%	13.730%	10.678%
Sharpe ratio	0.503	0.533	0.716	0.609	0.698	0.580

changing market conditions, which may reduce the likelihood of predicable price patterns. Regardless, all of the rules in the volume moving average category display exemplary performance in generating excess returns over the buy and hold strategy.

Transaction penalties

Much criticism of technical analysis by subscribers to the efficient market hypothesis is due to the frequent trading in and out of the market as a result of following buy and sell signals generated by trading rules. Table 6 on the next page shows the average number of transactions per year for each trading rule over the entire 54 year sample period. It is apparent that the technical trading rules do involve a substantially higher amount of trading in and out of the market than does buy and hold. The effect of frequent trading on excess returns can be determined by applying a transaction penalty to every trade, then recalculating the return gained by following a trading rule strategy.

Table 6
Average number of transactions per year for various investing strategies.

Investing Strategy	**Number of transactions**
Buy and hold	0.037
40WMA	3.074
10/40WMA	1.056
DMA	3.907
VMA P40V5	7.093
VMA P40V10	5.982
VMA P10V5	11.111
VMA P10V10	10.185
VMA P5V5	12.889
VMA P5V10	11.963

If transactions penalties counteract any excess returns over buy and hold, the trading rules would no longer be considered a valid method of investing if one's goal is to "beat the market". Given current trading fees, a realistic measure of a transaction penalty can be reasonably be set at 0.1% fee per trade. This measure is based on a $10,000 portfolio and a $10 transaction cost, which is a rate easily obtained with modern technology. The dataset does extend back to a period that begins in the 1950s during which trading technology was less present and trading costs were likely higher. Because of this, more conservative transaction penalties are also applied, including 0.25% and 0.5% per trade. Results are shown in Table 7.

The results in Table 7 show that even under conservative transaction penalty assumptions, every moving average trading rule still earns excess returns over the buy and hold strategy. The fees do have a negative effect on the trading rule returns, however the trading is not frequent enough for the transaction penalties to eliminate the surplus profitability.

The results shown by following these simple technical trading rules suggest that persistent underlying patterns in the market may exist which allow trading strategies to generate excess returns. They also imply that in an environment of relatively low transaction penalties, technical analysis should not be dismissed on the basis that it involves frequent trading. The high performance of the moving average trading rules justifies further examination into investing based on technical analysis. Advanced statistical models intended to capture the dynamics of the stock index are utilized and the results are presented in the following chapter.

Table 7
Transaction penalties applied to moving average trading rules. Rules are applied on the S&P 500 Index from 1954-2011. Excess returns over the buy and hold strategy (annualized return) are listed in parenthesis.

	0% Transaction Penalty	0.1% Transaction Penalty	0.25% Transaction Penalty	0.5% Transaction Penalty
40WMA	9.917% (2.48%)	9.789% (2.36%)	9.774% (2.34%)	9.772% (2.338%)
10/40 WMA	9.234% (1.80%)	9.234% (1.80%)	9.231% (1.797%)	9.121% (1.69%)
DMA	8.275% (0.84%)	8.155% (0.72%)	8.130% (0.70%)	8.119% (0.69%)
VMA P40V5	8.838% (1.41%)	8.725% (1.29%)	8.669% (1.24%)	8.612% (1.18%)
VMA P40V10	8.612% (1.18%)	8.502% (1.07%)	8.452% (1.02%)	8.414% (0.98%)
VMA P10V5	9.803% (2.37%)	9.746% (2.31%)	9.689% (2.26%)	9.575% (2.14%)
VMA P10V10	10.145% (2.71%)	9.860% (2.43%)	9.802% (2.37%)	9.689% (2.26%)
VMA P5V5	9.746% (2.33%)	9.745% (2.31%)	9.631% (2.20%)	9.573% (2.13%)
VMA P5V10	9.575% (2.14%)	9.518% (2.08%)	9.461% (2.03%)	9.348% (1.91%)

The following figure, Figure 1, shows a comparison of the level of wealth that would be earned following various investing strategies. Figure 1 shows the level of wealth comparing the buy and hold strategy to the two top performing trading rules: VMA P10V10 and 40WMA.

