Candlestick Technical Trading Strategies: Can They Create Value for Investors?

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Abstract

This thesis examines the profitability of the oldest known form of technical analysis, candlestick trading strategies. Unlike traditional technical analysis which is based around close prices, these strategies generate buy and sell signals that are based on the relationship between open, high, low and close prices within a day and over consecutive days. Traditional technical analysis, which has been the focus of previous academic research, has a long-term focus with positions being held for months and years. In contrast, candlestick technical analysis has a short-term focus with positions being held for ten days or less. This difference is significant as surveys of market participants indicate that they place 50 per cent more importance on technical analysis for horizons of a week than they do for horizons of a year.

Candlestick technical analysis was developed on rice data in Japan in the 1700s so the tests in this thesis, using Dow Jones Industrial Index (DJIA) component stock data for the 1992 - 2002 period, are clearly out of sample tests. These tests are more robust to criticisms of data snooping than is the existing technical analysis literature. Proponents of technical analysis in the Western world would have had the opportunity to have become aware of candlestick trading strategies by this study's timeframe and would also have had the opportunity to source the data and software necessary to implement these strategies. So, a direct test of market efficiency is possible. This was not achievable by authors of many previous papers, who used data starting in the early 1900s and techniques that could not have been implemented at that time.

Using an innovative extension of the bootstrap methodology, which allows the generation of random open, high, low and close prices, to test the profitability of candlestick technical trading strategies showed that candlestick technical analysis does not have value. There is no evidence that a trader adhering to candlestick technical analysis would out-perform the market.

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Finally, I want to note my sincere appreciation to Rock and Jared Cahan for their assistance with my Matlab queries. Rock, in particular, will never know how much I value his work in this area.

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A.3.11. EGARCH Function

```
function R = egarch_function(N,returns,residuals,C,MA,AR,K,GARCH,ARCH,L,sigma)
%EARCH_BOOTSTRAP bootstraps an egarch model.
%Input is residuals and fitted parameters from original egarch model. N is
%the number of realisations to create. Returns a T by N matrix of N return
%series of length T.

lead = 1000;

T = length(residuals);
R = zeros(T+lead,N);

for n=1:N

    epsilon = resample([residuals; residuals; residuals]);
    ht = std(residuals.*sigma)^2;
    R(1,n) = 0;

    for t=2:T+lead

        old_ht = ht;
        ht = exp(K  + GARCH*log(ht) + ARCH*(abs(epsilon(t-1)*sqrt(old_ht))/sqrt(ht)-sqrt(2/pi)) + L*(epsilon(t-1)*sqrt(old_ht))/sqrt(ht));
        R(t,n) = C + AR*R(t-1,n) + MA*(epsilon(t-1)*sqrt(old_ht)) + epsilon(t)*sqrt(ht);

%         old_ht = ht;
%         ht = exp(K  + GARCH*log(ht) + ARCH*(abs(epsilon(t-1))/sqrt(ht)-sqrt(2/pi)) + L*(epsilon(t-1))/sqrt(ht));
%         R(t,n) = C + AR*R(t-1,n) + MA*(epsilon(t-1)) + epsilon(t);

    end;

end;
```

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Chapter One: Introduction

Debate on the degree to which asset returns can be predicted has continued in Western finance communities for over fifty years. The importance of this debate to the global economy has resulted in a huge amount of research energy being devoted to this area. The academic and practitioner communities have historically been divided on this issue. Academics have traditionally believed that returns are not predictable because if they were, rational market participants would soon learn of this predictability and trade it away. In contrast, a large portion of the investment industry is based on the premise that value can be added by active management. In other words, professional managers are skilful at picking future movements in asset prices. Academics now generally accept that returns do have some predictability; however, most maintain that it is not possible to profit from this.

The worth of technical analysis is central to the return predictability debate. Technical analysis or charting involves making investment decisions about traded instruments based on the examination of past market data, such as prices and volume. If technical analysis is shown to have value then there is evidence that it is indeed possible to profit from return predictability. Alternatively, if technical analysis is shown to be worthless then the rationality of market participants who devote a large amount of resource to its pursuit needs to be questioned.

Technical analysis encompasses a huge spectrum of trading rules. These range from mechanical rules such moving average rules, which involve buying (selling) when price moves above (below) a moving average of past prices, to rules that are based on "patterns" in price data. An example is the head and shoulders pattern. This involves three peaks, the highest of which is in the middle. If price penetrates the bottom of the first peak, after completing this pattern, a sell signal is given. Traditional technical trading rules in the Western world require close price data; however, new more sophisticated rules - such as the Directional Movement Indicator - now combine open, high, low, and close data.

Surveys conducted among foreign exchange and equity market participants and financial journalists find that the shorter the forecasting horizon the greater the emphasis which individuals place on technical analysis. Despite this, academic research has focused on testing the profitability of long-term technical trading rules. Most studies have tested rules based around 50 to 200 days of historical data, which generate trading signals relatively infrequently.

The origins of technical analysis in the Western world can be traced to the late 1800s when Charles Dow proposed, among other things, that markets reflect every possible known factor that affects overall supply and demand and that price action displays trends that are repeated. At this time the West was unaware that technical analysis principles, which it now calls *candlestick technical analysis*, had been successfully applied to rice trading in Japan from at least the 1700s.

Robust tests of technical analysis have been limited to trading rules that have their origins in the Western world. The majority of this literature shows that technical analysis does not have value once transaction costs and risk adjustment are taken into account. A smaller strand of literature shows that the application of technical analysis does result in excess returns.

This thesis is unique in that the profitability of candlestick technical analysis is considered. Candlestick technical analysis was introduced to the western world by Steve Nison in 1991 when he published a book titled *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East*. Candlestick trading rules rely on one to three days of historical data to generate a signal. Positions are generally held for up to 10 days. This short-term focus makes them very popular with market participants, who favour technical analysis for short-term horizons. Nison (2004, p. 22) comments "since its introduction to the Western world candlestick technical analysis has become ubiquitous, available in almost every software and online charting package." However, no researchers have investigated its profitability in a robust manner.

In 1750 a wealthy Japanese merchant, Munehisa Homma, began trading at his local rice exchange in Sakata using his own personal candlestick analysis. Homma became a legendary rice trader and amassed a huge fortune. Today's Japanese candlestick methodology is credited to Homma's trading principles as he applied them to the rice markets. Candlestick technical analysis involves the consideration of the relationship between open, high, low, and close prices. These four prices are displayed as objects that resemble candles as shown in Figure 1 (when the close is above (below) the open the candle "body" is white (black) :

Figure 1. Open, High, Low and Close Prices Displayed as Candles

When the close is above (below) the open the candle "body" is white (black).

A daily candlestick is a graphical representation of the day's open, high, low, and close prices. Daily candlesticks are commonly referred to as "single lines". Some single lines are said to have forecasting power in their own right. Together, consecutive single lines can form continuation and reversal patterns. Continuation patterns indicate the prevailing trend will continue, while reversal patterns suggest there will be a change in trend.

In this thesis, the profitability of candlestick technical analysis is tested using individual stock data for those companies that were included in the Dow Jones Industrial Index (DJIA) during the 1/1/1992 – 31/12/2002 period. This data set was chosen to ensure that data snooping bias is minimised. Data snooping bias can occur if the data set that is used to develop a theory is used to test and verify that same theory. In this research, the use of U.S. stock data to test candlestick technical analysis, which were developed using Japanese rice data, is most clearly an out of sample test.

Market efficiency claims only that prices reflect all known information at that point in time, not information that may come to light in the future. For this reason the start point of 1 January 1992 was carefully chosen. Despite it having been a popular trading technique in Japanese financial markets for some considerable time, the seminal candlestick trading strategy book in English was not published until 1991. Therefore prior to 1992 large sections of the Western finance community may not have been aware of candlestick technical analysis.

Data choice is critically important to tests of technical analysis for several other reasons. Firstly, it is important that the chosen data are able to be traded in reality in the same manner in which they are tested. For instance, the use of index data in technical analysis research is a dubious approach if the index is unable to be traded in its own right in reality. Secondly, it is important that the data are from instruments of sufficient liquidity to enable market participants to make meaningful amounts of money. This liquidity aspect is also important to provide a fair test of technical analysis. Proponents of technical analysis claim that it is a measure of mass market psychology. It is therefore less useful for trading thinly traded stocks whose prices are more susceptible to being moved by as little as one market participant. Finally, it is important that theories are tested on data that are different from those on which they were developed. This ensures that the theories do not simply hold on the one data set.

The standard *t*-test methodology, which determines if the returns following a technical analysis buy (sell) signal are statistically significantly greater (less) than the unconditional return, was employed. However, this methodology is dependent on several assumptions that do not generally hold for financial data, so a bootstrapping methodology was also applied.

The bootstrapping approach involves fitting a null model (e.g. GARCH-M) to a close price stock series, then randomly resampling the residuals 500 times. These resampled residuals are then used to construct 500 stock series that are by construction random, but have the same time-series properties as the original series. The profitability of a technical trading rule is statistically significant at the level of 5% if the number of times that the rule produces more profit following a buy signal on the 500 random series than the original series is fewer than 25.

The bootstrapping methodology is established in the literature for trading rules that require only one price series. Candlestick technical analysis involves open, high, low, and close prices so an extension is required. The approach taken in this thesis, which appears to be a first, was to simulate a random close series in the manner outlined above. Once a randomly generated close series had been formed, vectors of the original (high-close)/close and (close-low)/close percentage differences were created. A random sample from these percentage difference vectors was then taken. Next these high-close (close-low) percentage differences were added (subtracted) to (from) the simulated close price to form simulated high and low prices. A similar process was used to generate simulated open prices. To ensure that the resampled open price was never higher than the high nor lower than the low the close-open percentage differences were resampled if this situation arose.

The remainder of this thesis is organised as follows: Chapter Two contains a review of the relevant literature. In Chapter Three the data and methodology employed in this thesis are outlined. The results are presented and discussed in Chapter Four. Chapter Five contains conclusions. Three appendices are also included.

Chapter Two is divided into three sections. In the first of these the traditional finance literature is reviewed. This includes literature on two of the most important concepts in modern finance: the random walk and efficient market hypotheses. The *random walk hypothesis* holds that *asset prices fluctuate randomly*, while the *efficient market hypothesis* contends that *it is not possible to make economic profits by trading on available information*. This section finishes with a brief review of some of the early empirical literature which explains evidence found that is inconsistent with the random walk hypothesis.

In Section Two the literature within the growing area of behavioural finance is examined. This work details attempts to explain departures from rational behaviour using psychology literature. The idea that there are limits to arbitrage that prevent inefficiencies from being traded away is closely linked to this area. A relatively new theory that stock markets act as complex adaptive systems is also considered. This theory is a contention that the behaviour of the market "emerges" from the interaction of investors and that the aggregate behaviour is more complicated than what would be predicted by combining the parts.

The voluminous literature on the profitability of technical analysis is reviewed in Section Three. The amount of empirical literature on technical analysis far outweighs theoretical work. Nonetheless, the theoretical hypotheses that have been developed are outlined. The characteristics of the markets that technical trading rules have been tested on are also described. The empirical literature is classified into two broad groups: that which is consistent with the efficient market hypothesis, in the sense that profits are not found to exist beyond the transaction costs incurred and risks taken in earning them, and that which does seem to indicate excess profitability. Different rules are considered separately within these two broad categories. Section Three finishes with a detailed description of candlestick technical analysis.

Chapter Three comprises two sections. The first contains an extensive discussion of the choice of data and the steps that have been taken to elevate this research above the criticism of data snooping. In general terms, *data snooping* occurs *when a researcher tests a theory using the same data that were employed in the development of the theory, and then claims that the empirical results support the original theory.* Section Two contains a detailed description of the choice of candlestick rules and the methodology used to test their profitability. This includes a standard *t*-test approach and an extension of the bootstrapping methodology to enable the generation of random open, high, low, and close prices. The four null models employed in the bootstrap methodology, the random walk, the AR(1), the GARCH-M, and EGARCH are also outlined.

The empirical results are presented and discussed in Chapter Four. Nine separate scenarios were considered to determine whether or not specific assumptions are driving the results. These scenarios involve varying the entry day from the closing price on the day of the signal to the opening and closing prices on the day following a signal. The number of days a position is kept open following a signal was also varied from ten days to two and five days. Finally, the specification of the variables that define candlestick single lines and patterns, and the definition of the prior trend were varied.

Three appendices are also included. The first provides a graphical depiction and explanation of candlestick single lines and reversal patterns. Appendix Two contains a description of the Dow Stocks used in this research. The final appendix contains the MATLAB code that was used to generate the results.

Chapter Two: Literature Review

2.1. Introduction

The literature review is divided into three major sections. In the first the extensive literature that covers the random walk and efficient market hypotheses, two of the most important concepts in modern finance are considered. In Section Two, the finance literature in which attempts are made to explain financial phenomena using psychology literature is discussed. This emerging area, known as *behavioural finance*, suggests that *seemingly irrational financial market behaviour can be explained by looking at the psychological make-up of market participants.* The extensive literature in which the profitability of technical trading strategies is considered is then discussed. In this section the empirical literature is divided into two categories: that which finds that technical trading strategies are not profitable once transaction costs and risk are taken into account, and that which finds that the profitability of these strategies is robust to these adjustments. The former finding is consistent with market efficiency while the latter is not.

2.2. Traditional Finance

2.2.1. Background

The traditional finance paradigm is a means by which an understanding of financial markets using models in which agents are "rational" is sought. It is assumed that agents process new information correctly and that they have enough information about the structure of the economy to figure out the true distribution for variables of interest. The random walk and efficient market hypotheses are central tenets of traditional finance.

2.2.2. Random Walk Hypothesis

One of the earliest and most enduring models of the behaviour of security prices is the random walk hypothesis, an idea that was conceived in the sixteenth century as a model of games of chance. Closely tied to the birth of probability theory, the random walk hypothesis has an illustrious history, with remarkable intellectual founding fathers such as Bachelier, Einstein, Kendall, Levy, Kolmogorow, and Wiener (Lo and MacKinlay, 1999).

The first complete development of a theory of random walks in security prices came from Louis Bachelier (1900) whose original work, contained in his dissertation submitted for his PhD in mathematics, appeared around the turn of the century. However, his work did not receive much attention from economists at the time, leading to subsequent "discoveries". The second discovery of the model was by Working (1934) who showed empirically that commodity prices fluctuate randomly. Economists appear to have paid surprisingly little attention to Working's (1934) ground-breaking studies. The next major investigation was by Cowles (1933) who found that stock market analysts could not predict prices. Subsequently, Cowles (1944) provided corroborative results for a large number of forecasts over a much longer sample period. Kendall (1953) analysed 22 UK stock and commodity price series and found that at fairly close intervals the random changes are so large that they swamp any systematic effect which may be present. Kendall (1953) concluded that the data behave like a "wandering series."

The main modern interest in the random walk model started in the late 1950s when papers by Roberts (1959) and Osborne (1959) explicitly stated that stock market prices obey such a model. By showing that a time series generated from a sequence of random numbers was indistinguishable from a record of U.S. stock prices, Roberts (1959) sought to highlight to security analysts the futility of their methods. In contrast, Osborne (1959) analysed stock prices out of pure academic interest. Using statistical mechanics he showed that stock prices have properties analogous to the movements of molecules.

Granger and Morgenstern (1970) unified much of the random walk literature up to that point and showed that there are three possible forms of the random walk model:

$$P_t = P_{t-1} + e_t$$

Where:

$E(e_t) = 0$

$Var(e_t)$ is finite

Now if:

a) e_t, e_{t-s} ($s \neq 0$) are independent, then P_t is a strict random walk.

b) e_t, e_{t-s} ($s \neq 0$) are uncorrelated, P_t is a second order martingale.

c) e_t, e_{t-s} ($s \neq 0$) are independent and e_t are all normally distributed, then P_t is a Wiener process.

Following Roberts (1959) and Osborne (1959) numerous papers, generally supportive of the model, were then written (Cowles 1960; Working, 1960; Alexander, 1961; Cootner, 1962; Osborne, 1962; Mandelbrot, 1963; Alexander, 1964; Fama, 1965; Fama and Blume, 1966). Although, not explicitly stated, the majority of these empirical investigations were on the martingale form as they concentrate on the observed correlation between e_t, e_{t-s} ($s \neq 0$).

In other papers runs tests were considered. In this method, the series of price changes is replaced by a series of symbols + when the price is positive and – when the change is zero or negative. A *run* is *a sequence of one or the other of the symbols*. In an extensive runs test study of 30 U.S. stocks, Fama (1965) found no indication of dependence between price changes of any importance from an investment or statistical point of view. Other research (Alexander, 1961, 1964; Fama and Blume, 1966; Ball, 1978) was focused on filter rule tests. These rules involve buying after price increases by x% and selling when it decreases by y%

(where x% and y% are typically both 0.5%). In this work excess profits were found but these disappeared after one-way transaction costs of 0.05% were taken into account.

2.2.3. Efficient Market Hypothesis

The term *efficient capital markets* has several related meanings. In general, the efficient markets hypothesis holds that *a market is efficient if it is impossible to make economic profits by trading on available information.* Unexpected price changes must behave as uncorrelated random drawings if the market is competitive and expected profits from trading are zero. These price changes reflect new information that cannot be deduced from prior information, therefore new information must be uncorrelated over time (Shanken and Smith, 1996).

Samuelson (1965) laid the foundation for the modern theoretical rationale underlying the efficient market hypothesis by drawing from the random walk literature. The assumptions underpinning Samuelson's (1965) "proof" that shows that properly anticipated (efficient) security prices fluctuate randomly have been challenged by subsequent work. Lo and MacKinlay (1999) pointed out that without the assumptions of constant expected returns and risk-neutral investors, unforecastable prices need not imply a well-functioning, efficient market with rational investors, and forecastable prices need not imply the opposite. Despite this criticism, Samuelson's (1965) paper stands as the seminal link between the random walk and efficient market hypotheses.

Building on Samuelson's (1965) microeconomic approach, together with taxonomy suggested by Roberts (1967), Fama (1970) assembled a comprehensive review of the theory and evidence of market efficiency. Though his paper proceeds from theory to empirical work, he noted that most of the empirical work preceded development of the theory. The theory involves defining an *efficient market* as one in which *trading on available information fails to provide an abnormal profit.* A market can be deemed efficient, therefore, only if a model is posited for returns. Tests of market efficiency are therefore joint tests of market behaviour and models of asset pricing (Dimson and Mussavian, 1998).

A major contribution of Fama (1970) is the classification of the efficient market hypothesis into three forms based on information. A market is said to be "weak form efficient" if it reflects all knowledge from past price information, "semi-strong form efficient" if it reflects all public information, and "strong form efficient" if it reflects all information.

Grossman (1976) and Grossman and Stiglitz (1980) criticised Samuelson's (1965) and Fama's (1970) version of the efficient markets hypothesis. They argued that perfectly efficient markets are an impossibility as this implies the return to gathering information is nil. This means there would be little reason to trade and markets would eventually collapse. Prices are said to adjust slowly because of the costs of acquiring and evaluating new information. Beja and Goldman (1980) added to the literature by showing that taxes and transaction costs can also cause prices to deviate from perfectly efficient levels. They argued that inefficiencies, which may be viewed as economic rents, exist to compensate investors for the costs of trading and information gathering.

This work on impediments to purely efficient prices led Jensen (1978) to develop a broader definition of the efficient markets hypothesis where market prices can differ from fundamentals only to the extent that it is undesirable to trade in the mispriced asset. Trading may be undesirable because of transaction costs, the costly nature of information, or arbitrageur risk aversion. The adoption of this definition allows leeway for significant deviations between price and value without violating the efficient market hypothesis.

Ball (1995) identified several limitations in the Jensen (1978) approach. He suggested that extremely large transactions costs imply few opportunities to profit from price errors, net of costs. Nevertheless, it makes little sense to describe such a market with large price errors as "efficient." Secondly, Ball (1995) highlighted the fact that varying transaction costs across investors leads to different definitions of efficiency for different investors. Despite these limitations, the Jensen (1978) definition has become the dominant approach.

2.2.4. Empirical Evidence against Market Efficiency

The focus of this thesis is to examine the profitability of the technical analysis technique of candlestick charting. Technical analysis uses past price information to generate trading signals, which are claimed to produce excess returns. If true, this is evidence against weak form market efficiency. Technical analysis techniques have largely been developed by the practitioner community and subsequently tested by academics. The academic community has also instigated research into the prediction of future stock returns based on current information. This "anomaly" literature typically takes the approach of comparing the returns generated from a particular strategy to those expected based on the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965), and Mossin (1966). This use of the dominant risk – return model in finance means that such tests are jointly investigating the CAPM and the theory against market efficiency.

The technical analysis literature is considered in detail in Part 3. In this section the voluminous literature that presents empirical results based on variables other than past prices - that some claim contradicts the efficient market hypothesis – is briefly considered.

Studies of short-term market efficiency use an event study methodology. This involves averaging the cumulative performance of stocks over time, from a specified number of time periods before an event to a specified number of periods after. Performance for each stock is measured after adjusting for market-wide movements in security prices (based on the CAPM). In the first event study paper, Fama, Fisher, Jensen, and Roll (1969) provided evidence that most of the price adjustment associated with stock splits is complete before the event is revealed to the market, and when the news is released the remaining price adjustment takes place rapidly and accurately. In contrast, Ball and Brown (1968) and Bernard and Thomas (1990) found that the market responds to earnings announcements up to a year after they have been announced.

One of the first papers to document a non-announcement anomaly was Basu (1977). He found that price/earnings ratios are useful in predicting stock returns. Low price/earnings securities outperformed their high price/earnings counterparts by more than 7% per year. Banz (1981) then found that small stocks outperformed large stocks by an average of 1% per month on a risk-adjusted basis. This study has been criticised as being affected by survivorship bias. However, Fama and French (1992) showed that size and book-to-market equity capture much of the cross-sectional variation in stock returns, and that beta has limited power to explain returns. Lakonishok, Shleifer, and Vishny (1994) proposed that ratios involving stock prices proxy for past performance. Firms with high (low) ratios of earnings to price, cash flow to price, and book-to-market equity tend to have poor (strong) past earnings growth. They hypothesised that the market overreacts to past growth and is surprised when the earnings growth mean reverts. As a result, past poor (strong) performers have high (low) future returns.

Other papers have documented predictability in stock returns based on prior information. Examples include Fama and Schwert (1977) (short-term interest rates), Keim and Stambaugh (1986) (spreads between high-risk corporate bonds and short-term interest rates, Campbell (1987) (spreads between long-term and short-term interest rates), French, Schwert, Stambaugh (1987) (stock volatility), Fama and French (1988) (dividend yields on aggregate stock returns), and Baker and Wurgler (2000) (proportion of new security issues that are equity issues). The anomaly literature also includes work relating to seasonalities, including month-of-the-year, week-of-the-month, day-of-the-week, and hour-of-the-day effects (see Rozeff and Kinney (1976) and Keim (1983), French (1980), and Harris (1986) respectively).

Other studies have documented negative autocorrelation in weekly security returns (Jegadeesh, 1990), positive autocorrelations in returns over monthly time horizons (Jegadeesh and Titman, 1993), and negative correlation in longer horizon returns over several years (DeBondt and Thaler, 1985). While this under- and overreaction literature is typically included in discussions on anomalies, in this thesis it is included in the technical analysis section. These studies formulate trading strategies based solely on past returns, so they fall into the general classification of technical analysis.

Other evidence of over- and underreaction is based on company-specific events. These include the overreaction to the poor long-term performance of initial public offerings (Ritter, 1991; Loughran and Ritter, 1995), and seasoned equity offerings (Loughran and Ritter, 1995; Spiess and Affleck-Graves, 1995). There is also other evidence of underreaction. Cusatis, Miles and Woolridge (1993) found positive returns for divesting firms and the firms they divest. Desai and Jain (1997) and Ikenberry, Rankine, and Stice (1996) found that firms that split their stock experience long-term abnormal returns both before and after the split. Lakonishok and Vermaelen (1990) found positive long-term abnormal returns when firms tender their stock. Ikenberry, Rankine, and Stice (1996) observed similar results for open market share repurchases. Finally, Michaely, Thaler and Womack (1995) found that stock prices seem to underreact to the negative information in dividend omissions and the positive information in dividend initiations.

Proponents of market efficiency have responded to the challenge of anomalies in different ways. They either reinterpret the facts as nonanomalous and argue that the abnormal profits compensate for time-varying risk, question their pervasiveness and robustness (Fama, 1998), or argue that markets may yet be "minimally rational," in the sense that they fail to supply opportunities for abnormal profits (Rubinstein, 2001). Others, now referred to as "behaviourists", have sought to explain anomalies using psychology literature (Barberis and Thaler, 2002).

2.3. Behavioural Finance

2.3.1. Background

Behavioural finance was developed by psychology researchers who saw the relevance of their work to finance. Slovic (1969, 1972) illustrated stockbroker and individual misconceptions about risk respectively. Tversky and Kahneman (1974) and Kahneman and Tversky (1979) then made significant advances by looking at heuristic-driven errors (where individuals use mental short-cuts in the decision making process) and frame dependence (where individuals' responses is dependent on form rather than substance) respectively.

2.3.2. Psychological Biases

With many of the psychological biases closely linked, their classification lacks consensus. In a recent review, Hirshleifer (2001) argued that psychological biases can be viewed as outgrowths of heuristic simplification, self-deception, and emotion-based judgements.

Heuristic simplification helps explain many different biases such as representativeness (judgements based on stereotypes), anchoring and adjustment, salience and availability effects (heavy focus on information that stands out or is often mentioned, at the expense of information that blends into the background), framing effects (where the description of a situation affects judgements and choices), money illusion (where nominal prices affect perceptions), and mental accounting (tracking gains or losses relative to arbitrary reference points).

Self-deception can explain overconfidence (a tendency to overestimate one's ability or judgment accuracy), and dynamic processes that support overconfidence such as biased self-attribution (a tendency to attribute success to one's own ability and failure to bad luck or other factors), confirmatory bias (a tendency to interpret evidence with one's pre-existing beliefs), hindsight bias (a tendency to think 'you knew it all along'), rationalisation (straining to come up with arguments in favour of one's past judgements and choices), and action-induced attitude changes of the sort that motivate cognitive dissonance theory (becoming more strongly persuaded of the validity of an action or belief as a direct consequence of adopting that action or belief).

Feeling or emotion-based judgements can explain mood effects such as the effects of irrelevant environmental variables (on optimism), certain kinds of attribution errors (attributing good mood to superior future life prospects rather than to immediate variables such as sunlight or a comfortable environment), and problems of self-control (such as difficulty in deferring immediate consumption) – hyperbolic discounting; and the effects of feelings such as fear on risky choices.

2.3.3. Limits to Arbitrage

Behavioural finance researchers argue that some features of asset prices are most plausibly interpreted as deviations from fundamental value and these deviations are brought about by the presence of traders who are not fully rational. Strategies designed to correct mispricing are said to be often costly and risky, rendering them unattractive. In other words, limits to arbitrage exist.

Barberis and Thaler (2002) identified fundamental risk as a key determinant of arbitrage activity. This refers to the possibility that the prices of two stocks with similar fundamentals may diverge owing to their unique characteristics rather than converge because of their similarities.

Noise trader and synchronisation risk also affect arbitrage activity in financial markets. De Long, Shleifer, Summers, and Waldmann (1990) highlighted the fact that there is a risk that the mispricing being exploited by the arbitrageur worsens in the short run forcing arbitrageurs to liquidate their positions early, resulting in losses. Abreu and Brunnermeier (2002) found that holding costs and uncertainty about when their peers will exploit an arbitrage opportunity, or synchronisation risk, causes arbitrageurs to delay arbitrage in an attempt to "time the market" rather than correct mispricing straight away.

The biggest friction impeding arbitrage in financial markets appears to be the costs associated with imperfect information (Merton, 1987; Fama, 1991). For arbitrage to keep prices at fundamental values, the arbitrageur must have a reasonable understanding of the economic situation. Mitchell, Pulvino and Stafford (2002) found that information costs are a significant factor behind the instances when the market value of a company is less than that of its subsidiary. Becoming informed about these opportunities is difficult when there is little evidence to examine.

2.3.4. The Stock Market as a Complex Adaptive System

Based on the many observations in the behavioural finance literature that individuals do not act rationally, Mauboussin (2002) proposed that stock markets should be viewed as complex adaptive systems. A complex adaptive system exhibits a number of essential properties and mechanisms. First, the behaviour of the market "emerges" from the interaction of investors. Second, agents within a complex adaptive system take information from the environment, combine it with their own interaction with the environment, and derive decision rules. This is consistent with the disappearance of "anomalies" over time as investors become aware of them. Third, the market is nonlinear in the sense that the aggregate behaviour is more complicated than what would be predicted by combining the parts. Fourth, feedback loops, where the output of one iteration becomes the input of the next iteration, exist. An example is momentum investors who use security price changes as a buy/sell cue, allowing for self-reinforcing behaviour.

Although research in this area is still in its infancy, the theory behind complex adaptive systems appears to do a good job of explaining the empirical evidence on the stock market. It helps explain the existence of non-normal distributions and the fact that markets do not quite follow a random walk due to the persistence of trends.

It also allows the relaxation of the assumption of rational investors and the associated assumption of risk/return efficiency.

An interesting proposition stemming from the theory of complex adaptive systems is that aggregate rationality at the market level can be generated, not only from individual rationality but also from individual irrationality. This is in stark contrast to the widely accepted lead steer metaphor where prices are assumed to be set by rational investors despite the presence of irrational investors.

2.4. Technical Analysis

2.4.1. Background

Technical analysis or charting involves making investment decisions about traded instruments based on the examination of past market data, such as prices and volume. The origins of technical analysis in the Western world can be traced to the late 1800s when Charles Dow proposed, among other things, that markets reflect every possible known factor that affects overall supply and demand and that price action displays trends that are repeated. At this time the West was unaware that technical analysis principles, which it now calls *candlestick technical analysis*, had been successfully applied to rice trading in Japan from at least the 1700s.

Practitioners in all fields of the investment industry quickly adopted technical analysis and its use is now widespread. When the key words "technical analysis" are typed into the Internet search engine Google, 22,500,000 urls are located compared to only 1,590,000 urls for "portfolio theory" (both searches were conducted on 29/3/05). Moreover, surveys of foreign exchange and equity market participants (e.g. Carter and Van Auken, 1990; Allen and Taylor, 1992; Lui and Mole, 1998; Oberlechner, 2001) consistently find that the majority of market participants use technical analysis over some forecasting horizon.

Despite its widespread acceptance and adoption by practitioners, technical analysis is described by Malkiel (1981) as an "anathema to the academic world." This is because of its conflict with market efficiency, one of the central pillars of academic finance.

2.4.2. Theoretical Foundations

Developing a robust justification of technical analysis has proved very challenging. Early work in this area focused on the principle of trends which can exist only if markets adjust to new information over a period of time rather than instantaneously. This seems quite conceivable in the case of private information. Jaffe (1974) and Seyhum (1986) documented the fact that holders of private information have the opportunity to earn abnormal profits as this information is leaked into the market. Other researchers (Beja and Goldman, 1980; Brown and Jennings, 1989; Blume, Easley and O'Hara, 1994; He and Wang, 1995) found that technical analysis has value in a model in which prices are not fully revealing and traders have rational conjectures about the relationship between prices and signals.

There is more debate over public information. Proponents of the efficient market hypothesis, such as Jain (1988), dismiss the existence of trends in studies which show that prices adjust rapidly to reflect new information. More recent studies have found evidence that is in conflict with this view. Jegadeesh and Titman (1993) showed that investors often underreact to news leading to momentum over three to twelve months, while DeBondt and Thaler (1985) showed that investors overreact over periods of three to five years.

Proponents of technical analysis believe that trends are reversed at support and resistance levels and gain momentum after these levels due to order clustering. Using a unique data set of foreign exchange orders Osler (2003) found evidence to support this. She found that executed take-profit orders cluster more strongly at round numbers than do stop-loss orders. Since take-profit orders should tend to reverse price trends, exchange rates should tend to reverse course at round numbers when they hit take-profit-dominated order flow. Executed stop-loss buy orders are shown to cluster most strongly just above round numbers, and executed stop-loss sell orders are shown to cluster most strongly just below round numbers. Since stop-loss orders should tend to propagate price trends, exchange rate trends should be relatively rapid after the rate crosses a round number and hits stop-loss-dominated order flow.

The evidence presented by Osler (2003) is consistent with three reasons why stop-loss and take-profit orders cluster at round numbers. First, the use of round numbers reduces the time and errors involved when customers communicate with their dealers

(Grossman, Cone, Miller, Fischel, and Ross, 1997). Second, round numbers may be easier to remember and to manipulate mentally (Goodhart and Curcio, 1991; Kandel, Sarig, and Wohl, 2001). Third, humans may simply prefer round numbers, even without rational arguments for their superiority (Yule, 1927). Once the pattern of order clustering is established, it may be self-reinforcing even in the presence of rational speculators.

Many authors have speculated that intervention by monetary authorities is the source of technical trading rule profitability in foreign exchange markets (Friedman, 1953; Dooley and Shafer, 1983; Corrado and Taylor, 1986; Sweeney, 1986; Kritzman, 1989). More recently, a seminal paper by LeBaron (1999) showed a remarkable correlation between daily U.S. official intervention and returns to a typical moving average rule. Further research has extended this result. Szakmary and Mathur (1997) found that monthly trading rule returns are correlated with changes in reserves – a proxy for official intervention. Saacke (2002) extended LeBaron's (1999) results using Bundesbank data and examined the profitability of intervention for both the U.S. and Germany. These findings further convinced many researchers that technical trading profits are generated by intervention (Neely, 2002).

More recently, Neely (2002) found evidence against this conclusion. Using high-frequency trading rule returns and five intervention series from four central banks he found the timing of signals / returns around intervention and the direction of trading are inconsistent with the idea that intervention generates technical trading rule profits. In particular, high trading rule returns are shown to precede U.S., German and Swiss intervention and trading rules are shown to consistently trade contrary to the direction of intervention. Neely (2002) proposed that intervention is correlated with trading rule returns because monetary authorities intervene in response to short-term trends from which trading rules have recently profited.

Another hypothesis is that noise traders, who make their trading decisions based upon prior directional movements in an instrument, dominate the market. Shleifer and Summers (1990) argued that this type of trading behaviour may push asset prices beyond their true value. Moreover, even if individual traders recognise mispricing, they may be unwilling or unable to "trade against the market" because of their own loss limit restrictions. In fact, individual traders may find it in their best interest to stimulate serial correlation if they feel that investor sentiment will remain stable in the short term. They can trade with the market in the short term and as a result serve to drive the market further away from its fundamental value (Shleifer and Summers, 1990).

2.4.3. Characteristics of Markets to which Technical Analysis is Applied

The earliest known form of technical analysis, candlestick charting, was first used in Japanese rice markets in the early 1700s. Up until 1710, the Dojima Rice Exchange, the centralised marketplace based in Osaka, dealt in actual rice. Merchants at the exchange graded the rice and bargained to set its price. After 1710, the Rice Exchange began to issue and accept rice warehouse receipts. These warehouse receipts, called *rice coupons* or *empty rice*, became the first futures contracts ever traded. Rice coupons quickly became a medium of exchange. By 1749 more than

1,300 rice dealers traded 110,000 bales of rice. Yet, throughout all of Japan there were only 30,000 bales of rice (Nison, 1991). There is no known documentation on the transactions costs of this early rice market.

The majority of technical trading rule literature uses DJIA stock market data for empirical tests. On the NYSE, liquidity is provided by the quotes of the specialist and limit orders from the public. Transaction costs include bid-ask spreads and commissions. Jones (2002) reported that the average one-way commissions on round-lot transactions in NYSE stocks were around 0.3% prior to the 1930s; they then steadily rose to a peak of approximately 0.9% in the mid-1970s, prior to the Securities and Exchange Commission's (SEC) breaking of the commission cartel. Commissions then began dramatically falling and are down to approximately 0.1% today. Commissions vary based on who is doing the trading. Floor traders face lower commissions than do money managers who-in turn- face lower commissions than do private individuals. Jones (2002) reported that average bid-ask spreads declined from 1.4% in the 1930s to 0.2% in 2000.

The foreign exchange market has also been widely studied in the technical analysis literature. This market is a quote-driven environment with market makers around the world quoting indicative two-way prices. Because the actual trade prices are not publicly available, studies typically use the average of the bid and ask quotes as a proxy of the trade price. Transactions in the foreign exchange market do not typically incur a commission, rather, dealers earn their revenue via the spread. Both Neely (2002) and Szakmary and Mathur (1997) stated that a reasonable estimate of the transactions costs faced by a large investor would be in the 0.05% - 0.1% range per round trip.

The technical trading literature has also used futures market data. Futures markets also adopt a dealer structure. Investors are faced with a commission and the bid-ask spread. Like other markets, it is reasonable to assume that transaction costs have declined over time. Kuserk and Locke (1993) estimated that bid-ask spreads are less than one tick (i.e. below $12.50). Allowing for a round-turn brokerage commission of $25 and a typical contract value of $60,000 yields total direct transactions costs in the 0.06-0.07% range.

2.4.4. Empirical Tests Consistent with the Efficient Market Hypothesis

The vast majority of empirical tests of technical trading strategies show that these strategies are unable to produce profits which exceed the transactions costs and additional risk that is incurred in implementing them. This is consistent with Jensen's (1978) proposition that markets are efficient to the point where the profits earned from implementing a strategy do not exceed the costs and risks incurred in doing so. The remainder of this thesis is focused on the Jensen (1978) definition of market efficiency unless specifically stated otherwise.

It is possible that technical trading strategies that have their profits eroded by transaction costs still have value. Corrado and Lee (1992) and Lee, Chan, Faff, and Kalev (2003) pointed out that a strategy that is not economically viable as a stand-alone strategy, may, in fact, be used as a value-adding 'overlay' strategy to assist fund managers in better timing the buying or selling of stocks as part of their normal trading activities. As these stock trades would have effectively occurred in the normal course of business, the transaction costs are already factored in (i.e. they have zero incremental cost).

Markellos (2004) also found that technical analysis has value beyond obtaining risk-adjusted excess returns. When active portfolio management based on technical analysis is combined with passive (buy-and-hold) strategies substantial diversification benefits are shown to occur. Market returns are able to be matched at a fraction of the risk, which could explain the popularity of "mixed" active-passive portfolio management techniques.

2.4.4.1. Filter Rule Tests

Early tests of filter rules, such as those conducted by Fama and Blume (1966), found that profits are subsumed by transaction costs. However, these studies used relatively small samples from both a cross-sectional and time-series perspective. For instance, Fama and Blume (1966) used 5 years of data for 30 stocks.

More recently, Corrado and Lee (1992) conducted an extensive test of the ability of filter rules to predict variation in daily stock returns. Using a sample of 120 DJIA and S&P 100 stocks from 1963-1989 and own-stock, other-stock, and market index filters, they found significant variation in the daily returns of individual stocks. However, a one-way transaction cost of 0.11% removes this profit.

2.4.4.2. Moving Average and Trading Range Break-Out Tests

Moving average trading rules have proved very popular in the literature. These rules involve constructing a short moving average (e.g. 10 days) and a longer moving average (e.g. 200 days). A buy (sell) signal is generated when the shorter moving average moves above (below) the longer moving average, because at this point a trend is considered to be initiated (Gartley, 1930).

Trading range break-out rules (also known as *channel* rules) are closely linked to the concepts of support and resistance. The principle is that once prices break free of the resistance (support) which has been at the top (bottom) of a recent trading range they tend to accelerate and move significantly higher (lower) (Wyckoff, 1910). Like moving average rules, trading range break-out rules are easy to construct and implement so many studies jointly test them both. Hence the inclusion of these two rules in the same section.

In a seminal paper on the use of the bootstrap methodology in finance, Brock, Lakonishok and LeBaron (1992) tested moving average and trading range break-out rules on the Dow Jones Industrial Index (DJIA) from 1897-1986. Their results indicate that these strategies are not consistent with four popular null models: the random walk, the AR(1), the GARCH-M, and the Exponential GARCH. Buy signals consistently generate higher returns than sell signals indicating that the trading rules had value. Transactions costs were not included by Brock et al. (1992). However, Bessembinder and Chan (1998) considered the Brock et al. (1992) study in relation to transaction costs and found that the estimated breakeven round trip transaction costs (0.39%) are similar or smaller than estimates of actual costs – a result that is consistent with market efficiency.

The bootstrapping methodology of Brock et al. (1992) allows for a comparison of the volatility of returns following buy and sell signals. This enables a judgement to be made on whether risk is driving the profitability of a trading strategy. Papers that find trading rule profitability is eroded by transaction costs (e.g. Bessembinder and Chan, 1998) tend not to consider the risk of trading rules beyond this approach. In contrast, papers that have found profitability can not be explained by transaction costs tend to give extra focus to risk (e.g. Kho, 1996) to see if it is an explanation for the trading rule profitability.

Numerous studies have applied the Brock et al. (1992) trading rules to other stock markets. Hudson, Dempsey and Keasey (1996) tested the Footsie 30 index, Detry and Gregoire (2001) tested European indices, Bessembinder and Chan (1995) tested Hong Kong and Japanese indices, and Parisi and Vasquez (2000) tested Chilean indices. They found the trading rules produce profits over and above a buy-and-hold strategy, but that these profits are eroded by round-trip transaction costs of 1% to 1.5% respectively. Ito (1999) found that time-varying risk is an important factor in technical trading rule returns. He found that the Brock et al. (1992) rules produce profits that exceed round-trip transaction costs ranging from 0.5% to 4% on the markets of Japan, the U.S., Canada, Indonesia, Mexico and Taiwan. However, these rules do not produce excess returns after time-varying risk is taken into account.