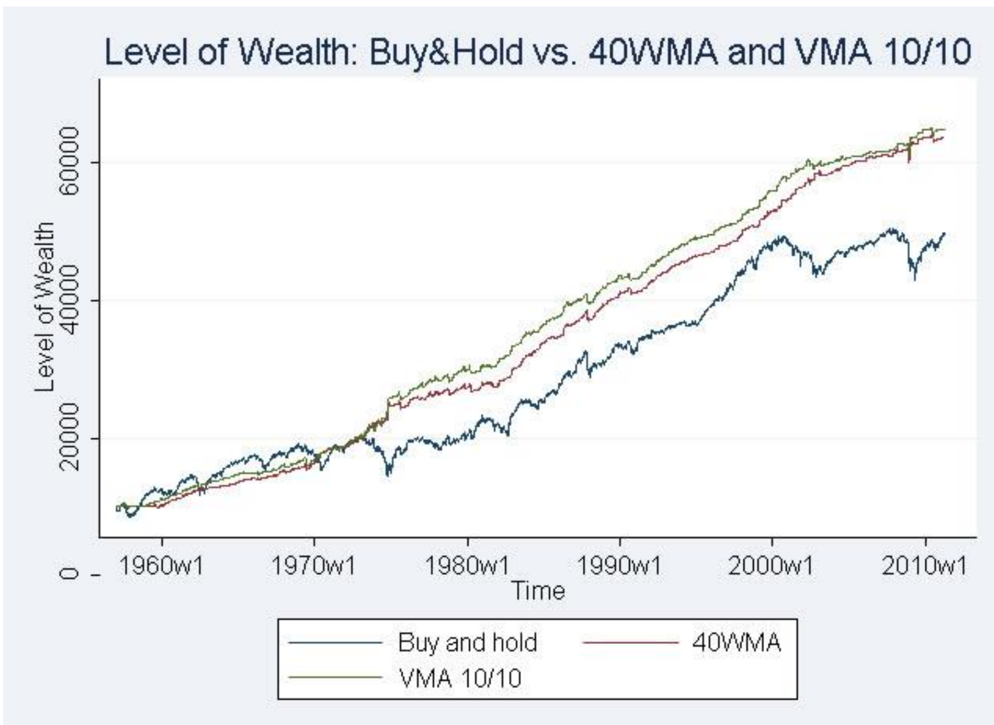

Figure 1. Level of wealth comparison

If an investor were to place $10,000 in the market at the beginning of the sample period, this is the amount of money the investor would have earned: The buy and hold strategy would be at a level of $50,117.38; 40WMA at a level of $63,828.22; and VMA P10V10 at a level of $65,141.19. Figure 1 shows a continuing upward trend for technical investors during the late 2000s, while the level of wealth for the buy and hold investor is volatile and not upward trending. The technical trading rules limit the technical investor's exposure during the 2007-2011 period, whereas the buy and hold investor experiences the full effect of the Financial Crisis. This explains the widening gap in the level of wealth between technical trading and the buy and hold investing strategy during the late 2000s. Additional figures comparing the buy and hold method to all of the price moving average strategies and the buy and hold method to all of the volume moving average strategies can be found in the Appendix.

Trading rule results during different holding periods

This section examines examples of how different investors would fare during four different ten year holding periods: 1970-79, 1980-89, 1990-1999, and 2000-09. The top performing technical trading rule was the VMA P10V10. We compare the performance of this rule to the buy and hold strategy over the four different holding periods to observe how the methods compare over different market conditions:

1. Technical trading outperforms buy and hold from 1/5/1970-12/31/1979

Buy and hold average annual return: 2.63%, Sharpe= 0.221

VMA P10V10 average annual return: 12.69%, Sharpe=0.789

The 1970s was a bear market for the stock market due to events such as the oil crisis and the Watergate Scandal. Investors who stayed in the market during this period did not see returns as high as technical investors who were able to avoid some of the unstable market conditions. Technical trading strategies rose in popularity during this time period.

2. Buy and hold outperforms technical trading from 1/7/1980- 12/26/1989

Buy and hold average annual return: 14.16%, Sharpe=0.525

VMA P10V10 average annual return: 13.69%, Sharpe=0.594

The 1980s saw a recovery from the market hardships of the previous decade. This bull market under Reagan's administration allowed the buy and hold investor to see profitable returns and an upward trending level of wealth. This period was also successful for the technical investor, but the buy and hold strategy did slightly outperform the trading rule. Sell signals that temporarily remove the technical trader from the market likely caused the investor to miss portions of rising returns during the 1980s.

3. Buy and hold outperforms technical trading from 1/2/1990-12/27/1999

Buy and hold average annual return: 15.05%, Sharpe=0.476

VMA P10V10 average annual return: 12.71%, Sharpe=0.634

The decade of the 1990s was a period of soaring prices as "dot-com" companies expanded their investor base and saw and unprecedented growth. Day trading grew in popularity during this time, but the explosive growth in the market allowed the buy and hold investor to realize higher returns than the technical trader. Following buy and sell signals caused the technical investor to fail to see critical times of rising market prices.

4. Technical trading outperforms buy and hold from 1/3/2000-12/28-2009

Buy and hold average annual return: -0.725%, Sharpe=-0.115

VMA P10V10 average annual return: 8.67%, Sharpe=0.429

This decade was a trying time for investors, with the Dot-Com Bubble burst beginning in 2000, and the Housing Bubble collapse and Financial Crisis beginning in 2007. Buy and hold investors felt the full force of the falling prices, and ended the decade with a negative overall return. Technical traders benefitted from following buy and sell signals, as they were out of the market and earning Treasury bill returns rather than the negative returns of the stock market.

The comparison of returns of buy and hold investing to a technical trading rule over the last 40 years reveals that the technical trader only beat buy and hold in two of the four decades that were examined. The average annual returns reveal an interesting insight that the success of technical analysis is more prominent during times when the index is significantly declining. The technical trading rule returned substantially higher gains during these periods than did buy and hold investing. Buy and hold outperformed the technical trading rule during strong bull markets, but this outperformance was relatively slight. The Sharpe Ratio is higher for the technical trading rule in every sub period, indicating these returns have more ability to compensate the investor for the level of risk. The success of the technical trading rule in protecting the investor during market declines is evidence of the value of using technical analysis as an investing strategy.

CHAPTER IV

REGRESSION MODEL RESULTS

Autoregressive models

Initial statistical testing of the trading rules utilizes nonlinear autoregressive models that allow the constant term to change in response to a previous positive or negative return. Nam et al. (2005) used a version of this method that revealed a potential link between the dynamic process of stock returns and the profitability of trading rules by identifying an asymmetric pattern in returns. They conclude that a positive or negative unconditional mean subsequently leads to a positive or negative return, and that this is a pattern that can be exploited to gain excess profits. However in this research, this consistent pattern was not found. As seen in the Table 8 on the following page, prior positive or negative returns seemed to have an insignificant effect on the current return. The results show that neither model under each case produce parameters that have a significant effect on returns by any traditional measure of statistical significance.

Perhaps the failure of this model to identify a persistent pattern in return dynamics is due to the use of weekly data rather than daily data. The models generated by Nam et al. (2005) led to results that conclude that strategies based on prior holding returns have a greater predictive power and potential profitability than do prior consecutive returns. The results here lead to no such conclusion due to the statistically zero effect of prior returns on current returns, giving no evidence of the predictive power of these models. Due to the failure of the autoregressive models to capture the market dynamics in this study, GARCH models are utilized to provide insight into the apparent success of the trading rules.

Table 8
Coefficient estimates on weekly S&P 500 returns from 1957-2011. T-statistics are listed in parenthesis.