In other studies the profitability of the Brock et al. (1992) moving average and trading range break-out rules on exchange rates has been considered. Lee, Gleason and Mathur (2001) found that these rules are not profitable in the currencies of Argentina, Barbados, Chile, Columbia, East Caribbean, Ecuador, Jamaica, Trinidad and Tobago, and Uruguay (all versus the USD). These tests are based on the mid- to late- 1990s period and included one-way transactions costs of 0.1%. Lee, Pan, and Liu (2001) also found that these rules are not profitable on a range of currencies (Hong Kong, Korea, Thailand, Malaysia, Taiwan, Singapore, Philippines, Australia, and New Zealand) versus the USD for the 1988-1995 period after one-way transaction costs of 0.1%.

Other work has investigated the profitability of moving average rules on cross rates. Lee and Mathur (1996a) used JPY/GBP, DMK/GBP, JPY/DMK, CHF/DMK, CHF/GBP, and JPY/CHF data. They found that these rules are not generally profitable once transactions costs of 0.1% are accounted for. Lee and Mathur (1996b) extended their (1996a) study by including Australian, Canadian, French and Italian cross rates and applying the channel rule as well. Their results are similar. Transactions costs of 0.1% remove profitable opportunities.

More recently, Martin (2001) found that moving average rules produce profits that exceed one-way transaction costs of 0.5% on the currencies of Argentina, Chile, Colombia, Israel, Malaysia, Mexico, Pakistan, Peru, and the Philippines (versus the USD). However, these rules are not profitable once risk is accounted for.

Similar results have been documented on futures markets. Lukac and Brorsen (1990) tested moving average and trading range break-out trading systems on 30 futures markets over the 1975-1986 period. They found significant gross returns, however net returns (after transactions costs) are largely insignificant. Taylor (1994) also studied the trading range break-out rule on futures contracts. Using currency futures data for the 1982-1990 period, he found rules are profitable (assuming 0.2% round-trip transaction costs) up to 1987 but not for the 1988-1990 period. Risk was not considered.

The aforementioned papers are consistent with Jensen's (1978) version of the efficient market hypothesis. That is, past price information cannot used by moving average and trading range break-out technical trading rules to produce profits that offset transactions costs. The findings in these papers are, however, evidence against Fama's (1970) "weak form" version of the efficient market hypothesis. Past prices, which are widely available to market participants, do possess valuable information about future price movements. This fact, together with the suggestions that technical analysis could be useful as timing mechanism for fund managers who need to rebalance their portfolios (Corrado and Lee, 1992), and that technical analysis can complement passive portfolio management (Markellos, 2004), has caused many researchers to re-investigate the Brock et al. (1992) finding using U.S. equity market data for a different period and / or different methodologies.

The large universe of moving average and trading break rules raises the possibility that the profitability of certain rules could be due to data snooping. Data snooping occurs when a given set of data is used more than once for the purposes of inference or model selection. When such data reuse occurs, there is always the chance that any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results. Sullivan, Timmermann and White (1999) found that data snooping does not affect the Brock et al. (1992) findings. The robustness of the Brock et al. (1992) results in different markets is further confirmation that data snooping is not the driver.

Day and Wang (2002) considered the impact of dividends and nonsynchronous prices on the Brock et al. (1992) trading strategies. Dividends are not included in the DJIA so Day and Wang (2002) hypothesised that the Brock et al. (1992) result may be understating the returns to a buy-and-hold strategy making technical analysis appear more profitable than it is. Day and Wang (2002, p. 432) also noted that "while the trading in today's market virtually assures that all DJIA stocks trade at the market close, average trading volumes on the NYSE was less than 4m shares in 1962, failing to reach 50m shares until 1982." This raises the possibility that the prices used to calculate the DJIA are stale and that nonsynchronous prices are biasing the returns. Using CRSP 1926-1996 data which include dividends, Day and Wang (2002) showed that the excess profits for trading rules for 1962-1986 are not statistically significant once nonsynchronous prices are adjusted for.

Studies that have re-tested the Brock et al. (1992) rules on U.S. equity data have also documented a decline in profitability over time. LeBaron (2000) used the same data as Brock et al. (1992) but added another ten years from 1998 to 1999 (to avoid the 1987 crash). For the later period LeBaron (2000) found that the buy return was no longer significantly larger than the sell return. In fact, it was less than both the sell return and the unconditional mean. Ready (2002) extended the Brock et al. (1992) data to 2000 (he included 1987) and found a similar result. Kwon and Kish (2002) applied these rules to CRSP NYSE and Nasdaq indices for the 1962-1996 and 1962-1996 periods respectively and also found weakening profits over time. More recently, Fong and Yong (2005) have found a recursive trading strategy that uses the best moving average rule (out of 800 alternatives) up to the previous day is not profitable when applied to technology stocks that rose strongly and then dramatically declined during the 1998 to 2002 period.

2.4.4.3. Genetic Programming

All of the studies described above used a range of rules chosen ex post. Even with the steps taken to minimise data snooping there is still a lot of latitude in choosing the exact form of the rules. For this reason, genetic programming searches for optimal trading rules over a very large population of trading rules using the principles of natural selection. This procedure was developed by Holland (1975) and extended by Koza (1992). The genetic programme creates successive populations of rules according to certain well-defined procedures. Profitable rules are more likely to have their components reproduced in subsequent populations. The basic features of the genetic programme are: (a) a means of encoding trading rules so that they can be built up from separate subcomponents; (b) a measure of the profitability or "fitness"; (c) an operation which splits and recombines existing rules in order to create new rules. While genetic programming does not totally eliminate bias because the search has to be limited to some degree, it is argued that it substantially reduces the bias (Neely and Weller, 2001).

Allen and Karjalainen (1999) were the first to use genetic programming to identify profitable trading rules (moving average and trading range break-out rules) in the stock market. Using daily S&P 500 data for the period 1929-1995 they found no evidence of economically significant excess returns over a buy-and-hold strategy after transactions costs are accounted for. Neely (2001) extended the Allen and Karjalainen (1999) study by including four risk-adjustment techniques. He found that risk-adjustment improves the attractiveness of the rules but risk-adjusted excess returns are not available after transaction costs.

Mihailov and Linowski (2002) tested the profitability of trading based on five different oscillators using genetic algorithms to optimise the parameters in each on the Latvian Stock Market. Oscillators are based on the principle that a sustained move in one direction is usually followed by a movement back in the other direction. All indicators outperform buy-and-hold returns before transaction costs, but none yield statistically significant returns once transaction costs of 0.25% are accounted for.

Finally, Neely and Weller (2003) used a genetic programme and an optimised linear forecasting model to test the profitability of intra-day technical analysis on four exchange rates. When realistic transaction costs and trading hours were taken into account there was no evidence of excess returns. The trading rules did, however, discover some remarkably stable patterns in the data.

2.4.4.4. Dow Theory

Technical analysis in the Western world can be traced to Charles Dow, the founding editor of *The Wall Street Journal*. Despite the length of time it has been in existence, it is only recently that a robust statistical test has been conducted on Dow Theory.

According to William Peter Hamilton (see Rhea, 1932), Dow's successor as editor, a key tenet of Dow Theory is that market movements reflect all real knowledge available. At first glance, this notion seems to simply reflect that markets are informationally efficient. Closer examination, however, reveals that it is in fact consistent with the notion that past market trends are predictive of future price movements. Prosperity is said to drive investors to excess and the repentance for the consequences of those excesses produces a corresponding depression. In other words, the bull and bear market cycles envisioned by the Dow Theory are due to "the irrational exuberance" of individual investors, which itself appears not to be rationally incorporated into prices. This assertion is one of the three main axioms of the Dow Theory, as interpreted by Rhea (1932). The other two axioms emphasise the existence of a primary trend in market movements and assert the fact that even though the theory is not infallible, it still is an invaluable aid for making speculations about the market's movements.

Brown, Goetzmann, and Kumar (1998) found that Dow Theory, as expressed in the market direction predictions made by Hamilton and published by Rhea (1932), has power to predict returns for the period 1902-1929. Brown et al. (1998) found that Hamilton's ratio of correct to incorrect calls is higher than would be expected by chance. They also applied market timing measures used to identify skill to the time-series of returns to the Hamilton strategy and found significant positive evidence. An event study analysis of the DJIA around Hamilton's editorials shows a significant difference in mean returns over a 40-day period following bull versus bear market calls. Brown et al. (1998) proved that Dow Theory does not result in being in the market in times of increased risk, based on Betas and the Sharpe Ratio. However, they did not account for the transactions costs incurred in acting on Dow Theory so they were unable to make a judgement on its implications for Jensen's (1978) definition of market efficiency.

2.4.4.5. Support and Resistance

Like the concept of trends which underpins Dow Theory, the concepts of support and resistance are fundamental to technical analysis. *Support* is "*a level or area on the chart under the market where buying interest is sufficiently strong to overcome selling pressure. As a result a decline is halted and prices turn back ... Resistance is the opposite of support.*" (Murphy, 1999, p. 55). While trading range break-out studies consider strategies based on buying (selling) after resistance (support) is broken, researchers in this category consider the strategy of selling (buying) as resistance (support) is met.

Using a unique data set of foreign exchange orders, Osler (2003) found evidence consistent with support and resistance. She found that executed take-profit orders cluster more strongly at round numbers and stop-loss orders cluster more strongly just above (below) round numbers. This explains why prices often appear to reverse at round numbers and trends develop when round numbers are crossed. Osler (2003) did not consider the profitability of a trading strategy based around these findings so there is no evidence to suggest that they contradict the concept of market efficiency.

2.4.4.6. Chart Patterns

As well as the mechanical rules outlined above, technical analysts use visual rules based on patterns in price data. There are numerous patterns documented in the practitioner literature (Bulkowski, 1999), but the academic literature focuses on the most popular patterns.

One of the most common patterns is the *head and shoulders pattern*. This involves *three peaks, the highest of which is in the middle*. This nonlinear pattern has been in use at least since it was described in Schabacker (1930) and is considered by technical analysts to be one of the most reliable chart patterns. Head and shoulders patterns are said to be a strong signal of trend reversal. Drawing a line from the bottom of the left shoulder to the bottom of the right shoulder produces a "neckline" which is critical for determining when to enter. If the price drops below the neckline or penetrates the extension of the neckline after the third peak, then the pattern is said to be *confirmed* and one should take a short position at this point. Head and shoulders can occur at the end of an uptrend, when they are called "tops" or at the end of a downtrend, when the role of peaks is taken by troughs and vice versa, and they are called "bottoms."

Osler (1998) tested the profitability of the head and shoulders trading strategy (specifically selling after a neckline break) using daily data for 100 firms chosen at random from the CRSP database over the 1962-1993 period and a bootstrap methodology. She found that the head and shoulder pattern is not profitable on the data she tested.

Chang and Osler (1999) tested the rationality of exchange rate forecasts based on the head and shoulders pattern using daily spot rates for six currencies versus the USD over the period 1973-1994. Using a bootstrap methodology they found excess profits after one-way transaction costs of 0.025% for the yen and DM but not for the other currencies.

Lo, Mamaysky and Wang (2000) proposed a systematic and automatic approach to technical pattern recognition using nonparametric kernel regression, and applied this method to a large number of U.S. stocks from 1962-1996. By comparing the unconditional empirical distribution of daily stock returns to the distribution conditional on specific technical indicators - such as head and shoulders or double bottoms - they found that the head and shoulders pattern provides incremental information. However, Jegadeesh (2000) found no evidence that the Lo et al. (2000) trading rules yield profits of any significance from an economic stand point.

Dawson and Steeley (2003) applied the Lo et al. (2000) pattern recognition methodology to the UK FTSE100 and FTSE250 indices over the period 1986-2001. Like Lo et al. (2000), Dawson and Steeley (2003) found that while the distributions of returns conditioned on technical patterns could be significantly different from the unconditional return distributions, the mean returns are not significantly different. This suggests that the differences must be the result of higher order moment differences. These are difficult to interpret in terms of market efficiency, which is primarily mean return based.

Another charting heuristic that has been tested is the "bull flag". This pattern consists of price fluctuations within a narrow range preceded and followed by sharp rises. Leigh, Paz and Purvis (2002) tested the bull flag charting heuristic using a template matching system, NYSE Composite Index data for the period 1980-1999, and a methodology which compares the results of applying the bull flag trading rule to the results of buying every day in the comparison and holding for the number of trading days specified in the trade rule. They found that the trading rule generates statistically significant excess returns. However, no consideration was given to transactions costs.

In the previous work in this section price patterns in data displayed on a line graph with days on the horizontal axis and price on vertical axis have been considered. Point and Figure charting is a method of displaying data that proponents believe gives added insight into price movements. Time is not represented on the horizontal axis, rather price changes (independent of time) are recorded via a series of X's for increasing price movements and O's for decreasing price movements. Anderson (2001) tested point and figure trading rules, which are widely used among practitioners, on the S&P futures contract between 1990-1998. He found profits after round-trip transaction costs of $100 per futures contract in certain periods but the profitability is not consistent.

2.4.4.7. Return Anomalies

While the evidence of positive and negative serial correlation in stock returns work is generally discussed as part of the anomaly literature, in this thesis this literature is included in the technical analysis section. This work uses only past prices - not any fundamental variables - to predict future stock returns, so it is consistent with the generally accepted definition of technical analysis.

2.4.4.7.1. Short Term

Jegadeesh (1990) and Lehmann (1990) showed that contrarian strategies that select stocks based on their returns in the previous week or month generate statistically significant abnormal returns. There is, however, debate about whether this effect is evidence of overreaction or other phenomena. Lo and MacKinlay (1990) showed that up to 50% of Lehmann's contrarian profits are due to lagged forecastability across large and small securities rather than to individual security negative autocorrelations. Conrad, Gultekin, and Kaul (1997) found that bid-ask bounce effects may explain a large portion of the profitability.

2.4.4.7.2. Intermediate Term

The momentum of individual stocks has been extensively examined. Jegadessh and Titman (1993) showed that one can obtain superior returns by holding a zero-cost portfolio that consists of long positions in stocks that have outperformed in the past

3-12 months (winners), and short positions in stocks that have underperformed during the same period (losers).

This phenomenon cannot be explained by a three-factor asset pricing model (Fama and French, 1996) suggesting that they are not compensation for excess risk, is present in other countries (Rouwenhorst, 1998), exists in international market indices (Chan, Hameed, and Tong (2000)), is present at the industry level (Moskowitz and Grinblatt, 1999), and does not seem to be related to earnings momentum (Chan, Chan, Jegadeesh and Lakonishok, 1996). More recently, Grinblatt and Moskowitz (2004) found that the consistency of past returns and tax-loss selling are important factors behind momentum profits.

The robustness of the momentum effect to trading costs has been the subject of recent debate. Jegadeesh and Titman (1993) maintain that momentum returns exceed the cost of trading. However, in more recent work by Lesmond, Schill, and Zhou (2004) it has been suggested that the Jegadeesh and Titman (1993) transaction cost proxy is inappropriate. Lesmond et al. (2004) found that more realistic transaction costs erode the profitability of the momentum strategy. Korajczyk and Sadka (2004) estimated realistic transaction costs to be lower than did Lesmond et al. (2004). They too found that weighting portfolios equally leads to profits less than transaction costs. However, the assumption of lower transaction costs leads to net profits for value-weighted and liquidity-weighted strategies.

Hogan, Jarrow, Teo, and Warachka (2004) also emphasised the importance of transaction costs in tests of momentum strategies. Using the concept of statistical arbitrage they are able to circumvent the joint hypothesis dilemma of traditional market efficiency tests because its definition is independent of any equilibrium model and its existence is incompatible with market efficiency. Hogan et al. (2004) found that momentum strategies are profitable using transaction costs lower than those of Lesmond et al. (2004), which further underscores the importance of transaction cost estimation to momentum profits.

2.4.4.7.3. Long Term

Transaction costs are less likely to explain long-term return anomalies due to the infrequent trading involved. The pioneering study in this area is DeBondt and Thaler (1985) who considered returns over long horizons. Using a winner – loser portfolio approach, they found that stocks which have underperformed the most over a 3- to 5-year period average the highest market-adjusted returns over the subsequent period and vice versa. They explained this pattern of reversal as an overreaction in the market in which prices diverge from fundamental value. However, in more recent work (Fama and French, 1996; Lee and Swaminathan, 2000; Grinblatt and Moskowitz, 2004) it has been found that this long-term reversal is not robust to risk adjustment.

Other research has investigated the long-term returns anomaly using advanced statistical techniques on time series data. This literature is distinct from the cross-sectional winner – loser overreaction literature. Unlike the technical analysis literature discussed in Chapter Three, which looks at the application of rules to profit, this work focuses on statistical properties of series and is typically silent on the ability to profit from applying a trading rule.

Studies in which the rescaled range statistic procedure, originally developed by Hurst (1951) and modified by Lo (1991) has been applied have produced mixed results. In early work evidence of dependence (Greene and Fielitz, 1977) was found, but in more recent work by Jacobsen (1996) and Batten, Ellis, and Fetherston (2004) it was found that this anomaly is dependent on methodological and time period issues. This raises the possibility that the earlier findings are statistical illusions as hypothesised by Fama (1998).

Pagan and Sossounov (2003) and Gonzalez, Powell, Shi, and Wilson (2002) both utilised an adaptation of the Bry and Boschan (1971) turning point algorithm, which was originally developed to detect turning points in economic cycles, to identify turning points in stock markets. Both these studies showed that stock markets can be classified into distinct bull and bear phases which have quite different return moments. However, these studies do not examine the profitability a trading strategy based on this theory.

2.5. Empirical Tests not Consistent with the Efficient Market Hypothesis

In several papers evidence has been found that is inconsistent with the Jensen (1978) definition of market efficiency. That is, trading rules are shown to produce returns that exceed the transaction costs and risk incurred in implementing them. As mentioned in Section 2.4.3, the level of transactions costs assumed is critical to this finding. The theory behind the estimation of transaction costs in the technical trading rule literature is typically less robust than that in the momentum literature, but in spite of this, this thesis includes research in this section if the trading rule gross profits exceed what the paper authors deem to be fair transaction costs.

2.5.1. Filter Rule Tests

Sweeney (1988) found that the long version of the Fama and Blume (1966) filter rules (buying after an x% increase and selling after a y% decrease – where x% and y% are typically 0.5%) are profitable on 1970-1982 daily CRSP data. Excluding the loss making Fama and Blume (1966) short rules allows for profits that exceed one-way transaction cots of 0.05%, which Sweeney (1988) proposed are less than those faced by floor traders. Using an adjustment technique that accounts for the proportion of days that a trading rule is in the market, Sweeney (1988) found that excess risk is not driving the excess returns. He noted that when variations in the risk premium on the benchmark portfolio have a long periodicity relative to the holding periods for positions signalled by a particular trading rule this adjustment technique is robust to time-varying risk premium.

More recently, Cooper (1999) found that filter rules that use both price and volume data strongly outperform a buy-and-hold strategy for investors faced with low transaction costs (0.5% round trip). Using weekly data for the "top 300 large-cap" NYSE and AMEX individual securities in the CRSP file between 1962-1993, Cooper (1999) found greater profits than did Fama and Blume (1966) and Sweeney (1988).

This is likely to be due to methodological differences. Cooper (1999) examined a broader range of filters, including some that are much more extreme than the filters of Fama and Blume (1966) and Sweeney (1988). Another difference from earlier work in Cooper (1999) is the requirement that the return filter be met in a fixed-time horizon, typically one to two weeks.

Filter rules are also shown to be profitable for trading exchange rate data. Using similar rules to Sweeney (1988), Sweeney (1986) found profits in foreign exchange markets for the 1973-1980 period. These can not be explained by transactions costs (estimated at one-way of 0.13%) or risk (based on the CAPM). Testing similar rules on currency futures data, Levich and Thomas (1993) found annual profits (in excess of one-way transactions costs of 0.025%) for the USD/GBP, USD/CAD, USD/DMK, USD/JPY, and USD/CHF for the period 1976-1990.

2.5.2. Moving Average and Trading Range Break-Out Tests

Ahmed, Beck and Goldreyer (2000) found that a range of specifications of moving average rules produce profits on the Thailand and Philippines stock markets for the 1994-1999 period after allowing for one-way transaction costs of 0.7-1.1%. Bessembinder and Chan (1995) showed that both moving average and trading range break-out rules produce profits of 1.57% on average, which they estimate is in excess of actual transaction costs for Malaysia, Taiwan, and Thailand for the 1975-1989 period. Ratner and Leal (1999) also presented evidence that moving average rules produce profit after transaction costs on the equity markets of Korea, the Philippines, Taiwan, and Mexico during the 1982-1995 period. Ratner and Leal (1999) used country-specific transactions costs which range from 0.16% to 2.0% (one-way).