	Prior Holding Week Return		**Prior Consecutive Week Return**	
	Model 1	**Model 2**	**Model 1**	**Model 2**
c_0	0.001 (0.79)	0.001 (0.55)	0.001 (0.79)	0.001 (1.93)
α_1	-0.011 (-0.85)	-0.067 (-0.88)	-0.011 (-0.85)	-.006 (-0.13)
α_2	-	0.020 (0.28)	-	0.044 (0.87)
c_1	-0.048 (-1.06)	0.087 (0.56)	-0.048 (-1.06)	0.050 (-0.91)
β_1	0.0009 (0.61)	0.086 (1.01)	0.0009 (0.61)	0.024 (0.31)
β_2	-	0.027 (0.35)	-	0.038 (0.50)
c_2	-0.037 (-0.40)	-0.036 (-0.49)	-0.037 (-0.40)	-0.034 (-0.71)
γ_1	-0.0015 (-0.81)	-0.007 (-1.04)	-0.0015 (-0.81)	-0.054 (-0.42)
γ_2	-	-0.027 (-0.42)	-	-0.025 (-0.20)

GARCH models

The generalized autoregressive conditional heteroskedasticity models tested in this study are developed directly from the trading rules used in preliminary testing. Financial time-series of data are heteroskedastic, having changing variance across time and therefore an ordinary least squares model is not appropriate for measuring changes in the equities market. This study implements GARCH models to examine the reliability of the trading rules in order to account for the varying volatility in the data and provide a measure of risk. Brock et. Al (1992), Kwon and Kish (2002), and a majority of recent financial literature assert the usefulness of ARCH/GARCH models in assessing financial data. Table 9 shows the estimated parameters for the price moving average trading rules under a GARCH regression for the full sample period.

The results show that lagged values of the moving averages have highly significant effects on current returns. Initially the negative parameter estimate on the short run moving average and the positive parameter estimate on the long run moving average for each rule seems counterintuitive. This seems to be opposite of the expected effect if the trading rules are generating excess returns. However when paired with the signal variable, the short run moving average crossing above the long run moving average produces a highly positive and significant effect on returns. This variable is equal to 1 when the SMA is greater than the LMA, and is equal to zero when the opposite is true. When the variable is included in the model, the constant term is much higher than when the variable drops out of the equation. The opposite signs on the parameter estimates of the SMA and LMA indicate that the trading rule does generate proper signals when these variables cross, but as the distance between the moving averages grows larger the realized returns fall in absolute value. This effect cannot be explained by the model.

Table 9
GARCH parameter estimates for price moving average trading rules. Rules are applied on the S&P 500 from 1954-2011. Z-statistics are listed in parenthesis. 5/40WMA represents the DMA strategy.

Short MA length	10 weeks	5 weeks	1 week
Long MA length	40 weeks	40 weeks	40 weeks
Signal dummy variable	0.0033 (4.26)	0.0038 (4.85)	0.0029 (4.14)
$\mathbf{Return_{t-1}}$	-0.0068 (-0.35)	-0.0073 (-0.45)	-.0081 (-0.51)
$\mathbf{Return_{t-2}}$	0.0231 (1.14)	0.0286 (1.21)	0.0216 (1.08)
$\mathbf{SMA_{t-1}}$	-0.00011 (-15.38)	-0.00018 (-15.86)	-0.00010 (-14.96)
$\mathbf{LMA_{t-1}}$	0.00011 (15.08)	0.00017 (15.65)	0.00010 (14.89)
Constant	0.0008 (1.55)	0.0007 (1.49)	0.00072 (1.52)
$\mathbf{ARCH_{t-1}}$	0.1255 (10.74)	0.1260 (10.76)	0.1226 (9.84)
$\mathbf{GARCH_{t-1}}$	0.8543 (65.95)	0.8503 (66.15)	0.8227 (63.21)
Constant	0.00001 (4.99)	0.00001 (4.96)	0.00001 (4.98)
Log likelihood	7265.406	7282.706	7262.664

Table 10 shows the GARCH regression statistics for the volume moving average trading rules. Similar to the price moving average trading rules, the moving averages for both price and volume have highly significant effects on returns. The short run moving averages for both price and volume have negative parameter estimates and the long run moving averages for price and volume have positive parameter estimates. This again seems to be the opposite effect of what is expected for the trading rules to generate excess returns, but when paired with the signal variable the positive effect on returns of the short run moving averages crossing above the long run moving averages is obvious. Overall, the GARCH regressions for all variations of the trading rules endorse the practice of using technical trading rules as a valuable method of investing.