In several papers it has been found that moving average and trading range break-out tests are profitable on exchange rates. Lee, Gleason and Mathur (2001) found these rules to be profitable after one-way transactions costs of 0.1% for the Brazilian real, Mexican peso, Peruvian new sol, and Venezuelan bolivar for the mid-to-late-1990s. More recently, Okunev and White (2003) evaluated 354 moving average rules for eight currencies from 1980 to 2000. Using an approach that is similar to Jegadeesh and Titman (1993, 2001) technical indicators were used to rank stocks from best to worst. A long/short position was then established by buying the strongest momentum currency and shorting the weakest momentum currency. This simple strategy produces profits of over 6% per annum which is vastly more than the transaction costs incurred in implementing them. These profits are also robust to risk adjustment and the base currency used.

Other research indicates that the profitability of technical trading rules in foreign exchange markets may be declining over time. Olson (2004) showed that risk-adjusted trading rule profits from moving average rules on 18 currencies have declined over time from an average of over 3% in the late 1970s and early 1980s to about zero in the 1990s. Olson (2004) concludes that market inefficiencies reported in previous studies may have been only temporary inefficiencies.

2.5.3. CRISMA

A hybrid system which combines three different trading rules and which has received wide coverage in the literature is the CRISMA system developed by Pruitt and White (1989). CRISMA is an acronym that represents the component parts of the system (Cumulative Volume, Relative Strength, Moving Average). More specifically, the three criteria are explained as follows. First, the 50-day price moving average graph must intersect the 200-day price moving average graph from below when the slope of the latter graph is greater than or equal to zero. Of course, this phenomenon occurs only when a stock's price is rising relative to previous time periods. Second, the relative strength graph, from beginning to ending point over the previous four weeks, must have a slope greater than, or equal to, zero. This filter assures that the stock's price performance over the most recent time period has been at least equal to that of the market as a whole. Finally, the cumulative volume graph from beginning to ending point over the previous four weeks must have a slope greater than zero. This filter is based on the empirically supported premise that increases in trading volume are associated with rising stock price levels (Pruitt, Tse and White, 1992).

Using 204 CRSP stocks for the 1976-1985 period, Pruitt and White (1988) found statistically significant profits after accounting for risk and round trip transaction costs of 2%. The annualised excess profits range from 6.13% to 15.13% depending on the return generating model used. Pruitt, Tse and White (1992) re-tested the CRISMA system using CRSP data for the 1986-1990 period and found that the system produced superior results to those documented in their 1992 paper. On both occasions the Mean Adjusted Model, Market Adjusted Model, OLS Market Model and Scholes and Williams (1977) model are used to adjust returns for risk.

More recently, doubt has been raised about the robustness of the CRISMA trading system. Goodacre, Bosher, and Dove (1999) found that CRISMA is not profitable on the UK equity market for the 1987-1996 period, while Goodacre and Kohn-Speyer (2001) found that CRISMA is not profitable on a different sample of U.S. stocks.

2.5.4. Neural Networks

There is growing evidence that non-parametric methods, which aim to capture features in time series that are not fully accounted for by a linear model, have predictive value. A subset of these methods, neural networks, can approximate a large class of functions with adequate accuracy given a sufficiently large set of previous data for training.

Gencay (1998) found strong predictive ability for DJIA average returns using moving average trading rules as inputs to neural networks. However he did not include transactions costs. Jasic and Wood (2004) conducted a comprehensive study of the statistical significance and profitability of one-step ahead forecasts of market index returns provided by univariate neural networks. They found that a simple trading strategy based on neural network predictions and data from the S&P 500, German DAX and FTSE indices for the 1965-1999 period, and the Japanese TOPIX index for the 1969-1999 period yields profits after trading costs of 0.5% that are statistically significant when compared to buy-and-hold returns. One-way transaction costs of 1% eliminate the profitability of some short-term rules, but other multiperiod rules remain profitable.

2.5.5. Nearest Neighbour Techniques

Another non-parametric approach is the *nearest neighbour* technique, which was introduced by Farmer and Sidorowich (1987). This tool is used to automate the testing of trading rules based on patterns in data that is only evident in graphical form. This approach works by selecting geometric segments in the past of the time series similar to the last segment available before the observation to be forecast. Therefore rather than extrapolating past values into the immediate future as in moving average models, *nearest neighbour methods select relevant prior observations based on their levels and geometric trajectories*, not their location in time.

Using EMS currencies against the Deutschemark for the 1978-1994 period Fernandez-Rodriguez, Sosvilla-Rivero and Andrada-Felix (2000) found that nearest neighbour rules outperformed linear moving average rules and that the returns to nearest neighbour techniques are significantly different from zero after one-way transaction costs of 0.025% are accounted for. The nearest neighbour rule was also of a higher economic value as measured by the Sharpe Ratio.

Modem (2002) found a similar result when nearest neighbour techniques were applied to the CAC 40 for the 1987-1997 period. Modem (2002) found that the nearest neighbour rules produce gross profits that have higher Sharpe Ratios than a buy-and-hold strategy. Break even costs are as high as 1.76% in some sub-periods but fall to 0.02% in others, suggesting that the result may not be robust.

2.5.6. Genetic Programming

Genetic programming is another nonparametric technique. This involves selecting optimal trading rules from a large population of trading rules using the principles of natural selection.

Using genetic programming techniques selected in the 1978-1980 period and the bootstrap methodology Neely, Weller and Dittmar (1997) found strong evidence of economically significant (after one-way trading costs of 0.05%) out of sample excess returns for six exchange rates over the period 1981-1995. Betas calculated for the return provide no evidence that these returns are compensation for bearing systematic risk. In a follow-up study using similar techniques on four exchange rates during the 1975-1980 (in sample) and 1981-1998 (out of sample) period. Neely and Weller (2001) also found evidence of abnormal returns after round-trip transaction costs of 0.05%.

Karjalainen (1998) investigated the profitability of applying a genetic algorithm to S&P 500 futures data for the 1982-1993 period. Karjalainen (1998) found that the average profit, after round-trip transactions costs of $100 per futures contract, for the trading rules is higher than is that for a buy-and-hold strategy. Trading rule risk is measured by the Sharpe ratio and maximum draw down of equity. Both suggest that trading rule risk is lower than the buy-and-hold risk so the trading rules lead to risk-adjusted profits. However, Karjalainen (1998) found that the rules do not consistently beat the market. He states that they might make profits by assuming a risk of rare events that did not materialise during the time period studied.

2.6. Candlestick Charting

Candlestick charting is the oldest known form of technical analysis. Dating back to the 1700s, the earliest candlestick charts were used to predict rice prices. In 1750, a wealthy Japanese merchant, Munehisa Homma, began trading at his local rice exchange in Sakata using his own personal candlestick analysis. Homma became a legendary rice trader and amassed a huge fortune. Today's Japanese candlestick methodology is credited to Homma's trading principles as he applied them to the rice markets (Pring, 2002).

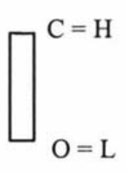
The introduction of candlestick charting in the Western world is attributed to Steve Nison. In 1991 Nison published a book titled *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Techniques of the Far East*. Nison's inspiration came from the first candlestick charting book translated into English *The Japanese Chart of Charts* by Seiki Shimzu and translated by Greg Nicholson. This book, which was originally written in Japanese in the early 1970s, was translated into English in 1986 but did not reach a wide audience.

Candlestick technical analysis involves the consideration of the relationship between open, high, low and close prices. These four prices are displayed as objects that resemble candles as shown in Figure 1 (page 4).

A daily candlestick is a graphical representation of the day's open, high, low and close prices. Daily candlesticks are commonly referred to as "single lines". Some single lines are said to have forecasting power in their own right. For instance, a White Marubozu (shown in Figure 2) is said to be a single line that suggests further price increases because prices open at the day's low and rise throughout the day to close at the day's high. A White Marubozu is said to indicate a situation where buyers overwhelm sellers and bid up prices during the day. The odds are that this supply / demand imbalance will lead to further price rises in the future. Other single lines are neutral giving no indication of future price movements.

Figure 2: White Marubozu Candlestick

A day when prices open at the low and rise throughout the day to close at their high. O = open price, C = close price, H = high price, and L = low price.



Together, consecutive single lines can form continuation and reversal patterns. Continuation patterns indicate that the prevailing trend will continue, while reversal patterns suggest that there will be a change in trend. All single lines and most continuation and reversal patterns have a bullish and a bearish variety. In this context, the term *bullish* (*bearish*) suggests future price increases (decreases),

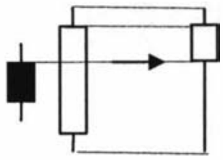
There are numerous combinations of single lines that are neither continuation nor reversal patterns. In addition, some continuation and reversal patterns are said to have very little, or no, forecasting power. To determine whether a continuation or reversal pattern has strong forecasting power, proponents of candlestick technical analysis developed a system of combining the two or three individual single lines that make up the pattern to form an overall single line for the two- or three-day period. The characteristics of this overall single line indicate whether or not the pattern does have forecasting power.

The rule for combining the single lines that make up a pattern into an overall single line is as follows: the combined high is the high on individual single lines, the combined low is the low on individual single lines, the combined open is the open from the first single line, and the combined close is the close from the last single line (Morris, 1995).

An example of a bullish reversal pattern is the Bullish Engulfing pattern (shown in Figure 3). The Bullish Engulfing pattern involves a short black candle being followed by a long white candle which opens below, but closes above, the previous day. The overall single line formed by combining the two individual single lines that make up the Bullish Engulfing pattern is bullish, which confirms that the Bullish Engulfing pattern is said to have power to predict price increases.

Figure 3: Bullish Engulfing Candlestick Pattern

A short black candle followed by a long white candle that opens below, but closes above, the previous day. Combining these two candles results in a bullish candle with close above open.



A full description of the candlestick single lines and patterns used in this research can be found in Appendix One.

Despite its popularity amongst practitioners, to the best of the author's knowledge the profitability of candlestick charting has not been rigorously tested in an academic study.

2.7. Conclusion

Current convention suggests that a market is efficient if the gains from pursuing a particular strategy do not offset the costs and additional risk incurred. Based on this definition there is no consistent evidence of market inefficiency in stock, foreign exchange or futures markets. Numerous studies document inefficiencies that are claimed to violate this definition, but these are generally refuted by subsequent work on the basis that they do not adequately account for the risks and transaction costs that are incurred in executing the strategy. Another problem with some work in this area is a lack of realism. In some studies index data that are not tradable in reality are used, while in others complex strategies are adopted on historical data. The problem with this approach is that just because these strategies were profitable before they were created (i.e. on data that pre-date this point) does not mean that they are still profitable or that the principle of market efficiency has been violated.

Despite the debate on the profitability of technical trading strategies, after transactions costs have been accounted for, there is consistent evidence that these strategies are useful for predicting returns. This means that they may still be valuable for fund managers for whom transactions costs are a sunk cost. Fund managers often have to rebalance their portfolios to remain within agreed asset allocation parameters. This means that technical trading strategies may be a useful technique for them.

Chapter Three: Data and Methodology

3.1. Introduction

The choice of data and methodology are critical to any research. Many technical trading rule studies can be criticised for failings in this area. Careful consideration has been given to the data and methodology employed in this research in an attempt to elevate it above such criticism. The data section starts with a detailed description of the Dow Jones Industrial Average (DJIA) component stock data used in this research. These data have several advantages over the more commonly used index data. Firstly, all the Dow stocks are tradable in their own right. The profits documented are therefore not just hypothetical, they could have been earned by anyone pursuing the trading rules. The second part of the data section outlines the steps that have been taken to minimise the effects of data snooping bias. Data snooping can occur when a trading technique is developed using a set of data and then tested to verify its worth using the same set of data.

The methodology section contains a detailed description of the candlestick trading strategies employed in this research. This includes an outline of candlestick single lines, formed by the open, high, low, and close prices on a given day and reversal patterns, which are formed by combining consecutive single lines over two or three days. There are many single lines that lack forecasting power and combinations of single lines that do not result in reversal patterns, so the process that was undertaken to select the single lines and reversal patterns is also described.

The methodology section finishes with a description of the *t*-test and bootstrap methodology used to test the statistical significance of the differences in returns following a candlestick buy or sell signal and the unconditional return. The *t*-test methodology is standard, but the bootstrapping methodology involves an extension to the conventional methodology to allow the generation of random open, high, low, and close prices. Previous research has adopted a bootstrapping methodology that focuses solely on close prices.

3.2. Data

3.2.1. Data Used

Price data in open, high, low and close format were sourced from Reuters. These data are not adjusted for dividends but are adjusted for stock splits and stock dividends.

Many studies of technical analysis ignore dividends due to their focus on index data and the difficulty associated with adjusting an index for dividends. Day and Wang (2002) pointed out that excluding dividends biases the buy-and-hold return downwards, and favours technical analysis. They therefore recommended the inclusion of dividend data. Following Day and Wang (2002) cumulative dividends were added to each of the four price series for each stock at each ex-date. Dividend data were sourced from CRSP.

The majority of the current literature uses raw returns rather than excess returns to test trading strategies. This is desirable as traders use raw data when implementing their strategies. This approach is appropriate for short-term candlestick rules, as variations in the risk premia are likely to have a long periodicity relative to the holding period (Sweeney, 1986).

The sample includes stocks that were part of the Dow Jones Industrial Average (DJIA) index for the 1 January 1992 – 31 December 2002 period. The starting point was carefully chosen to ensure that investors would have been aware of candlestick technical analysis and have had the ability to apply it. These two factors are important for any test of market efficiency.

Technical analysis is said to be most effective on actively traded stocks. For this reason data for the period that a stock was actually in the DJIA was used. When a stock was removed from the DJIA it was replaced in this study with its replacement in the DJIA (with three exceptions). During the period of the study there were eight changes made to the DJIA. Reuters data were missing for three companies, Westinghouse Electric, Texaco Incorporated and Woolworth. These were replaced in the DJIA on 17 March 1997 by Travelers Group (now Citigroup), Hewlett-Packard Company and Wal-Mart Stores respectively. Each of these replacement companies was very actively traded prior to its inclusion in the DJIA so all three were included in the sample for the entire period. A full description of the companies included in this research can be found in Appendix Two.

3.2.2. Data Snooping

It is clear that the application of new trading rules or new specifications of existing trading rules to historical data introduces the possibility of data snooping bias. It is quite possible that the rules have been tailored to the data series in question and are profitable only because of this. There is nothing to suggest that the rules will be profitable out of sample, or that someone would have chosen those exact specifications ex ante to form a profitable trading rule. Pesaran and Timmerman (1995, p. 102) concluded that "as far as possible, rules for predicting stock returns should be formulated and estimated without the benefit of hindsight."

There are three approaches to minimising the effects of data snooping bias. The most effective approach involves verifying that the rules being tested were in existence prior to the start of the data set being used in the tests. Both Lo and MacKinlay (1990) and Lakonishok and Smidt (1988) maintain that new data are the best protection against data snooping.

A second approach involves adjusting the statistical significance of a particular trading rule by taking account of the universe of all trading rules from which it is drawn. Sullivan, Timmermann, and White (1999) pioneered this approach and applied it to the Brock, Lakonishok, and LeBaron (1992) trading rules.[1] However, LeBaron (2000) and Ready (2002) highlighted the fact that the Sullivan et al. (1999) data snooping adjustment technique is not perfect, as it depends on simulating the snooping process that has been occurring. There are no formal tests to ascertain this.

[1] Sullivan et al. (1999) found no evidence that data snooping bias drove the Brock et al. (1992) results.

In other words, it is not possible to quantify the entire universe of technical analysis rules from which one rule might have been drawn.

A more recent approach involves the assumption that agents trade recursively using rule specifications that are considered "best performing" based on information up to the previous day (Fong and Yong, 2005). The weakness in this approach is that it still involves a researcher selecting a rule type to test ex post. In the case of Fong and Yong (2005) moving average rules were selected and agents are simply assumed to select moving average parameters on the basis of past performance.

In this research it is argued that candlestick technical analysis is more robust to the criticism of data snooping than are tests of other technical trading rules such as the moving average approach. Candlestick technical analysis was developed by the Japanese using rice price data in the 1700s. Testing candlestick technical analysis using U.S. stock data is therefore, most clearly, an out-of-sample test. This approach survives even the weak criticism that it is simply a test of another technical trading rule on U.S. data. The use of open, high, low and close prices by candlestick technical analysis differentiates it from previous technical trading studies in which close price data only have been used.

Data choice is critically important to studies of technical analysis for reasons other than data snooping. The use of DJIA component stock data for the 1992-2002 period in this research has several advantages over the more traditional choice of 50-100 years of DJIA data. Firstly, until the recent introduction of the Diamonds Exchange Traded Fund, the DJIA was not able to be traded in its own right. Any technical trading signals on the DJIA would therefore be unable to be implemented without purchasing each of the DJIA components in the correct proportions.

Secondly, as Day and Wang (2002) documented, tests of technical trading rules on index data can be biased due to nonsynchronous trading. Jokivuolle (1995, p. 465) explained that "the problem is created by the fact that the value of an asset over a certain time cannot be observed if the asset does not trade in that period." Since most indices are computed on the basis of the most recent transaction prices of the constituent stocks, the reported index becomes stale in the presence of infrequent trading. This results in the observed index not reflecting the true value of the underlying stock portfolio. One consequence of infrequent trading is the spurious serial correlation it induces in the observed index return.

After correcting for nonsynchronous prices in the DJIA Day and Wang (2002) found that moving average rules are of no value. This suggests that earlier studies that document results to the contrary may be biased by nonsynchronous prices. The use of individual stock data is attractive because it overcomes the issues associated with nonsynchronous trading. If a stock does not trade on any particular day then there will be no data for that day, preventing candlestick analysis from being undertaken.

Thirdly, Miller (1990) pointed out that the development of financial theories alters behaviour. So testing models with data occurring before the models were developed is less than adequate. More specifically, weak and semi-strong market efficiency claims only that prices reflect all known information at that point in time, not information that may come to light in the future. Recently developed technical trading rules that are reliant on substantial computer power and reveal profits on 50-100 years of historical data are therefore not necessarily evidence against market efficiency. For this reason, the start point of 1 January 1992 was carefully chosen. Despite being a popular trading technique in Japanese financial markets for some considerable time, the seminal candlestick trading strategy book in English was not published until 1991.[2] Major data providers, such as Reuters, also started making open, high, low and close data available from the middle of 1991. Users of technical analysis therefore would have been aware of candlestick techniques and have had the ability to implement them from the start of 1992.

Finally, technical analysts claim that their methods are most reliable on actively traded stocks (Morris, 1995). This makes the DJIA component stocks an obvious choice. They are also an important choice from a market microstructure perspective. Trading on the NYSE begins with a call auction. The specialist sets a single price at which the accumulated order imbalance from market-open and limit orders clears (Madhavan and Panchapagesan, 2000). The assumption that investors could buy DJIA component stocks at the recorded opening price therefore seems reasonable.

3.3. Methodology

3.3.1. Candlestick Patterns

A daily candlestick is a graphical representation of the day's open, high, low, and close prices. Daily candlesticks are commonly referred to as "single lines". Some

[2] Nison, S. (1991). *Japanese candlestick charting techniques: A contemporary guide to the ancient investment technique of the Far East.* New York Institute of Finance.

single lines are said to have forecasting power in their own right. For instance, a White Marubozu (as shown in Figure 2 on page 56) is said to be a single line that suggests further price increases because prices open at the day's low and rise throughout the day to close at the day's high. A White Marubozu is said to indicate a situation where buyers overwhelm sellers and bid up prices during the day. The odds are that this supply / demand imbalance will lead to further price rises in the future. Other single lines are neutral, giving no indication of future price movements.

Together, consecutive single lines can form continuation and reversal patterns. Continuation patterns indicate that the prevailing trend will continue, while reversal patterns suggest that there will be a change in trend. All single lines and most continuation and reversal patterns have a bullish and a bearish variety. In this context, the term *bullish* (*bearish*) suggests future price increases (decreases),

There are numerous combinations of single lines that are neither continuation nor reversal patterns. In addition, some continuation and reversal patterns are said to have very little, or no, forecasting power. To determine whether a continuation or reversal pattern has strong forecasting power, proponents of candlestick technical analysis developed a system of combining the two or three individual single lines that make up the pattern to form an overall single line for the two- or three-day period. The characteristics of this overall single line indicate whether or not the pattern does have forecasting power.

The rule for combining the single lines that make up a pattern into an overall single line is as follows: the combined high is the high on individual single lines, the combined low is the low on individual single lines, the combined open is the open from the first single line, and the combined close is the close from the last single line (Morris, 1995).

An example of a bullish reversal pattern is the Bullish Engulfing pattern (as shown in Figure 3 on page 58). The Bullish Engulfing pattern involves a short black candle being followed by a long white candle which opens below, but closes above, the previous day. The overall single line formed by combining the two individual single lines that make up the Bullish Engulfing pattern is bullish. This confirms that the Bullish Engulfing pattern is said to have power to predict price increases.