Table 10
GARCH parameter estimates for volume moving average trading rules. Ruled are applied on the S&P 500 Index from 1954-2011. Z-statistics are listed in parenthesis. The results for rules VMA P5V5 and VMA P5V10 are not included due to a flat log likelihood that did not allow the regression to converge, and therefore reported statistics would not be reliable.

Short MA length	1 week	1 week	1 week	1 week
Long MA length	10 weeks	10 weeks	40 weeks	40 weeks
Short VMA length	1 week	1 week	1 week	1 week
Long VMA length	10 weeks	5 weeks	5 weeks	10 weeks
Signal dummy variable	0.0070 (9.99)	0.0061 (8.97)	0.0049 (5.65)	0.0053 (6.29)
$Return_{t-1}$	-0.0138 (-0.77)	-0.0086 (-0.48)	-0.0107 (-0.54)	-0.0170 (-0.86)
$Return_{t-2}$	0.0157 (0.82)	0.0205 (1.07)	0.0184 (0.90)	0.0154 (0.76)
SMA_{t-1}	-0.0004 (-27.45)	-0.0004 (-27.06)	-0.0001 (-14.04)	-0.0001 (-14.08)
LMA_{t-1}	0.0004 (27.29)	0.0004 (26.89)	0.0001 (14.40)	0.0001 (14.35)
$SVMA_{t-1}$	-0.00008 (-6.98)	-0.00007 (-4.76)	-0.00005 (-2.91)	-0.00008 (-6.55)
$LVMA_{t-1}$	0.00009 (7.37)	0.00007 (4.79)	0.00005 (2.64)	0.00009 (5.92)
Constant	0.0003 (0.73)	0.0005 (1.07)	0.0009 (1.96)	0.0009 (2.10)
$ARCH_{t-1}$	0.1361 (10.25)	0.1280 (10.26)	0.1254 (10.57)	0.1261 (10.67)
$GARCH_{t-1}$	0.8388 (54.59)	0.8470 (56.86)	0.8516 (61.45)	0.8513 (62.30)
Constant	0.00001 (4.97)	0.00001 (4.92)	0.00001 (5.03)	0.00001 (4.96)
Log likelihood	7480.664	7466.51	7272.015	7281.076

Tables 11a and 11b examine the GARCH results over two sub periods to examine the consistency and validity of the results.

Table 11a
GARCH parameter estimates sub period a. Results are shown for price and volume moving average trading rules on the S&P 500 Index from 1954-1984.

Short MA length	10 weeks	5 weeks	1 week	1 week	1 week	1 week	1 week
Long MA length	40 weeks	40 weeks	40 weeks	10 weeks	10 weeks	40 weeks	40 weeks
Short VMA length	–	–	–	1 week	1 week	1 week	1 week
Long VMA length	–	–	–	10 weeks	5 weeks	5 weeks	10 weeks
Signal dummy variable	0.0030 (6.34)	0.0022 (6.72)	0.0072 (7.59)	0.011 (13.57)	0.011 (12.47)	0.0093 (8.14)	0.0098 (8.95)
$Return_{t-1}$	0.0735 (2.35)	0.0743 (2.38)	0.0786 (2.49)	0.0118 (0.596)	0.0261 (1.14)	0.0586 (2.01)	0.0414 (1.42)
$Return_{t-2}$	-0.0090 (-0.30)	-0.0087 (-0.29)	-0.0067 (-0.22)	-0.0267 (-0.61)	-0.0177 (-0.79)	-0.0213 (-0.79)	-0.0271 (-1.01)
SMA	-0.0020 (-14.44)	-0.0001 (-12.05)	-0.0006 (-14.76)	-0.0045 (-34.91)	-0.0042 (-33.12)	-0.0011 (-14.76)	-0.0012 (-15.38)
LMA	0.0021 (14.10)	0.0001 (12.00)	0.0007 (14.96)	0.0044 (33.40)	0.0042 (31.60)	0.0011 (13.22)	0.0012 (14.02)
SVMA	–	–	–	-0.00009 (-10.37)	-0.00007 (-7.94)	-0.00001 (-2.56)	-0.00004 (-4.51)
LVMA	–	–	–	0.00009 (10.54)	0.00007 (8.11)	0.00001 (2.79)	0.00004 (3.84)
Constant	0.00001 (1.30)	0.00019 (1.20)	0.00015 (0.96)	-0.0007 (-0.68)	-0.0007 (-0.39)	0.0019 (0.88)	0.0002 (0.11)
$ARCH_{t-1}$	0.1456 (6.68)	0.1455 (6.76)	0.1495 (6.80)	0.1575 (7.28)	0.1420 (6.84)	0.1393 (6.46)	0.1387 (6.47)
$GARCH_{t-1}$	0.8235 (33.46)	0.8242 (33.95)	0.8188 (32.74)	0.8021 (33.29)	0.8204 (36.20)	0.8133 (29.37)	0.8093 (28.46)
Constant	0.00001 (3.47)	0.00001 (3.44)	0.00001 (3.48)	0.000009 (4.26)	0.000009 (4.16)	0.00001 (3.81)	0.00002 (3.95)
Log likelihood	3729.417	3728.001	3727.654	4092.581	4055.015	3820.403	3832.477

Table 11b
GARCH parameter estimates sub period b. Results are shown for price and volume moving average trading rules on the S&P 500 Index from 1984-2011.

Short MA length	10 weeks	5 weeks	1 week	1 week	1 week	1 week	1 week
Long MA length	40 weeks	40 weeks	40 weeks	10 weeks	10 weeks	40 weeks	40 weeks
Short VMA length	–	–	–	1 week	1 week	1 week	1 week
Long VMA length	–	–	–	10 weeks	5 weeks	5 weeks	10 weeks
Signal dummy variable	0.0024 (6.14)	0.0064 (6.44)	0.0036 (5.89)	0.0124 (10.64)	0.0123 (10.48)	0.013 (7.07)	0.012 (6.54)
$Return_{t-1}$	-0.0917 (-3.16)	-0.0910 (-3.13)	-0.0916 (-3.16)	-0.0662 (-2.90)	-0.0615 (-2.64)	-0.0827 (-3.01)	-0.0926 (-3.37)
$Return_{t-2}$	0.0308 (0.99)	0.0315 (1.01)	0.0303 (0.98)	0.0301 (1.16)	0.0374 (1.45)	0.0240 (0.82)	0.0185 (0.64)
SMA	-0.0060 (-14.50)	-0.0005 (-13.56)	-0.0008 (-15.06)	-0.0004 (-27.60)	-0.0004 (-26.91)	-0.0001 (-13.50)	-0.0001 (-12.80)
LMA	0.0058 (14.46)	0.0006 (14.62)	0.0007 (14.11)	0.0004 (27.36)	0.0004 (26.68)	0.0001 (13.81)	0.0001 (13.04)
SVMA	–	–	–	-0.00009 (-8.43)	-0.00008 (-5.60)	-0.00007 (-4.14)	-0.00001 (-7.60)
LVMA	–	–	–	0.00009 (8.72)	0.00008 (5.58)	0.00007 (3.65)	0.00001 (6.67)
Constant	0.0003 (3.02)	0.00097 (3.29)	0.00034 (3.44)	-0.0001 (-0.14)	0.0002 (0.22)	0.0008 (0.87)	0.0011 (1.16)
$ARCH_{t-1}$	0.1385 (10.46)	0.1337 (10.22)	0.1287 (9.34)	0.1325 (7.81)	0.1352 (8.17)	0.1214 (8.31)	0.1152 (8.04)
$GARCH_{t-1}$	0.8402 (52.03)	0.8467 (53.83)	0.8529 (53.55)	0.8507 (43.90)	0.8432 (41.85)	0.8600 (49.34)	0.8700 (52.92)
Constant	0.00001 (3.88)	0.00001 (3.81)	0.00001 (3.76)	0.000008 (3.17)	0.00001 (3.38)	0.00001 (3.32)	0.000009 (3.16)
Log likelihood	3483.800	3483.796	3484.73	3724.103	3717.524	3547.331	3549.605