In selecting the single lines and patterns to test, the following approach was adopted. Firstly, all single lines and patterns documented by practitioner books were excluded.[3] The material in these books was checked against an English translation of Shimizu (1986), the seminal Candlestick book in Japanese, to ensure that nothing from the Japanese candlestick literature was missing from, or adapted by, these books. Secondly, all single lines and patterns that do not have explanatory power were excluded. The method of forming an overall single line from a pattern, as documented by Morris (1995) and Nison (1991) was used. Finally, single lines and patterns that occur very infrequently were excluded. These were defined as those that occur fewer than 10 times in the total sample.

Although the universe of candlestick single lines and patterns is greater than those tested in this research, this approach results in tests of single lines and patterns that

[3] These books include: Bigalow (2002), Fischer and Fischer (2003), Morris (1995), Nison (1991, 1994), Pring (2002), Wagner & Matheny (1993).

are most likely to be used by exponents of candlestick technical analysis. They are certainly the ones that the candlestick technical analysis literature says have power. It therefore seems logical to use these ones. There is less value in testing rare patterns as tests would not be robust. In addition, rare patterns are not that likely to be used by candlestick technical analysts as it is probable that they would want to observe at least a couple of realisations of a pattern and subsequent returns before they traded based on the pattern.

Table 1 displays how many single lines and patterns do not have explanatory power. The number that occur infrequently and the number that are subsequently tested are also shown. Tests were conducted on bullish and bearish single lines (seven of each) and bullish and bearish reversal patterns (seven of each). No continuation patterns meet the criteria outlined above. A detailed description of the candlestick single lines and patterns is provided in Appendix One.

Table 1: Number of Candlestick Patterns Tested

	Single Lines	Reversal Patterns	Continuation Patterns
Total in Morris (1995)	18	44	14
Do not Have Explanatory Power	4	22	10
Occur Infrequently	0	8	4
Lines / Patterns Tested	14	14	0

Single lines and patterns are defined as they are outlined in the major candlestick technical analysis books. These books are explicit on some issues. For example, when a white single line must have similar open and low prices and similar close and high prices Morris (1995, p. 25) stated that the difference "should be less than 10% of the open-close range." However, candlestick books point out that there is some flexibility in defining other aspects of single lines such as the distance between open and close for the candle to be classified as a long candlestick.

Single lines are said to have forecasting power regardless of the underlying trend in the market. In contrast, reversal patterns require the existing trend to be identified. Candlestick technical analysis is a short-term technique so candlestick books advocate that a ten-day moving average of prices be used to determine the trend. If price is above (below) the ten-day moving average an uptrend (downtrend) is said to exist (Morris, 1995). Following Morris (1995), the base tests use an exponential moving average which gives more weight to the most recent observations.

The challenge of correctly specifying technical trading rules is faced by all researchers in this area. In fact, the issue is far more serious in papers such as those of Lo, Mamaysky, and Wang (2000) in which patterns, such as the head and shoulders formation, which are far more difficult to define are tested. Lo et al. (2000, p. 1714) stated that they "settle on an acceptable bandwidth for their pattern detection algorithm by trial and error." In this research this issue affects only single lines as books are clear on what combinations of single lines constitute a continuation or reversal pattern. As a final check of the single line specifications, sensitivity analysis was conducted to see how changing the single line and trend definition affects the results in terms of both the number of patterns and profitability.

3.3.2. Measures of Candlestick Trading Strategy Profitability

The profitability of candlestick trading strategies was tested using *t*-statistics and the bootstrapping methodology. Sensitivity analysis was conducted around the holding period, but the core tests are for ten days. Morris (1995) pointed out that candlestick technical analysis has a short-term focus and that a holding period of ten days is appropriate. The methodology description is therefore based on a ten-day holding period.

The approach is to firstly investigate whether there is any statistical significance to the profits from following candlestick signals. Consistent with Brock et al. (1992), in this research raw returns rather than excess returns were used. This approach is appropriate for short-term rules, as variations in the risk premia are likely to have a long periodicity relative to the holding period (Sweeney, 1986).

3.3.2.1. *T*-Test

If a candlestick trading rule does not have any price forecasting power then the returns on days when the rule gives a buy signal should not differ appreciably from the returns on days when the rule does not emit a signal. Returns were measured on a daily basis as the log difference of price relatives. Consistent with previous research, such as that by Brock et al. (1992), this hypothesis was tested using standard *t*-statistics. The *t*-statistics for the buy (sell) signals versus no signals are:

$$\frac{\mu_{b(s)} - \mu}{(\sigma^2_{b(s)} / N_{b(s)} + \sigma^2 / N\ )^{1/2}} \tag{1}$$

where $\mu_{b(s)}$ and $N_{b(s)}$ are the mean return following a buy (sell) signal for the ten day holding period and the number of signals for buys (sells). μ and N are the unconditional mean and number of observations. $\sigma^2_{b(s)}$ is the variance of returns following a buy signal and σ^2 is the variance for the entire sample.

3.2.3.2. Bootstrapping Methodology

In addition to this *t*-statistic methodology, a bootstrapping methodology - which has its origins in Efron (1979) - was also applied. This methodology has several advantages. Firstly, unlike *t*-statistics bootstrapping can accommodate well known characteristics of stock return data such as skewness, leptokurtosis (fat tails), autocorrelation, and conditional heteroskedasticity. A second benefit of the bootstrap methodology is that it can be used to examine the standard deviation of returns for each trading rule, which gives an indication of the riskiness of the different candlestick rules.

The first step in applying the bootstrap methodology is the choice of null models to fit the data. To ensure consistency with previous papers in this research four widely used processes for stock prices were adopted: a random walk, an autoregressive process of order one (AR(1)), a GARCH in-Mean (GARCH-M) model and an Exponential GARCH (EGARCH) model.

Previous papers have all recorded the testing of trading rules that are based solely on close prices. Although in this thesis open, high, low, and close prices are considered, their approach was followed to start with. This involved resampling close returns for the random walk model and fitting the respective null models to the original close price series for the AR(1), GARCH-M and EGARCH models.[4] This process was conducted separately for each stock because it makes no sense to try and fit a null model to a long series of returns that has been created by joining together series of individual stock returns.

The AR(1) model is provided in equation 2:

$$r_t = b + \rho r_{t-1} + \varepsilon_t, \quad |\rho| < 1 \tag{2}$$

where r_t is the return on day t and ε_t is independent, identically distributed. The parameters (b, ρ) and the residuals ε_t are estimated from the DJIA component stock series using OLS regression. Conrad and Kaul (1988) have documented first order autocorrelation in stock series so the AR(1) model is used to investigate the possibility that any profit accruing to the candlestick technical trading strategies is simply due to autocorrelation.

The GARCH-M model is shown below in equations 3a, 3b and 3c:

$$r_t = \alpha + \gamma\sigma_t^2 + \beta\varepsilon_{t-1} + \varepsilon_t \tag{3a}$$

[4] To ensure the accuracy of this bootstrap code the data used in Brock et al. (1992) were sourced from Blake LeBaron and their results were replicated.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{3b}$$

$$\varepsilon_t = \sigma_t z_t \qquad\qquad z_t \sim N(0,1) \tag{3c}$$

In this model, the error, ε_t, is conditionally normally distributed and serially uncorrelated. The conditional variance, σ_t^2, is a linear function of the square of the last period's errors and of the last period's conditional variance, which implies positive serial correlation in the conditional second moment of the return process. Periods of high (or low) volatility are likely to be followed by periods of high (low) volatility. The conditional returns in this model are a linear function of the conditional variance and the past disturbance, ε_{t-1},. Under this return-generating process, volatility can change over time and the expected returns are a function of volatility as well as of past returns.[5] The parameters and standardized residuals were estimated for each DJIA component stock using the maximum likelihood criterion.

The fourth null model adopted in this thesis is an Exponential GARCH (EGARCH) model. The specification used is shown below in equations 4a, 4b and 4c:

$$r_t = \alpha + \gamma r_{t-1} + \beta \varepsilon_{t-1} + \varepsilon_t \tag{4a}$$

$$\log \sigma_t^2 = \kappa + G \log \sigma_{t-1}^2 + A_j \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{2/\pi} \right] + L \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) \tag{4b}$$

$$\varepsilon_t = \sigma_t z_t \qquad\qquad z_t \sim N(0,1) \tag{4c}$$

The EGARCH model has two important differences from the GARCH-M model. Firstly, the log of the conditional variance follows an autoregressive process.

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[5] See Engle, Lilien, and Robins (1987).

Secondly, it allows previous returns to affect future volatility differently depending on their sign. This is designed to capture a phenomenon in asset returns observed by Black (1976) where negative returns are generally followed by larger volatility than are positive returns.

In accordance with Brock et al. (1992), the residuals of the GARCH-M and EGARCH models were standardised using estimated standard deviations for the error process. The estimated residuals for the AR(1) model and standardised residuals for the GARCH-M and EGARCH models were then redrawn with replacement to form a scrambled residuals series which was used, along with the estimated parameters, to form new representative close return series. These returns were then expontiated to form new close price series for each stock. These scrambled series have the same drift in prices, the same volatility, and the same unconditional distribution. However, by construction the returns are independent and identically distributed. The residuals / standardised residuals were not restricted to a particular distribution, such as Gaussian, by this procedure.

Once a randomly generated close series had been formed vectors of the original (high – close)/close and (close-low)/close percentage differences were created. A random sample from these percentage difference vectors was then taken. Next these high-close (close-low) percentage differences were added (subtracted) to (from) the simulated close price to form simulated high and low prices. A similar process was used to generate simulated open prices. To ensure that the resampled open price was never higher than the high nor lower than the low the close-open percentage differences were resampled if this situation arose.

This process was replicated 500 times for each stock so there were 500 simulated sets of open, high, low and close series for each stock in the sample for each null model. Efron and Tibshirani (1986) suggested that 500-1000 simulations are enough to approximate the true estimator. Convergence before 500 simulations was also found in this research.

The proportion of times that a candlestick trading rule produces more profit on the bootstrapped series than on the original series following a signal is a simulated *p*-value for the null hypothesis that the trading rule has no value. For a bullish candlestick to have statistically significant forecasting power at the 5% level the simulated *p*-value should be less than 0.05. In other words, more profit should be produced on the random series than the original less than 5% of the time. For a bearish candlestick to have forecasting power at the 5% level the simulated *p*-value should be more than 0.95. In other words, more profit should be produced on the random series than on the original more than 95% of the time.

The difference between two approaches of calculating an overall *p*-value for all the DJIA component stocks was investigated. Firstly, the individual stock *p*-values for each rule were averaged to arrive at an overall *p*-value for the DJIA component stocks. Secondly, a cumulative *p*-value was calculated by summing the number of times that there was more profit on the bootstrapped series than on the original and dividing by the total number of bootstrapped series (35×500). Results for the second approach are presented because it lessens the impact of an extreme result on any one stock. The *p*-values were very consistent across these two methods and the results from the first approach are available from the author upon request.

Bootstrapping also allows the consideration of return variation following a candlestick signal. Using the same approach as outlined for mean returns, simulated p-values were calculated for the null hypothesis that the trading rule is more risky on random series than on the original series. This was achieved by measuring the standard deviation of returns following a signal on the original and on the bootstrapped series and calculating the proportion of times that the standard deviation was larger on the bootstrapped series than on the original series.

As a check of the robustness of the results, the variation in profits stemming from entering the market following a signal at close t, close $t+1$, and open $t+1$ (where t is the day that the signal is received) were investigated. When entering at the close price was considered the bootstrap process was conducted as described above and the conditional returns on the bootstrapped close series are compared to the original close series. When entering at the open price was considered, the open series was bootstrapped first and high, low, and close series were generated from this in a similar fashion to that outlined for the close price series.

3.4. Conclusion

The approaches taken to data choice and methodology selection are aimed at overcoming the criticism that has been levelled at past work showing shortcomings in this area. Testing candlestick trading strategies on DJIA component stock data is an out-of-sample test, given that these strategies were developed on Japanese rice data. This greatly reduces the likelihood that the results are suffering from data snooping bias.

The use of DJIA component stock data has several other advantages. Firstly, unlike index data, these instruments are tradable so the results obtained are not just hypothetical – they could have been achieved by anyone applying candlestick technical analysis. Secondly, Dow stock data are very liquid which makes them ideal for tests of technical analysis. Technical analysis is supposed to capture mass market psychology so it is important that it is applied to liquid series where one or two market participants are unlikely to be able to move the price. This high level of liquidity also ensures that any returns documented are available to large amounts of capital. In other words, market impact costs are not high.

Chapter Four: Results

4.1. Introduction

This section contains the summary statistics for the stocks used in this research and the results of the tests of the statistical significance of returns following candlestick buy and sell signals. As discussed in the literature review and data and methodology sections, *bullish* (*bearish*) single lines and patterns are those that practitioner books (e.g Morris, 1995) suggest lead to further price increases (decreases).

The core *t*-statistic and bootstrap results are based around entering the market at the open price on the day after a signal is generated. This appears to be the most realistic assumption. In contrast, most research follows Brock et al. (1992) and assumes that a technical trader could buy a stock at the close price on the same day that a signal is generated. In reality, this is very difficult as the close price of the stock is what determines whether a trading signal will be generated. A technical analyst following this approach would have to firstly feed estimates of the close price into his/her trading system to see if they generated a signal. If one did s/he would then need to submit a "market at close" order. At this point s/he could not be sure that the actual close price would be sufficiently similar to the estimated close price to have generated the signal so there is a risk of acting on an invalid signal.

Another option is entering at the close on the day after a signal. This is obviously achievable in reality, but in this thesis it is proposed that it is more likely that a trader would enter the market at the first available opportunity following a technical signal. More specifically, the trader would buy at the open price on the day following the signal. In this thesis this assumption is used as the base case, but sensitivity analysis was conducted to determine if the results are significantly different if the trader enters on the day of, or day after, a signal.

Sensitivity analysis was also conducted on the number of days a trade is held open for (holding period), and the length of the moving average used to determine the prior trend (for reversal patterns only). More specifically, in Scenario A it is assumed that a trade is initiated at the closing price on the day that the entry signal is generated, that the trade is kept open for ten days, and a ten-day exponential moving average is used to determine the prior trend for reversal patterns. Scenario B is identical to Scenario A except that in Scenario B it is assumed that a trade is initiated at the closing price on the day after the entry signal is generated.

Scenario C adopts what this research deems to be the most realistic assumptions and is therefore the base case. Under this scenario it is assumed that a trade is initiated at the open price on the day after an entry signal is generated, that the trade is kept open for ten days, and that a ten-day exponential moving average is used to determine the existence of a prior trend. Given that Scenario C, which has identical assumptions to Scenario B, except for the assumption on when the trade is initiated, has very similar results to Scenario B, the remaining scenarios consider the impact of changing one of the assumptions in Scenario C.

Scenario D is identical to Scenario C except for the assumption that positions are kept open for five days instead of ten days. Scenario E is identical to Scenario C except for the assumption that positions are kept open for two days instead of ten days. Under Scenario F each candlestick parameter is increased by 20%, while all other Scenario C assumptions are maintained. Under Scenario G all candlestick parameters are reduced by 20% while all other Scenario C assumptions are maintained. The impact of varying the length of the exponential moving average is investigated in Scenarios H and I. In Scenario H it is reduced from ten days to five days, while in Scenario I it is decreased from ten days to two days.

4.2. Summary Statistics

The summary statistics for the thirty-five stocks that are part of the sample for the period of the study (1 January 1992 – 31 December 2002) are included in Table 2.

Table 2: Summary Statistics

	Open	High	Low	Close
N	83220	83220	83220	83220
Mean	0.0003	0.0003	0.0003	0.0003
Std. Dev.	0.0200	0.0174	0.0187	0.0198
Skewness	-0.3710**	-0.2376**	-0.9980**	-0.3939**
Kurtosis	37.7218**	56.8085**	57.0827**	36.1342**

** indicates statistical significance at the 1% level

There are 83,220 daily returns across the stocks in the sample. *Return* is defined as *the natural logarithm of price relatives.* Following Lo et al. (2000) the mean, standard deviation, skewness and kurtosis of the returns of all the sample stocks were calculated together. As expected, the mean returns of each of the four series are similar. Volatility is also similar across the four series with high and low only slightly less volatile than open and close. All four series display negative skewness. The four series are all lepotokurtic, with high and low displaying this characteristic more strongly than open and close.

4.3. Statistical Tests

4.3.1. Scenario A: Trade initiated at the Close Price on the Day of the Signal, a Ten-Day Holding Period, and a Ten-Day Exponential Moving Average to Determine Prior Trend

Under Scenario A a trade is assumed to be initiated at the close price on the day of the signal and held for ten days. A ten-day exponential moving average was used to determine the prior trend for bullish and bearish reversal patterns.

Results from the Scenario A bullish single lines and patterns are presented in Panels A and B of Table 3. N(Buy) is the number of buy signals in the data. This ranges from 17 for the relatively rare Three Inside Up pattern to 2,952 for the commonly observed Long White single line. The tests are based around a ten-day holding period, but daily returns are used in the statistical tests so that their power is increased. This means that the number of signals needs to be multiplied by ten to arrive at the number of returns used in the statistical tests. For instance, there are 170 daily returns associated with the Three Inside Up pattern.

Table 3: Scenario A: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2952	0.4768	0.0002	-0.886
White Marubozu	644	0.4595	0.0004	0.374
Closing White Marubozu	1565	0.4663	0.0001	-1.341
Opening White Marubozu	1611	0.4730	0.0001	-1.363
Dragonfly Doji	270	0.4341	-0.0004	-2.280*
White Paper Umbrella	567	0.4702	0.0004	-0.011
Black Paper Umbrella	728	0.4640	0.0002	-0.984
Panel B: Bullish Reversal Patterns				
Hammer	57	0.5018	0.0009	0.780
Bullish Engulfing	252	0.4829	0.0006	0.565
Piercing Line	138	0.4797	-0.0002	-0.918
Bullish Harami	115	0.5009	0.0009	0.771
Three Inside Up	17	0.4824	0.0012	0.570
Three Outside Up	56	0.4696	-0.0003	-0.799
Tweezer Bottom	354	0.4616	0.0002	-0.372
Candlestick	**N(Sell)**	**Sell>0**	**Mean**	***T*-Stat**
Panel C: Bearish Single Lines				
Long Black	2663	0.4899	0.0007	2.083*
Black Marubozu	558	0.4858	0.0012	2.891**
Closing Black Marubozu	1022	0.4945	0.0010	3.240**
Opening Black Marubozu	1738	0.4803	0.0004	0.321
Gravestone Doji	192	0.4661	0.0010	1.575
White Shooting Star	520	0.4883	0.0006	0.875
Black Shooting Star	465	0.4886	0.0006	1.187
Panel D: Bearish Reversal Patterns				
Hanging Man	84	0.4833	0.0009	0.789
Bearish Engulfing	289	0.4941	0.0005	0.467
Dark Cloud Cover	117	0.4940	0.0004	0.115
Bearish Harami	396	0.4689	0.0001	-0.916
Three Inside Down	34	0.4559	-0.0009	-1.195
Three Outside Down	36	0.5222	0.0019	1.526
Tweezer Top	407	0.4764	0.0007	1.351

**statistically significant at the 1% level, *statistically significant at the 5% level

The column Buy>0 reports the proportion of returns following a buy signal that are greater than zero. The returns following all the bullish single lines are greater than zero less than fifty percent of the time. While this is indicative of a poorly performing rule, it is not definitive as it does not take the size of returns into account. It is possible that a rule that is correct less than fifty percent of the time yields substantially bigger profits than losses making it profitable overall. In addition, the Buy > 0 column results make no comparison to unconditional returns. The only bullish reversal patterns to yield returns greater than zero more than fifty percent of the time are the Hammer and Bullish Harami patterns.

The mean returns conditional on bullish single line signals are all positive with the exception of the Dragonfly Doji. Despite this, none of the bullish single lines yield statistically significant profits at the 5% level. Rather, all of the *t*-statistics except those for the White Marubozu are negative. This indicates that the mean returns conditional on all the non-White Marubozu bullish single line signals are lower than the unconditional mean return. The returns following Dragonfly Doji lines are negative and statistically significant at the 5% level. This is exactly the opposite to what candlestick technical analysis theory suggests. Rather than indicating positive future returns, there is evidence that this single line indicates negative future returns. The *t*-statistics for the Hammer, Bullish Engulfing, Bullish Harami, and Three Inside Up bullish reversal patterns are positive, indicating that the conditional returns are greater than the unconditional returns. However, none of these are statistically significant.

The results from bearish single lines and patterns are presented in Panels C and D of Table 3. The number of bearish single lines and patterns is similar to the number of their bullish counterparts. The returns following all bearish single lines are greater than zero less than fifty percent of the time, which means that they are less than zero more than fifty percent of the time. This is what one would expect for a bearish candlestick. The bearish reversal patterns are also greater than zero less than fifty percent of the time, with the exception of the Three Outside Down pattern.

Other than the Three Inside Down pattern, the means of the bearish single lines and reversal patterns are all positive. The Long Black conditional minus unconditional mean is statistically significant at the 5% level and the Black Marubozu and Closing Black Marubozu conditional minus unconditional means are statistically significant at the 1% level. This suggests that, contrary to candlestick theory, these bearish lines indicate higher than average returns over the next ten days. The *t*-statistics for the Bearish Harami and Three Inside Down bearish reversal patterns are negative (as expected), but none of these are statistically significant.