The results from both sub periods are consistent with those of the overall sample. The estimated parameters on the moving average variables seem to be the opposite sign of what is expected, however when paired with the coefficient on the signal variable the trading rule seems valid. Exceptionally high Z-values on the GARCH parameters show the regression model's success in capturing the heteroskedasticity of the time series. In comparing the advanced statistical results to the results of simple testing in Chapter III, the GARCH regressions reflect the patterns revealed by the trading rules. The log likelihood function shows that although the excess returns generated by the trading rules persist over time, the first sub period saw more success in terms of profitability. The coefficients on the moving averages in all the GARCH regressions appear to have equal but opposite signs. Hypothesis testing confirms that this is the case, however when combined with the coefficient of the buy signal dummy variable short run moving averages have a larger effect on current returns than do long run moving averages.

CHAPTER V

SUMMARY AND CONCLUSIONS

This paper explores several variations of moving average trading rules to test the premise of technical analysis versus the efficient market hypothesis. Using a simple trading process to generate buy and sell signals, the trading rules displayed significant outperformance of the buy and hold method of investing. A possible link between the excess returns and the dynamics of the markets is examined through generalized autoregressive conditional heteroskedasticity models based off of the trading rules. The success of the GARCH models in reflecting the results of the trading rules suggest that the market is not an unpredictable random walk, but rather a dynamic process with patterns that may be exploited for profits.

The methods used in this paper cannot be guaranteed to successfully give superior returns into the future, and the better results in the first sub period may suggest the diminishing success of these trading rules over time. However, the results do suggest that there are persistent underlying patterns in the market that allow technical analysis strategies to generate excess returns. The highly significant parameters of the moving average variables in the GARCH regressions demonstrate the strong effect of previous returns on current returns.

Further validation of the success of technical analysis is revealed through the inspection of the trading rules under transactions costs. Even in an environment of conservatively high transactions penalties to account for possibly more expensive trades in the early years of the sample period, all of the trading rules tested still exhibited outperformance of the buy and hold strategy. Additionally, calculated Sharpe Ratios give evidence of better rewards-to-risk when following the trading rules rather than buy and hold.

In conclusion, this paper is consistent with the findings of recent literature on technical trading rules. The persistence of excess returns over time generated by trading rules implies that discounting the usefulness of technical analysis under the premise of the efficient market theory is becoming more difficult. Advances in statistical methodologies may be able to capture the complicated the returns-generating process of stocks. Why the rules work is still a question to be explored in future research, however the GARCH models drawn directly from the trading rules presented in this paper make steps toward explaining the pattern of the equities market.

The theoretical battle between the efficient market theory and technical analysis is far from over, as this paper does not prove with certainty the ability of trading rules to forecast future prices from past prices. However this research along with other recent studies on the field of technical analysis is consistent with the ability of trading rules to have predictive power.