Table 4: Scenario A: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5374	0.2801	0.5290	0.2839	0.5638	0.4494	0.5654	0.3541
White Marubozu	0.5065	0.5203	0.4958	0.5123	0.5119	0.7149	0.5129	0.7048
Closing White Marubozu	0.5469	0.4613	0.5475	0.4565	0.5906	0.5742	0.5961	0.5205
Opening White Marubozu	0.5296	0.3542	0.5319	0.3563	0.5945	0.4783	0.5862	0.4045
Dragonfly Doji	0.6134	0.8695	0.6133	0.8680	0.5962	0.7687	0.5993	0.7730
White Paper Umbrella	0.4755	0.7840	0.4781	0.7806	0.4906	0.7091	0.4918	0.7037
Black Paper Umbrella	0.5329	0.7133	0.5351	0.7044	0.5528	0.7162	0.5599	0.6953
Panel B: Bullish Reversal Patterns								
Hammer	0.4584	0.6104	0.4533	0.6061	0.4519	0.5556	0.4413	0.5006
Bullish Engulfing	0.4819	0.3402	0.4905	0.3266	0.4513	0.3714	0.4304	0.2920
Piercing Line	0.5251	0.4172	0.5745	0.3465	0.5565	0.3651	0.5472	0.3208
Bullish Harami	0.5171	0.2919	0.4792	0.2664	0.4525	0.3132	0.4484	0.2667
Three Inside Up	0.5235	0.4865	0.5465	0.3546	0.4034	0.4545	0.4317	0.3880
Three Outside Up	0.4939	0.4303	0.5261	0.4318	0.5058	0.3898	0.5061	0.3572
Tweezer Bottom	0.5123	0.5426	0.5085	0.5353	0.5007	0.4976	0.4879	0.4439

Candlestick	RW Sell	RW σ_s	AR(1) Sell	AR(1) σ_s	GARCH-M Sell	GARCH-M σ_s	EGARCH Sell	EGARCH σ_s
Panel C: Bearish Single Lines								
Long Black	0.4117	0.1833	0.4137	0.1822	0.3796	0.3539	0.3606	0.2426
Black Marubozu	0.4420	0.4108	0.4315	0.4151	0.3419	0.5526	0.3327	0.5204
Closing Black Marubozu	0.4154	0.3594	0.4242	0.3548	0.3615	0.4451	0.3506	0.3834
Opening Black Marubozu	0.5011	0.2604	0.5038	0.2562	0.4914	0.3571	0.4808	0.2619
Gravestone Doji	0.3284	0.7679	0.3241	0.7735	0.3792	0.7008	0.3765	0.6919
White Shooting Star	0.4858	0.5505	0.4805	0.5444	0.4871	0.5591	0.4892	0.5329
Black Shooting Star	0.4050	0.7416	0.4033	0.7395	0.4298	0.6833	0.4199	0.6671
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4709	0.5038	0.4780	0.4963	0.4676	0.5465	0.4893	0.6007
Bearish Engulfing	0.5025	0.4474	0.5027	0.4504	0.5049	0.5032	0.5307	0.5513
Dark Cloud Cover	0.4767	0.4535	0.4865	0.4814	0.4985	0.4869	0.5175	0.5328
Bearish Harami	0.5291	0.4464	0.5217	0.4500	0.5532	0.5054	0.5814	0.5569
Three Inside Down	0.4414	0.4324	0.5055	0.3736	0.5493	0.4225	0.5561	0.4559
Three Outside Down	0.3286	0.4952	0.4174	0.4913	0.3907	0.4214	0.4193	0.4508
Tweezer Top	0.4731	0.6110	0.4625	0.6077	0.4711	0.5687	0.4902	0.6301

Table 4 contains the Scenario A bootstrap results. The numbers refer to the proportion of the 500 simulated bootstrapped series that have higher average returns and standard deviations following a buy (sell) signal from a bullish (bearish) rule than the original series. These numbers can be thought of as simulated p-values. For the bullish candlestick buy returns a value of zero indicates that none of the bootstrapped series have a return following a buy signal that is larger than that on the original series. This indicates that the rule has significant power. For a bearish candlestick, a value of one indicates that all of the bootstrapped series have returns that are larger than those on the original series following a sell signal. Again, this indicates that the rule has significant power. For a rule to have statistically significant forecasting power at the 5% level, consistent with candlestick theory, a simulated p-value has to be less than 0.05 (greater than 0.95) for bullish (bearish) rules.

Panels A-D indicate that the results are very consistent across the four null models. The buy proportions for the single lines are all around 0.5, which indicates that none of these candlesticks generate conditional returns that are statistically significantly different from the unconditional returns. It is evident from the Panel A results that the Dragonfly Doji, Closing White Marubozu, and Long White line have the highest values, indicating that it is more common for the randomly generated bootstrap series to have higher returns than the original for these lines.

If a trading rule has statistically significantly different returns, an obvious question to ask is whether or not this difference is due to additional risk being undertaken. The σ_b column displays the proportion of times that the standard deviation of returns following a buy signal is greater on the bootstrapped series than on the original series. If a trading rule is in the market in more risky times, σ_b will be close to one. The results in Panel A indicate that there is no clear relationship in the standard deviation proportions for the bullish single lines. Some proportions are closer to zero while others are closer to one. None are statistically significant at the 5% level.

From the Panel B results it is evident that the returns following bullish reversal patterns are also not statistically significant, indicating that bullish reversal patterns have no forecasting power. Similarly to the bullish single lines there is no clear pattern in the standard deviations. Returns on the original series are sometimes more volatile than 50% of the bootstrapped series, and sometimes less volatile.

Returns are greater on the bootstrap series than on the original series less than fifty percent of the time for all bearish single lines (except the Opening Black Marubozu).

This is the opposite to what one would expect for bearish rules, but is broadly consistent with the t-statistic results which show that in some instances bearish single lines forecast negative rather than positive future returns. The sell p-values from the bearish reversal patterns are also less than 0.5, with the exception of the Bearish Engulfing and Bearish Harami patterns. The standard deviation p-values for the bearish single lines and reversal patterns show no clear trend.

The fact that none of the bootstrap results are statistically significant indicates that the t-statistic results, which showed statistical significance in five cases, may be influenced by one of the t-statistic assumptions being violated. The summary statistics in Table 2 show that the return series are not normally distributed (as required for the t-test to be accurate), but rather display characteristics of negative skewness and leptokurtosis.

Tables 5 and 6 contain the Scenario A means and standard deviations for the Random Walk, AR(1), GARCH-M, and EGARCH null models respectively. Bootstrap Buy and σ_b are the mean buy return and standard deviation of buy returns across the 500 bootstrapped series respectively. These are calculated as an average of the 500 series across the 35 stocks. Dow Buy and σ_b are the average buy return and standard deviation of buy returns across the original series for each of the 35 stocks.

A comparison with Panels A and B of Table 5 show that there is usually the situation where the size of the bootstrap p-value for the mean or standard deviation is indicative of the relative size of the means or standard deviations for the bootstrap and the original series. For instance, if the buy proportion for a bullish rule is greater than 0.5, indicating that the bootstrap return is greater than the original return in excess of 50% of the time, then the bootstrap mean is in fact greater than the original mean. An example of this is the Long White candle under the random walk null model which has a *p*-value of 0.5374 and mean return of 0.0002 and 0.0001 on the bootstrap and original series respectively. This is not always the case though. It is possible that the bootstrap return is greater than the original return over 50% of the time but that the remaining bootstrap returns are very small, resulting in an overall bootstrap mean that is less than the original mean. An example of this is the White Paper Umbrella which has a bootstrap *p*-value of 0.4735 and means of 0.0002 and 0.0001 on the bootstrapped and original series respectively (under the random walk null model).

Panels C and D of Table 5 display the average sell returns and standard deviation of sell returns on the original series and bootstrapped series for bearish candlesticks. These results are very similar to the bullish results in Panels A and B. The size of the bootstrap proportion is usually indicative of the relative size of the means and standard deviations for the bootstrapped and original series.

Candlestick signals are reasonably rare and their forecasting power is only a short-term phenomenon (Morris, 1995) so it is not appropriate to consider their daily returns on an annual basis. Large daily returns are not able to be earned over a sustained period of time. More specifically, a particular candlestick pattern might produce an average daily return of 1% over a ten-day holding period in a particular stock, but if the pattern signals only one entry per year on average it is not realistic to conclude that it produces an annual return in excess of 250% (obtained by annualising the daily returns).

There is a small chance that the results are not consistent across the entire eleven year period of this study. This is investigated by dividing the data into two equal sub-samples and running the tests on each of these. The results are very consistent across these sub-samples and contribute little. They are therefore not presented.

Table 5: Scenario A: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0102	0.0001	0.0103	0.0002	0.0102	0.0001	0.0103
White Marubozu	0.0002	0.0094	0.0001	0.0087	0.0002	0.0093	0.0001	0.0087
Closing White Marubozu	0.0002	0.0098	0.0000	0.0098	0.0002	0.0099	0.0000	0.0098
Opening White Marubozu	0.0002	0.0097	-0.0001	0.0101	0.0002	0.0096	-0.0001	0.0101
Dragonfly Doji	0.0002	0.0097	-0.0002	0.0075	0.0002	0.0098	-0.0002	0.0075
White Paper Umbrella	0.0002	0.0098	0.0001	0.0084	0.0002	0.0098	0.0001	0.0084
Black Paper Umbrella	0.0002	0.0096	-0.0001	0.0084	0.0002	0.0097	-0.0001	0.0084
Panel B: Bullish Reversal Patterns								
Hammer	0.0001	0.0083	0.0004	0.0076	0.0002	0.0082	0.0004	0.0076
Bullish Engulfing	0.0001	0.0090	0.0002	0.0103	0.0001	0.0089	0.0002	0.0103
Piercing Line	0.0000	0.0101	-0.0002	0.0107	0.0003	0.0098	-0.0002	0.0107
Bullish Harami	0.0000	0.0092	0.0005	0.0107	0.0004	0.0089	0.0005	0.0107
Three Inside Up	-0.0003	0.0057	0.0006	0.0084	0.0038	0.0117	0.0006	0.0084
Three Outside Up	0.0001	0.0083	0.0001	0.0094	0.0001	0.0083	0.0001	0.0094
Tweezer Bottom	0.0002	0.0086	0.0002	0.0098	0.0002	0.0085	0.0002	0.0098

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0001	0.0102	0.0003	0.010B	0.0002	0.0102	0.0003	0.0108
Black Marubozu	0.0002	0.0098	0.0004	0.0098	0.0001	0.0097	0.0004	0.0098
Closing Black Marubozu	0.0002	0.0101	0.0006	0.0103	0.0002	0.0100	0.0006	0.0103
Opening Black Marubozu	0.0002	0.0099	0.0001	0.0109	0.0002	0.0099	0.0001	0.0109
Gravestone Doji	0.0002	0.0098	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0098	-0.0001	0.0099	0.0002	0.0098	-0.0001	0.0099
Black Shooting Star	0.0002	0.0101	-0.0001	0.0091	0.0002	0.0101	-0.0001	0.0091
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0087	0.0006	0.0083	0.0001	0.0088	0.0006	0.0083
Bearish Engulfing	0.0002	0.0095	0.0001	0.0094	0.0003	0.0096	0.0001	0.0094
Dark Cloud Cover	0.0002	0.0101	0.0001	0.0094	0.0001	0.0102	0.0001	0.0094
Bearish Harami	0.0002	0.0096	0.0000	0.0097	0.0002	0.0096	0.0000	0.0097
Three Inside Down	-0.0002	0.0088	0.0001	0.0096	-0.0002	0.0084	0.0001	0.0096
Three Outside Down	0.0000	0.0091	0.0010	0.0096	0.0002	0.0091	0.0010	0.0096
Tweezer Top	0.0002	0.0093	0.0003	0.0083	0.0002	0.0093	0.0003	0.0083

Table 6: Scenario A: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0111	0.0001	0.0103	0.0002	0.0104	0.0001	0.0103
White Marubozu	0.0002	0.0107	0.0001	0.0087	0.0002	0.0101	0.0001	0.0087
Closing White Marubozu	0.0002	0.0111	0.0000	0.0098	0.0002	0.0104	0.0000	0.0098
Opening White Marubozu	0.0002	0.0111	-0.0001	0.0101	0.0001	0.0104	-0.0001	0.0101
Dragonfly Doji	0.0002	0.0099	-0.0002	0.0075	0.0002	0.0096	-0.0002	0.0075
White Paper Umbrella	0.0002	0.0103	0.0001	0.0084	0.0002	0.0098	0.0001	0.0084
Black Paper Umbrella	0.0002	0.0105	-0.0001	0.0084	0.0002	0.0098	-0.0001	0.0084
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0088	0.0004	0.0076	0.0001	0.0077	0.0004	0.0076
Bullish Engulfing	0.0000	0.0098	0.0002	0.0103	0.0000	0.0090	0.0002	0.0103
Piercing Line	0.0001	0.0095	-0.0002	0.0107	0.0001	0.0092	-0.0002	0.0107
Bullish Harami	0.0002	0.0091	0.0005	0.0107	0.0001	0.0085	0.0005	0.0107
Three Inside Up	0.0003	0.0082	0.0006	0.0084	0.0002	0.0081	0.0006	0.0084
Three Outside Up	0.0001	0.0086	0.0001	0.0094	0.0000	0.0079	0.0001	0.0094
Tweezer Bottom	0.0001	0.0089	0.0002	0.0098	0.0000	0.0082	0.0002	0.0098

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0111	0.0003	0.0108	0.0002	0.0104	0.0003	0.0108
Black Marubozu	0.0002	0.0108	0.0004	0.0098	0.0002	0.0101	0.0004	0.0098
Closing Black Marubozu	0.0002	0.0110	0.0006	0.0103	0.0002	0.0103	0.0006	0.0103
Opening Black Marubozu	0.0002	0.0111	0.0001	0.0109	0.0001	0.0104	0.0001	0.0109
Gravestone Doji	0.0002	0.0103	0.0006	0.0075	0.0002	0.0097	0.0006	0.0075
White Shooting Star	0.0002	0.0107	-0.0001	0.0099	0.0002	0.0100	-0.0001	0.0099
Black Shooting Star	0.0002	0.0108	-0.0001	0.0091	0.0001	0.0102	-0.0001	0.0091
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0100	0.0006	0.0083	0.0004	0.0100	0.0006	0.0083
Bearish Engulfing	0.0002	0.0103	0.0001	0.0094	0.0003	0.0103	0.0001	0.0094
Dark Cloud Cover	0.0002	0.0102	0.0001	0.0094	0.0003	0.0102	0.0001	0.0094
Bearish Harami	0.0002	0.0104	0.0000	0.0097	0.0003	0.0104	0.0000	0.0097
Three Inside Down	0.0003	0.0090	0.0001	0.0096	0.0004	0.0094	0.0001	0.0096
Three Outside Down	0.0001	0.0091	0.0010	0.0096	0.0003	0.0092	0.0010	0.0096
Tweezer Top	0.0003	0.0097	0.0003	0.0083	0.0003	0.0098	0.0003	0.0083

4.3.2. Scenario B: Trade initiated at the Close Price on the Day after the Signal, a Ten-Day Holding Period, and a Ten-Day Exponential Moving Average to Determine Prior Trend

Under Scenario B a trade is assumed to be initiated at the close price on the day after the signal and held for ten days. A ten-day exponential moving average was used to determine the prior trend for bullish and bearish reversal patterns.

The Scenario B *t*-test results are displayed in Table 7. The number of buy and sell signals is very similar to Scenario A. This indicates that only small differences arise from the varying assumptions about entry lags. It should be noted that all results presented in this thesis are based on tests that are conducted on the assumption that if a particular rule has given a signal and the holding period has not expired, then any subsequent signals are ignored. This is the most practical working assumption because a second buy signal following an earlier buy signal that resulted in an investor becoming fully invested would simply be seen as confirmation of the earlier signal. An alternative approach is the inclusion of all signals and thus overlapping holding periods. For instance, if the Long White candle signals a buy on day *t+1* and signals another buy on day *t+3* a long position would be entered on both days.[6]

Table 7: Scenario B: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2947	0.4754	0.0001	-1.933
White Marubozu	642	0.4586	0.0003	-0.307
Closing White Marubozu	1565	0.4711	0.0003	-0.332
Opening White Marubozu	1611	0.4681	-0.0001	-2.710**
Dragonfly Doji	270	0.4433	-0.0001	-1.556
White Paper Umbrella	567	0.4750	0.0005	0.682
Black Paper Umbrella	727	0.4708	0.0003	-0.278
Panel B: Bullish Reversal Patterns				
Hammer	57	0.4947	0.0007	0.377
Bullish Engulfing	252	0.4869	0.0007	0.831
Piercing Line	138	0.4812	-0.0003	-1.034
Bullish Harami	115	0.5026	0.0008	0.758
Three Inside Up	17	0.4588	0.0006	0.155
Three Outside Up	56	0.4732	-0.0003	-0.744
Tweezer Bottom	354	0.4636	0.0001	-0.658

[6] Tests were also conducted on this basis but the results are very similar so they are not reported.

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2661	0.4883	0.0007	2.105*
Black Marubozu	557	0.4783	0.0009	2.083*
Closing Black Marubozu	1022	0.4833	0.0006	1.338
Opening Black Marubozu	1737	0.4811	0.0005	1.220
Gravestone Doji	191	0.4597	0.0008	1.071
White Shooting Star	520	0.4808	0.0004	0.233
Black Shooting Star	465	0.4813	0.0005	0.711
Panel D: Bearish Reversal Patterns				
Hanging Man	84	0.4786	0.0006	0.384
Bearish Engulfing	289	0.4965	0.0009	1.645
Dark Cloud Cover	117	0.4872	0.0004	0.072
Bearish Harami	396	0.4699	0.0000	-1.102
Three Inside Down	34	0.4353	-0.0011	-1.324
Three Outside Down	36	0.5111	0.0017	1.342
Tweezer Top	407	0.4747	0.0007	1.305

**statistically significant at the 1% level, *statistically significant at the 5% level

The Scenario B results are very similar to their Scenario A counterparts, which indicates that a lag of one day does materially affect the profitability of candlestick technical analysis. The bullish single lines and reversal patterns still result in returns that are greater than zero less than 50% of the time (with the exception of the Bullish Harami). A similar number of *t*-statistics to those in Scenario A are positive and negative indicating that some patterns lead to higher returns than the unconditional return and others lead to lower returns. Again, only one of these mean differences is statistically significant and it is negative. The only difference is that it is the Opening White Marubozu instead of the Dragonfly Doji. The bearish single line and reversal pattern results displayed in Panels C and D of Table 7 are also very similar to their Scenario A counterparts. The Long Black and Black Marubozu mean differences are still positive, the opposite to what candlestick theory suggests. The bullish reversal patterns conditional minus unconditional mean differences are not statistically significant.

The results displayed in Table 8 indicate that the bootstrap results are also very similar between Scenarios A and B. There is some variation across rules, but the simulated *p*-values tend to be greater than 0.5 following buy signals and less than 0.5 following sell signals. This suggests that the rules are not even close to having forecasting power. If this was the case you would expect the *p*-values to be less than 0.5 and closer to zero for buy signals. In other words, the profitability of the signal on the randomly generated series would be expected to exceed those on the original series less than 50% of the time. Consistent with the Scenario A, the results are very similar across the four null models. There is no consistent trend in the standard deviation *p*-values across either the buy or sell signals.