APPENDIX

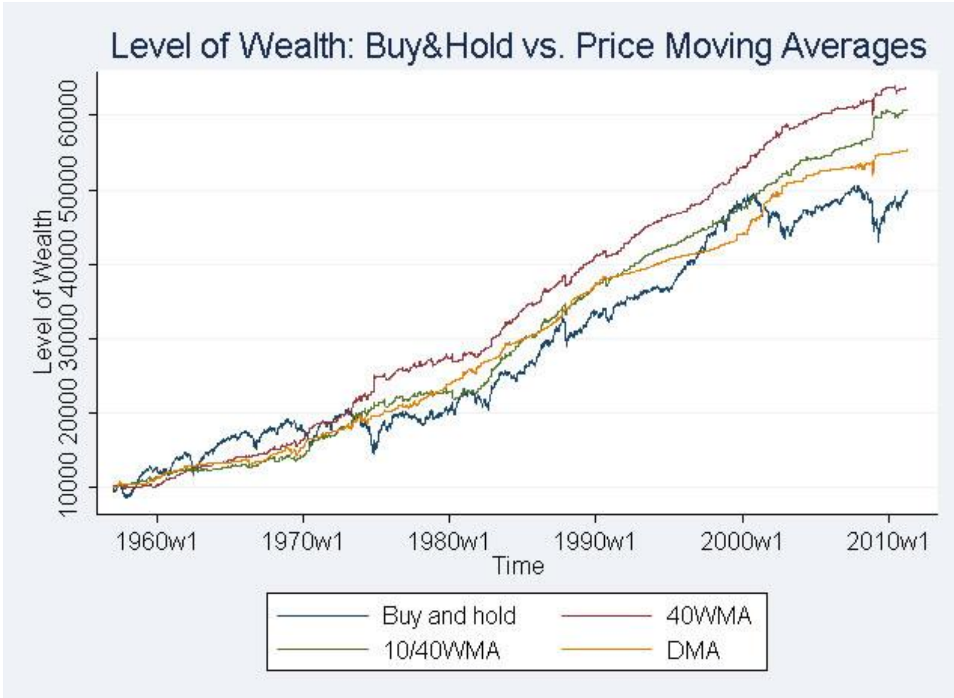

Figure 2. Price moving average level of wealth

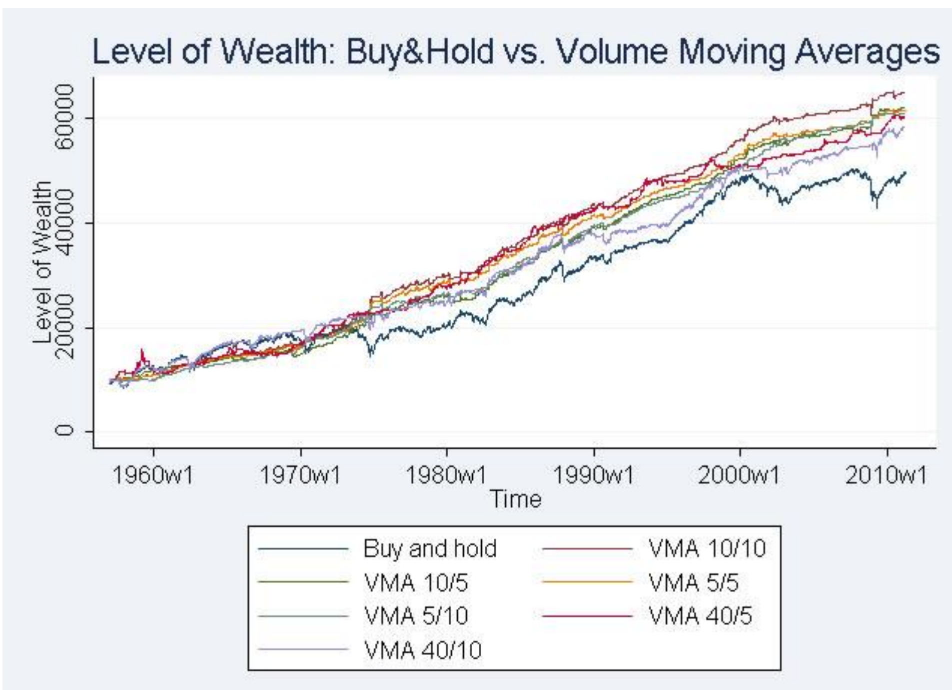

Figure 3. Volume moving average level of wealth

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