Table 8: Scenario B: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5805	0.2963	0.5718	0.2953	0.6291	0.4597	0.6309	0.3640
White Marubozu	0.5092	0.5198	0.5025	0.5159	0.5460	0.7028	0.5464	0.7065
Closing White Marubozu	0.5205	0.4736	0.5251	0.4709	0.5470	0.5945	0.5463	0.5385
Opening White Marubozu	0.5577	0.3692	0.5514	0.3760	0.6591	0.4907	0.6614	0.4269
Dragonfly Doji	0.5401	0.8882	0.5428	0.8856	0.5314	0.7639	0.5438	0.7706
White Paper Umbrella	0.4240	0.7536	0.4303	0.7530	0.4439	0.6887	0.4492	0.6819
Black Paper Umbrella	0.5092	0.6964	0.5126	0.6956	0.5153	0.7069	0.5175	0.6858
Panel B: Bullish Reversal Patterns								
Hammer	0.4756	0.6190	0.4856	0.5986	0.4675	0.5578	0.4497	0.5087
Bullish Engulfing	0.4797	0.3477	0.4737	0.3569	0.4407	0.3818	0.4243	0.3075
Piercing Line	0.5243	0.3693	0.5390	0.3724	0.5747	0.3823	0.5656	0.3533
Bullish Harami	0.4885	0.3215	0.4982	0.3007	0.4583	0.3102	0.4550	0.2737
Three Inside Up	0.6173	0.3368	0.5150	0.6567	0.5327	0.4299	0.5030	0.4061
Three Outside Up	0.5000	0.4507	0.5060	0.4320	0.4918	0.4405	0.5083	0.3826
Tweezer Bottom	0.5012	0.5274	0.4984	0.5217	0.4982	0.4738	0.4901	0.4304

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.4179	0.1818	0.4156	0.1819	0.3634	0.3507	0.3487	0.2407
Black Marubozu	0.4622	0.4321	0.4586	0.4230	0.3804	0.5611	0.3689	0.5302
Closing Black Marubozu	0.4646	0.3691	0.4564	0.3663	0.4347	0.4575	0.4307	0.3890
Opening Black Marubozu	0.4838	0.2609	0.4807	0.2655	0.4270	0.3611	0.4203	0.2634
Gravestone Doji	0.3673	0.7685	0.3714	0.7667	0.4201	0.6928	0.4224	0.6967
White Shooting Star	0.5164	0.5794	0.5222	0.5780	0.5306	0.5761	0.5308	0.5500
Black Shooting Star	0.4380	0.7438	0.4430	0.7470	0.4599	0.6867	0.4551	0.6798
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4884	0.5165	0.4902	0.5160	0.4736	0.5670	0.4923	0.5945
Bearish Engulfing	0.4709	0.4384	0.4733	0.4396	0.4414	0.4851	0.4721	0.5410
Dark Cloud Cover	0.4774	0.4818	0.4708	0.4649	0.4981	0.5004	0.5194	0.5298
Bearish Harami	0.5259	0.4455	0.5374	0.4486	0.5621	0.5035	0.5881	0.5470
Three Inside Down	0.5000	0.2963	0.4725	0.4396	0.5547	0.4236	0.5703	0.4444
Three Outside Down	0.4010	0.5411	0.4056	0.4779	0.4137	0.4510	0.4371	0.4943
Tweezer Top	0.4769	0.5919	0.4829	0.5892	0.4725	0.5611	0.4981	0.6127

The results displayed in Tables 9 and 10 indicate that the *p*-values for a particular rule tend to be indicative of the difference between the mean returns and standard deviations on the original and bootstrapped series. For instance, the mean daily return following a Long White single line on the random walk bootstrapped series is 0.0002 whereas the mean daily return following a Long White single line on the Dow stock series is 0.0000. This is expected because the corresponding simulated *p*-value of 0.5805 suggests that the returns following a Long White single line are larger on the bootstrapped series 58% of the time. The alternative situation is a *p*-value that indicates higher returns on the bootstrapped series than the original Dow stock series more than 50% of the time and lower mean daily returns on the bootstrap series than the original. This is a rare occurrence. One example is the Black Shooting Star and the random walk null model. The *p*-value is 0.4380 indicating that the returns following the pattern are larger on the bootstrapped series than the original 43.8% of the time. However, the mean daily return following this pattern on the random walk bootstrapped series is 0.001 compared to -0.002 on the original. This suggests there are a few very small returns on the bootstrap series and / or very large returns on the original series that are influencing the mean returns.

The consistency of the results across the four null models is also very evident. The mean returns on the bootstrapped series following the Hammer single line are 0.0002, 0.0002, 0.0003, and 0.0001 for the random walk, AR(1), GARCH-M, and EGARCH models respectively. The corresponding standard deviations on each of the bootstrapped series are 0.0083, 0.0081, 0.0089, and 0.0077 respectively.

Table 9: Scenario B: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0102	0.0000	0.0103	0.0001	0.0102	0.0000	0.0103
White Marubozu	0.0002	0.0093	0.0000	0.0087	0.0002	0.0094	0.0000	0.0087
Closing White Marubozu	0.0002	0.0099	0.0000	0.0097	0.0002	0.0099	0.0000	0.0097
Opening White Marubozu	0.0002	0.0097	-0.0002	0.0101	0.0002	0.0098	-0.0002	0.0101
Dragonfly Doji	0.0002	0.0097	0.0000	0.0075	0.0002	0.0097	0.0000	0.0075
White Paper Umbrella	0.0002	0.0098	0.0003	0.0085	0.0002	0.0098	0.0003	0.0085
Black Paper Umbrella	0.0002	0.0096	-0.0001	0.0090	0.0002	0.0096	-0.0001	0.0090
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0083	0.0004	0.0076	0.0002	0.0081	0.0004	0.0076
Bullish Engulfing	0.0001	0.0089	0.0003	0.0101	0.0001	0.0091	0.0003	0.0101
Piercing Line	0.0000	0.0097	-0.0002	0.0105	0.0001	0.0097	-0.0002	0.0105
Bullish Harami	0.0002	0.0093	0.0005	0.0105	0.0003	0.0092	0.0005	0.0105
Three Inside Up	0.0017	0.0090	0.0003	0.0084	0.0021	0.0091	0.0003	0.0084
Three Outside Up	0.0002	0.0085	-0.0001	0.0092	0.0000	0.0082	-0.0001	0.0092
Tweezer Bottom	0.0001	0.0085	0.0003	0.0098	0.0001	0.0085	0.0003	0.0098

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0102	0.0003	0.0108	0.0002	0.0102	0.0003	0.0108
Black Marubozu	0.0002	0.0099	0.0002	0.0098	0.0001	0.0098	0.0002	0.0098
Closing Black Marubozu	0.0002	0.0101	0.0005	0.0103	0.0001	0.0101	0.0005	0.0103
Opening Black Marubozu	0.0001	0.0099	0.0002	0.0108	0.0001	0.0098	0.0002	0.0108
Gravestone Doji	0.0002	0.0099	0.0005	0.0076	0.0002	0.0098	0.0005	0.0076
White Shooting Star	0.0002	0.0097	-0.0003	0.0098	0.0002	0.0098	-0.0003	0.0098
Black Shooting Star	0.0001	0.0101	-0.0002	0.0092	0.0002	0.0101	-0.0002	0.0092
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0087	0.0005	0.0083	0.0002	0.0087	0.0005	0.0083
Bearish Engulfing	0.0002	0.0095	0.0004	0.0095	0.0003	0.0096	0.0004	0.0095
Dark Cloud Cover	0.0002	0.0101	0.0001	0.0092	0.0001	0.0102	0.0001	0.0092
Bearish Harami	0.0002	0.0095	0.0000	0.0097	0.0002	0.0095	0.0000	0.0097
Three Inside Down	0.0000	0.0079	-0.0001	0.0097	-0.0002	0.0094	-0.0001	0.0097
Three Outside Down	0.0003	0.0088	0.0010	0.0096	0.0001	0.0091	0.0010	0.0096
Tweezer Top	0.0002	0.0093	0.0002	0.0083	0.0002	0.0092	0.0002	0.0083

Table 10: Scenario B: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0111	0.0000	0.0103	0.0001	0.0105	0.0000	0.0103
White Marubozu	0.0002	0.0107	0.0000	0.0087	0.0002	0.0101	0.0000	0.0087
Closing White Marubozu	0.0002	0.0110	0.0000	0.0097	0.0002	0.0104	0.0000	0.0097
Opening White Marubozu	0.0002	0.0110	-0.0002	0.0101	0.0001	0.0104	-0.0002	0.0101
Dragonfly Doji	0.0001	0.0101	0.0000	0.0075	0.0002	0.0096	0.0000	0.0075
White Paper Umbrella	0.0002	0.0104	0.0003	0.0085	0.0002	0.0097	0.0003	0.0085
Black Paper Umbrella	0.0002	0.0105	-0.0001	0.0090	0.0002	0.0099	-0.0001	0.0090
Panel B: Bullish Reversal Patterns								
Hammer	0.0003	0.0089	0.0004	0.0076	0.0001	0.0077	0.0004	0.0076
Bullish Engulfing	0.0000	0.0097	0.0003	0.0101	0.0000	0.0090	0.0003	0.0101
Piercing Line	0.0001	0.0094	-0.0002	0.0105	0.0000	0.0089	-0.0002	0.0105
Bullish Harami	0.0002	0.0092	0.0005	0.0105	0.0001	0.0085	0.0005	0.0105
Three Inside Up	0.0003	0.0088	0.0003	0.0084	0.0003	0.0083	0.0003	0.0084
Three Outside Up	0.0002	0.0087	-0.0001	0.0092	0.0002	0.0080	-0.0001	0.0092
Tweezer Bottom	0.0001	0.0088	0.0003	0.0098	0.0001	0.0081	0.0003	0.0098

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0111	0.0003	0.0108	0.0001	0.0104	0.0003	0.0108
Black Marubozu	0.0002	0.0107	0.0002	0.0098	0.0002	0.0102	0.0002	0.0098
Closing Black Marubozu	0.0001	0.0110	0.0005	0.0103	0.0001	0.0105	0.0005	0.0103
Opening Black Marubozu	0.0002	0.0110	0.0002	0.0108	0.0001	0.0104	0.0002	0.0108
Gravestone Doji	0.0002	0.0103	0.0005	0.0076	0.0002	0.0098	0.0005	0.0076
White Shooting Star	0.0002	0.0106	-0.0003	0.0098	0.0002	0.0100	-0.0003	0.0098
Black Shooting Star	0.0002	0.0107	-0.0002	0.0092	0.0002	0.0102	-0.0002	0.0092
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0100	0.0005	0.0083	0.0003	0.0100	0.0005	0.0083
Bearish Engulfing	0.0002	0.0103	0.0004	0.0095	0.0003	0.0104	0.0004	0.0095
Dark Cloud Cover	0.0002	0.0102	0.0001	0.0092	0.0003	0.0103	0.0001	0.0092
Bearish Harami	0.0002	0.0104	0.0000	0.0097	0.0003	0.0105	0.0000	0.0097
Three Inside Down	0.0003	0.0090	-0.0001	0.0097	0.0003	0.0096	-0.0001	0.0097
Three Outside Down	0.0000	0.0090	0.0010	0.0096	0.0002	0.0092	0.0010	0.0096
Tweezer Top	0.0002	0.0098	0.0002	0.0083	0.0003	0.0097	0.0002	0.0083

4.3.3. Scenario C: Trade initiated at the Open Price on the Day after the Signal, a Ten-Day Holding Period, and a Ten-Day Exponential Moving Average to Determine Prior Trend

Scenario C moves to a more realistic stance on entry points. It is based around entering the market at the opening price on the day following a signal. The results displayed in Table 11 suggest that results are not sensitive to this assumption change. Bullish single lines and reversal patterns do not reflect higher than average returns. If anything, the results suggest that future returns are likely to be lower. In contrast to Scenarios A and B, the returns following the Long White line are statistically significantly less than the unconditional mean, but consistent with Scenario A (Scenario B) the Dragonfly Doji (Opening White Marubozu) is followed by returns that are statistically significantly less than the unconditional return. The results in

Panels C and D indicate that the Scenario C bearish single lines and reversal pattern results are very similar to their Scenario B counterparts. The conditional minus unconditional mean differences are all positive with the exception of the Bearish Harami and Three Inside Down patterns. The Long Black, Black Marubozu, and Closing Black Marubozu means are positive and statistically significant. This suggests that the returns following these three bearish single lines are larger than the unconditional market return, the exact opposite to what candlestick technical analysis theory suggests.

Table 11: Scenario C: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2947	0.4760	0.0000	-2.131*
White Marubozu	642	0.4581	0.0004	0.028
Closing White Marubozu	1565	0.4726	0.0002	-0.540
Opening White Marubozu	1611	0.4703	0.0000	-2.054*
Dragonfly Doji	270	0.4419	-0.0003	-2.084*
White Paper Umbrella	567	0.4771	0.0005	0.659
Black Paper Umbrella	727	0.4670	0.0002	-0.814
Panel B: Bullish Reversal Patterns				
Hammer	57	0.4965	0.0007	0.457
Bullish Engulfing	252	0.4905	0.0004	0.193
Piercing Line	138	0.4717	-0.0004	-1.334
Bullish Harami	115	0.5087	0.0006	0.404
Three Inside Up	17	0.5000	0.0010	0.428
Three Outside Up	56	0.4839	-0.0002	-0.693
Tweezer Bottom	354	0.4768	0.0001	-0.535

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2661	0.4919	0.0007	2.499*
Black Marubozu	557	0.4867	0.0011	2.503*
Closing Black Marubozu	1022	0.4877	0.0009	2.485*
Opening Black Marubozu	1737	0.4856	0.0005	1.064
Gravestone Doji	191	0.4644	0.0009	1.301
White Shooting Star	520	0.4829	0.0005	0.579
Black Shooting Star	465	0.4884	0.0005	0.778
Panel D: Bearish Reversal Patterns				
Hanging Man	84	0.4833	0.0009	0.917
Bearish Engulfing	289	0.5000	0.0007	0.921
Dark Cloud Cover	117	0.4718	0.0004	0.125
Bearish Harami	396	0.4753	0.0002	-0.549
Three Inside Down	34	0.4735	-0.0007	-1.020
Three Outside Down	36	0.5111	0.0020	1.622
Tweezer Top	407	0.4737	0.0007	1.410

**statistically significant at the 1% level, *statistically significant at the 5% level

Evidence of the poor performance of the bullish single lines under the Scenario C assumptions is also evident in the bootstrapping results displayed in Table 12 Panel A. The returns following a buy signal are greater on all the randomly generated null model bootstrap series than the original more than 50% of the time for all rules other than the White Paper Umbrella under all null models and White Marubozu under the AR(1) null model.

The consistency of results across the four models is evident once again. The proportion of times that there are higher returns on the bootstrapped series than the original for the Long Black single line (Panel C) is 0.3931 for the random walk model, 0.3944 for the AR(1) model, 0.4038 for the GARCH-M model, and 0.3871 for EGARCH.

Table 12: Scenario C: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5791	0.2850	0.5810	0.2806	0.5916	0.3855	0.5884	0.3179
White Marubozu	0.5171	0.5118	0.4989	0.5152	0.5113	0.4410	0.5092	0.4603
Closing White Marubozu	0.5194	0.4521	0.5117	0.4483	0.5178	0.4155	0.5304	0.4146
Opening White Marubozu	0.5592	0.4215	0.5520	0.4284	0.5619	0.4170	0.5631	0.3988
Dragonfly Doji	0.6061	0.8849	0.6046	0.8857	0.6129	0.8649	0.6032	0.8559
White Paper Umbrella	0.4567	0.6802	0.4494	0.6730	0.4603	0.6422	0.4525	0.6307
Black Paper Umbrella	0.5510	0.7665	0.5493	0.7662	0.5580	0.7395	0.5474	0.7194
Panel B: Bullish Reversal Patterns								
Hammer	0.4597	0.6599	0.4486	0.6549	0.4533	0.5657	0.4698	0.5644
Bullish Engulfing	0.4902	0.3460	0.4936	0.3548	0.4825	0.3081	0.4991	0.3109
Piercing Line	0.5730	0.3483	0.5460	0.3937	0.5601	0.3798	0.5607	0.3894
Bullish Harami	0.4953	0.2804	0.4468	0.2726	0.4732	0.2780	0.4958	0.2706
Three Inside Up	0.3749	0.3854	0.5013	0.3025	0.5054	0.5112	0.5833	0.5113
Three Outside Up	0.5189	0.4104	0.5236	0.3949	0.5413	0.3884	0.5064	0.3734
Tweezer Bottom	0.5086	0.5724	0.5054	0.5659	0.5092	0.4679	0.4986	0.4171
	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.3931	0.1495	0.3944	0.1479	0.4038	0.2706	0.3871	0.1997
Black Marubozu	0.4344	0.4289	0.4264	0.4284	0.4333	0.3810	0.4320	0.3854
Closing Black Marubozu	0.4476	0.3514	0.4461	0.3443	0.4458	0.3388	0.4535	0.3336
Opening Black Marubozu	0.4768	0.2490	0.4741	0.2551	0.4694	0.2984	0.4828	0.2726
Gravestone Doji	0.3377	0.7754	0.3412	0.7777	0.3450	0.7640	0.3402	0.7575
White Shooting Star	0.4845	0.6023	0.4882	0.6099	0.4934	0.5933	0.4787	0.5509
Black Shooting Star	0.4409	0.6918	0.4444	0.6952	0.4485	0.6492	0.4450	0.6332
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4790	0.5754	0.4890	0.5797	0.4714	0.5104	0.4910	0.5696
Bearish Engulfing	0.4879	0.4142	0.4865	0.4201	0.4819	0.3444	0.4832	0.3509
Dark Cloud Cover	0.4883	0.4151	0.4632	0.4525	0.4993	0.4528	0.4917	0.4300
Bearish Harami	0.5194	0.4419	0.5159	0.4604	0.5246	0.3864	0.5273	0.3998
Three Inside Down	0.5921	0.3289	0.4978	0.3939	0.4884	0.2636	0.5221	0.3133
Three Outside Down	0.4762	0.5238	0.3618	0.3769	0.3622	0.3676	0.4192	0.3939
Tweezer Top	0.4751	0.6199	0.4688	0.6253	0.4640	0.5069	0.4889	0.5467

Tables 13 and 14 indicate that the Scenario C assumptions lead to similar sized bootstrapping and original series means as Scenario A and B. The bootstrapped *p*-value is generally indicative of the size of the bootstrapped and original series means (e.g. the Long White single line under the random walk null model), but this is not always the case (e.g. the Three Outside Down pattern under the random walk null model).

Table 13: Scenario C: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0103	0.0000	0.0104	0.0001	0.0103	0.0000	0.0104
White Marubozu	0.0003	0.0096	0.0000	0.0085	0.0002	0.0095	0.0000	0.0085
Closing White Marubozu	0.0002	0.0099	0.0000	0.0098	0.0002	0.0098	0.0000	0.0098
Opening White Marubozu	0.0002	0.0099	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0098	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0097	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0099	-0.0002	0.0089	0.0002	0.0099	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0083	0.0003	0.0071	0.0001	0.0082	0.0003	0.0071
Bullish Engulfing	0.0002	0.0090	0.0002	0.0102	0.0002	0.0090	0.0002	0.0102
Piercing Line	0.0001	0.0098	-0.0003	0.0104	0.0001	0.0105	-0.0003	0.0104
Bullish Harami	0.0003	0.0090	0.0004	0.0108	0.0000	0.0091	0.0004	0.0108
Three Inside Up	-0.0003	0.0076	0.0004	0.0085	0.0008	0.0076	0.0004	0.0085
Three Outside Up	0.0001	0.0086	0.0001	0.0100	0.0005	0.0081	0.0001	0.0100
Tweezer Bottom	0.0001	0.0089	0.0002	0.0099	0.0002	0.0088	0.0002	0.0099

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0103	0.0003	0.0110	0.0002	0.0102	0.0003	0.0110
Black Marubozu	0.0002	0.0096	0.0004	0.0097	0.0001	0.0096	0.0004	0.0097
Closing Black Marubozu	0.0001	0.0100	0.0005	0.0104	0.0001	0.0098	0.0005	0.0104
Opening Black Marubozu	0.0002	0.0100	0.0002	0.0109	0.0002	0.0101	0.0002	0.0109
Gravestone Doji	0.0002	0.0099	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0100	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Black Shooting Star	0.0002	0.0099	-0.0002	0.0093	0.0002	0.0100	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0092	0.0005	0.0082	0.0002	0.0092	0.0005	0.0082
Bearish Engulfing	0.0002	0.0096	0.0002	0.0099	0.0002	0.0096	0.0002	0.0099
Dark Cloud Cover	0.0002	0.0104	0.0001	0.0100	-0.0001	0.0105	0.0001	0.0100
Bearish Harami	0.0002	0.0096	0.0001	0.0097	0.0002	0.0097	0.0001	0.0097
Three Inside Down	0.0004	0.0087	0.0002	0.0094	-0.0001	0.0091	0.0002	0.0094
Three Outside Down	0.0004	0.0088	0.0011	0.0096	0.0001	0.0087	0.0011	0.0096
Tweezer Top	0.0002	0.0095	0.0003	0.0083	0.0002	0.0095	0.0003	0.0083

Table 14: Scenario C: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0107	0.0000	0.0104	0.0001	0.0103	0.0000	0.0104
White Marubozu	0.0003	0.0095	0.0000	0.0085	0.0001	0.0094	0.0000	0.0085
Closing White Marubozu	0.0002	0.0099	0.0000	0.0098	0.0002	0.0097	0.0000	0.0098
Opening White Marubozu	0.0002	0.0102	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0004	0.0103	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0100	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0103	-0.0002	0.0089	0.0002	0.0099	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0084	0.0003	0.0071	0.0001	0.0078	0.0003	0.0071
Bullish Engulfing	0.0002	0.0088	0.0002	0.0102	0.0001	0.0087	0.0002	0.0102
Piercing Line	0.0002	0.0108	-0.0003	0.0104	0.0000	0.0109	-0.0003	0.0104
Bullish Harami	0.0001	0.0090	0.0004	0.0108	0.0004	0.0088	0.0004	0.0108
Three Inside Up	0.0005	0.0078	0.0004	0.0085	0.0006	0.0079	0.0004	0.0085
Three Outside Up	0.0003	0.0091	0.0001	0.0100	0.0000	0.0086	0.0001	0.0100
Tweezer Bottom	0.0002	0.0085	0.0002	0.0099	0.0001	0.0080	0.0002	0.0099

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0003	0.0110	0.0001	0.0103	0.0003	0.0110
Black Marubozu	0.0002	0.0096	0.0004	0.0097	0.0001	0.0095	0.0004	0.0097
Closing Black Marubozu	0.0002	0.0100	0.0005	0.0104	0.0002	0.0098	0.0005	0.0104
Opening Black Marubozu	0.0002	0.0103	0.0002	0.0109	0.0002	0.0099	0.0002	0.0109
Gravestone Doji	0.0002	0.0103	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0004	0.0105	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Black Shooting Star	0.0002	0.0103	-0.0002	0.0093	0.0002	0.0099	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0093	0.0005	0.0082	0.0003	0.0094	0.0005	0.0082
Bearish Engulfing	0.0002	0.0091	0.0002	0.0099	0.0002	0.0091	0.0002	0.0099
Dark Cloud Cover	0.0002	0.0111	0.0001	0.0100	0.0002	0.0103	0.0001	0.0100
Bearish Harami	0.0002	0.0093	0.0001	0.0097	0.0002	0.0092	0.0001	0.0097
Three Inside Down	-0.0001	0.0078	0.0002	0.0094	0.0006	0.0082	0.0002	0.0094
Three Outside Down	0.0003	0.0087	0.0011	0.0096	0.0004	0.0081	0.0011	0.0096
Tweezer Top	0.0002	0.0091	0.0003	0.0083	0.0003	0.0093	0.0003	0.0083

4.3.4. Scenario D: Trade initiated at the Open Price on the Day after the Signal, a Five-Day Holding Period, and a Ten-Day Exponential Moving Average to Determine Prior Trend

The results displayed in Table 15 indicate that moving to the shorter holding period of five days leads to an increase in the number of observations of each pattern. For example, there are now 3,727 instances of the Long White compared to 2,952 in Scenario A. It is also evident that the move to a shorter moving average does not improve the performance for candlestick trading rules over that which is documented in Scenarios A-C. Three of the bullish single lines lead to returns that are statistically significantly less than the unconditional return.

In addition, the proportion of returns following a bullish single line that are positive, has also declined. However, there is less deterioration in the bullish reversal patterns. In fact, the Bullish Engulfing pattern now leads to returns that are statistically significantly greater than the unconditional return. This is what candlestick theory suggests. However, this result is the only one that provides support for the claim that candlestick technical analysis is more effective over a five-day horizon. The performance of bearish single lines has also declined further. The differences between the conditional and unconditional returns for the Long Black, Black Marubozu, and Closing Black Marubozu are all more strongly statistically significantly than in Scenarios A to C.

Table 15: Scenario D: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	3727	0.4717	-0.0001	-2.451*
White Marubozu	681	0.4426	-0.0003	-2.143*
Closing White Marubozu	1741	0.4555	-0.0003	-2.932**
Opening White Marubozu	1802	0.4690	-0.0001	-2.002
Dragonfly Doji	287	0.4279	-0.0004	-1.780
White Paper Umbrella	602	0.4731	0.0006	0.758
Black Paper Umbrella	766	0.4684	0.0002	-0.545
Panel B: Bullish Reversal Patterns				
Hammer	58	0.5034	0.0011	0.729
Bullish Engulfing	259	0.5097	0.0020	2.716**
Piercing Line	143	0.4783	-0.0004	-0.991
Bullish Harami	115	0.5078	0.0009	0.587
Three Inside Up	17	0.4235	-0.0017	-1.233
Three Outside Up	56	0.4786	0.0005	0.065
Tweezer Bottom	362	0.4801	0.0003	0.004

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	3354	0.5029	0.0011	4.130**
Black Marubozu	604	0.4921	0.0013	2.568*
Closing Black Marubozu	1106	0.5051	0.0017	4.549**
Opening Black Marubozu	1955	0.4887	0.0006	0.998
Gravestone Doji	202	0.4406	-0.0001	-1.014
White Shooting Star	536	0.4854	0.0004	0.208
Black Shooting Star	479	0.4914	0.0005	0.444
Panel D: Bearish Reversal Patterns				
Hanging Man	84	0.4905	0.0018	1.778
Bearish Engulfing	296	0.5169	0.0009	1.206
Dark Cloud Cover	117	0.4581	-0.0001	-0.440
Bearish Harami	404	0.4733	0.0002	-0.287
Three Inside Down	34	0.4706	-0.0005	-0.550
Three Outside Down	36	0.5389	0.0034	1.983
Tweezer Top	417	0.4839	0.0010	1.858

**statistically significant at the 1% level, *statistically significant at the 5% level

The bootstrap results displayed in Table 16 are consistent with the *t*-test results from Table 15. The bootstrap means proportions are higher (lower) than their Scenario C counterparts for bullish (bearish) single lines. While not statistically significant, this indicates that the bullish (bearish) single lines are more likely to signal price decreases (increases) than would be expected by chance. This is the opposite to what candlestick technical analysis theory suggests.

The consistency of results across the four null models is once again evident. The White Paper Umbrella has buy return *p*-values of 0.4761, 0.4653, 0.4745, and 0.4704 for the random walk, AR(1), GARCH-M, and EGARCH null models respectively.

Table 16: Scenario D: Bootstrap Proportions for all Null Models

Candlestick	RW Buy	RW σ_b	AR(1) Buy	AR(1) σ_b	GARCH-M Buy	GARCH-M σ_b	EGARCH Buy	EGARCH σ_b
Panel A: Bullish Single Lines								
Long White	0.5903	0.2822	0.5885	0.2786	0.5991	0.3575	0.5957	0.3076
White Marubozu	0.5443	0.4781	0.5429	0.4872	0.5413	0.4290	0.5439	0.4487
Closing White Marubozu	0.5527	0.4273	0.5463	0.4274	0.5462	0.4096	0.5541	0.4143
Opening White Marubozu	0.5536	0.3719	0.5624	0.3866	0.5567	0.3816	0.5591	0.3715
Dragonfly Doji	0.6466	0.8215	0.6457	0.8214	0.6458	0.8058	0.6502	0.8026
White Paper Umbrella	0.4761	0.6670	0.4653	0.6742	0.4745	0.6454	0.4704	0.6398
Black Paper Umbrella	0.5305	0.7365	0.5241	0.7383	0.5306	0.7225	0.5361	0.7094
Panel B: Bullish Reversal Patterns								
Hammer	0.4887	0.5810	0.4742	0.5850	0.4712	0.5429	0.4627	0.5066
Bullish Engulfing	0.4234	0.3675	0.4306	0.3753	0.4195	0.3354	0.4308	0.3384
Piercing Line	0.5627	0.3514	0.5259	0.3592	0.5875	0.3858	0.5929	0.3894
Bullish Harami	0.4729	0.2671	0.4900	0.3190	0.4592	0.2727	0.4625	0.2662
Three Inside Up	0.5455	0.6364	0.5655	0.3850	0.4625	0.3580	0.4356	0.4156
Three Outside Up	0.5253	0.3733	0.5157	0.4395	0.5221	0.3735	0.5362	0.3489
Tweezer Bottom	0.5033	0.5055	0.5138	0.5028	0.5032	0.4412	0.4995	0.3865

Candlestick	RW Sell	RW σ_s	AR(1) Sell	AR(1) σ_s	GARCH-M Sell	GARCH-M σ_s	EGARCH Sell	EGARCH σ_s
Panel C: Bearish Single Lines								
Long Black	0.3483	0.1557	0.3434	0.1533	0.3477	0.2547	0.3406	0.1887
Black Marubozu	0.4281	0.4035	0.4266	0.4075	0.4182	0.3802	0.4306	0.3850
Closing Black Marubozu	0.4044	0.3415	0.4035	0.3371	0.3976	0.3358	0.4019	0.3332
Opening Black Marubozu	0.4735	0.2518	0.4827	0.2534	0.4804	0.2882	0.4830	0.2671
Gravestone Doji	0.4669	0.7878	0.4552	0.7890	0.4680	0.7714	0.4587	0.7689
White Shooting Star	0.5262	0.6302	0.5230	0.6281	0.5295	0.6248	0.5168	0.6032
Black Shooting Star	0.4659	0.6623	0.4711	0.6640	0.4751	0.6412	0.4756	0.6383
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4633	0.5944	0.4509	0.6008	0.4530	0.5470	0.4654	0.5828
Bearish Engulfing	0.4630	0.4108	0.4731	0.4165	0.4750	0.3570	0.4655	0.3778
Dark Cloud Cover	0.4942	0.4313	0.5149	0.4034	0.5143	0.3883	0.5093	0.4211
Bearish Harami	0.5020	0.4250	0.5099	0.4303	0.5118	0.3840	0.5140	0.3872
Three Inside Down	0.5042	0.3167	0.5378	0.3307	0.5316	0.3502	0.5404	0.2596
Three Outside Down	0.3263	0.3474	0.3854	0.3958	0.3548	0.3333	0.3051	0.3517
Tweezer Top	0.4584	0.5673	0.4530	0.5700	0.4432	0.4880	0.4705	0.5394

The results displayed in Tables 17 and 18 indicate that the means and standard deviations of the original and bootstrapped series are very similar to their Scenario C counterparts. For instance, the Long White single line under the random walk null model has a mean return (standard deviation of returns) of 0.002 and 0.0103 in Scenario C and 0.002 and 0.0102 in Scenario D.

The bootstrapped means continue to be very consistent across the four null models. The mean returns following the Hanging Man bearish reversal pattern are 0.0003, 0.0002, 0.0002, and 0.0003 for the random walk, AR(1), GARCH-M, and EGARCH models respectively. This confirms the robustness of the results.

Table 17: Scenario D: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0102	-0.0001	0.0106	0.0002	0.0101	-0.0001	0.0106
White Marubozu	0.0002	0.0092	-0.0004	0.0084	0.0002	0.0092	-0.0004	0.0084
Closing White Marubozu	0.0002	0.0095	-0.0002	0.0095	0.0002	0.0095	-0.0002	0.0095
Opening White Marubozu	0.0002	0.0098	-0.0003	0.0101	0.0002	0.0098	-0.0003	0.0101
Dragonfly Doji	0.0002	0.0097	-0.0004	0.0074	0.0002	0.0098	-0.0004	0.0074
White Paper Umbrella	0.0002	0.0096	0.0001	0.0082	0.0002	0.0096	0.0001	0.0082
Black Paper Umbrella	0.0002	0.0099	0.0000	0.0083	0.0002	0.0098	0.0000	0.0083
Panel B: Bullish Reversal Patterns								
Hammer	0.0003	0.0080	0.0004	0.0070	0.0002	0.0080	0.0004	0.0070
Bullish Engulfing	0.0001	0.0086	0.0010	0.0100	0.0001	0.0087	0.0010	0.0100
Piercing Line	-0.0001	0.0095	-0.0004	0.0101	-0.0002	0.0093	-0.0004	0.0101
Bullish Harami	0.0004	0.0090	0.0003	0.0109	0.0002	0.0090	0.0003	0.0109
Three Inside Up	-0.0021	0.0118	-0.0012	0.0079	0.0023	0.0101	-0.0012	0.0079
Three Outside Up	0.0001	0.0076	0.0002	0.0093	-0.0001	0.0092	0.0002	0.0093
Tweezer Bottom	0.0001	0.0085	0.0002	0.0093	0.0002	0.0084	0.0002	0.0093

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0102	0.0005	0.0113	0.0002	0.0102	0.0005	0.0113
Black Marubozu	0.0002	0.0092	0.0010	0.0089	0.0002	0.0093	0.0010	0.0089
Closing Black Marubozu	0.0002	0.0096	0.0009	0.0103	0.0002	0.0096	0.0009	0.0103
Opening Black Marubozu	0.0002	0.0099	0.0001	0.0110	0.0002	0.0099	0.0001	0.0110
Gravestone Doji	0.0002	0.0099	0.0003	0.0074	0.0002	0.0098	0.0003	0.0074
White Shooting Star	0.0002	0.0100	-0.0001	0.0097	0.0002	0.0099	-0.0001	0.0097
Black Shooting Star	0.0001	0.0098	0.0000	0.0090	0.0001	0.0098	0.0000	0.0090
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0089	0.0008	0.0078	0.0002	0.0090	0.0008	0.0078
Bearish Engulfing	0.0002	0.0091	0.0003	0.0096	0.0002	0.0093	0.0003	0.0096
Dark Cloud Cover	0.0003	0.0102	0.0000	0.0102	0.0002	0.0098	0.0000	0.0102
Bearish Harami	0.0002	0.0091	0.0001	0.0098	0.0003	0.0093	0.0001	0.0098
Three Inside Down	0.0002	0.0084	0.0003	0.0098	0.0003	0.0079	0.0003	0.0098
Three Outside Down	-0.0003	0.0083	0.0016	0.0105	0.0006	0.0085	0.0016	0.0105
Tweezer Top	0.0002	0.0090	0.0005	0.0084	0.0002	0.0091	0.0005	0.0084

Table 18: Scenario D: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0107	-0.0001	0.0106	0.0002	0.0102	-0.0001	0.0106
White Marubozu	0.0003	0.0092	-0.0004	0.0084	0.0002	0.0091	-0.0004	0.0084
Closing White Marubozu	0.0002	0.0096	-0.0002	0.0095	0.0002	0.0095	-0.0002	0.0095
Opening White Marubozu	0.0002	0.0101	-0.0003	0.0101	0.0002	0.0098	-0.0003	0.0101
Dragonfly Doji	0.0002	0.0102	-0.0004	0.0074	0.0002	0.0098	-0.0004	0.0074
White Paper Umbrella	0.0002	0.0099	0.0001	0.0082	0.0002	0.0096	0.0001	0.0082
Black Paper Umbrella	0.0002	0.0103	0.0000	0.0083	0.0002	0.0099	0.0000	0.0083
Panel B: Bullish Reversal Patterns								
Hammer	0.0003	0.0081	0.0004	0.0070	0.0001	0.0074	0.0004	0.0070
Bullish Engulfing	0.0002	0.0086	0.0010	0.0100	0.0002	0.0084	0.0010	0.0100
Piercing Line	-0.0004	0.0103	-0.0004	0.0101	0.0004	0.0107	-0.0004	0.0101
Bullish Harami	0.0002	0.0085	0.0003	0.0109	0.0000	0.0090	0.0003	0.0109
Three Inside Up	0.0014	0.0055	-0.0012	0.0079	-0.0020	0.0064	-0.0012	0.0079
Three Outside Up	0.0000	0.0083	0.0002	0.0093	-0.0002	0.0077	0.0002	0.0093
Tweezer Bottom	0.0001	0.0083	0.0002	0.0093	0.0000	0.0076	0.0002	0.0093

Candlestick	GARCH-M Bootstrap Sell	GARCH-M Bootstrap σ_s	GARCH-M Dow Sell	GARCH-M Dow σ_s	EGARCH Bootstrap Sell	EGARCH Bootstrap σ_s	EGARCH Dow Sell	EGARCH Dow σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0005	0.0113	0.0002	0.0103	0.0005	0.0113
Black Marubozu	0.0002	0.0092	0.0010	0.0089	0.0002	0.0091	0.0010	0.0089
Closing Black Marubozu	0.0002	0.0097	0.0009	0.0103	0.0001	0.0096	0.0009	0.0103
Opening Black Marubozu	0.0002	0.0102	0.0001	0.0110	0.0002	0.0099	0.0001	0.0110
Gravestone Doji	0.0002	0.0102	0.0003	0.0074	0.0002	0.0098	0.0003	0.0074
White Shooting Star	0.0002	0.0103	-0.0001	0.0097	0.0001	0.0100	-0.0001	0.0097
Black Shooting Star	0.0002	0.0101	0.0000	0.0090	0.0002	0.0097	0.0000	0.0090
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0090	0.0008	0.0078	0.0003	0.0091	0.0008	0.0078
Bearish Engulfing	0.0002	0.0088	0.0003	0.0096	0.0002	0.0088	0.0003	0.0096
Dark Cloud Cover	0.0002	0.0103	0.0000	0.0102	-0.0001	0.0102	0.0000	0.0102
Bearish Harami	0.0002	0.0092	0.0001	0.0098	0.0001	0.0090	0.0001	0.0098
Three Inside Down	0.0004	0.0079	0.0003	0.0098	0.0000	0.0073	0.0003	0.0098
Three Outside Down	0.0004	0.0078	0.0016	0.0105	0.0000	0.0084	0.0016	0.0105
Tweezer Top	0.0002	0.0087	0.0005	0.0084	0.0003	0.0090	0.0005	0.0084

4.3.5. Scenario E: Trade initiated at the Open Price on the Day after the Signal, a Two-Day Holding Period, and a Ten-Day Exponential Moving Average to Determine Prior Trend

In section 4.3.5 the possibility of achieving short-term candlestick profitability by considering two-day holding periods is investigated. It is possible that the profitability of candlestick technical analysis may cease after very short holding periods. If this is the case, candlestick technical analysis might not be able to be used profitably as a stand alone strategy due to its incursion of high transaction costs. However, it might be a valuable timing mechanism for fund managers who have to buy or sell shares for portfolio rebalancing purposes. As expected, there is considerably more realisations of each candlestick under this scenario. For instance, the Long White single line is observed 4,483 times compared to 2,947 times in Scenario C.

The results displayed in Panels A and B suggest that the bullish lines and reversal patterns are less effective than they were under the Scenario C assumptions. All of the bullish single line conditional minus unconditional mean returns are negative and all the bullish reversal patterns, except the Hammer and Bullish Engulfing patterns, have negative mean differences. The results displayed in Panels C and D indicate that the bearish single lines and reversal patterns are also poorer performers under the two-day holding period assumption. The conditional minus unconditional means are all positive, with the exception of the Dark Cloud Cover. This indicates that the bearish candlesticks actually indicate higher than average conditional returns, the opposite to what candlestick theory suggests.

Table 19: Scenario E: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	4483	0.4539	-0.0007	-4.289**
White Marubozu	709	0.4457	-0.0001	-0.855
Closing White Marubozu	1900	0.4384	-0.0009	-3.979**
Opening White Marubozu	1937	0.4750	0.0001	-0.753
Dragonfly Doji	299	0.4181	-0.0007	-1.539
White Paper Umbrella	620	0.4613	0.0003	-0.075
Black Paper Umbrella	795	0.4409	-0.0004	-1.718
Panel B: Bullish Reversal Patterns				
Hammer	58	0.5517	0.0027	1.712
Bullish Engulfing	261	0.4962	0.0022	1.888
Piercing Line	143	0.4720	-0.0016	-1.533
Bullish Harami	117	0.5171	-0.0001	-0.279
Three Inside Up	17	0.4706	-0.0005	-0.322
Three Outside Up	56	0.4286	-0.0030	-1.872
Tweezer Bottom	362	0.4986	0.0003	-0.075

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	3940	0.5187	0.0021	5.960**
Black Marubozu	625	0.5064	0.0020	3.060**
Closing Black Marubozu	1159	0.5267	0.0025	4.628**
Opening Black Marubozu	2156	0.4947	0.0006	0.654
Gravestone Doji	208	0.4663	0.0012	1.151
White Shooting Star	557	0.5090	0.0008	0.897
Black Shooting Star	498	0.5120	0.0013	1.856
Panel D: Bearish Reversal Patterns				
Hanging Man	85	0.4765	0.0022	1.400
Bearish Engulfing	297	0.5320	0.0005	0.241
Dark Cloud Cover	118	0.4746	0.0002	-0.065
Bearish Harami	417	0.4976	0.0010	0.882
Three Inside Down	34	0.5588	0.0013	0.318
Three Outside Down	36	0.5694	0.0056	2.220*
Tweezer Top	422	0.4917	0.0014	1.981

**statistically significant at the 1% level, *statistically significant at the 5% level

The bullish single line and reversal pattern bootstrap results presented in Panels A and B of Table 20 are consistent with the *t*-test counterparts (with the exception of Hammer, Bullish Engulfing, and Tweezer Bottom patterns). The bootstrap buy proportions are all greater than 0.5. In addition, they are generally higher than their Scenario C counterparts. This indicates that it is more likely that there is more profit on the random series than on the original series when a two-day holding period is used.

A similar trend is evident in the Panel C results. All the bootstrap proportions are less than 0.5 and they are consistently smaller than their Scenario C counterparts. This indicates that it is less likely for there to be higher returns on the bootstrap series than on the original. Again, this is the opposite to what was expected. If a two-day holding period enhanced candlestick performance, one would expect the proportion of times that there are higher returns on the bootstrap than on the original series to be lower.

Table 20: Scenario E: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.6316	0.3428	0.6332	0.3426	0.6336	0.3934	0.6341	0.3487
White Marubozu	0.5114	0.3571	0.5131	0.3543	0.5178	0.3388	0.5203	0.3474
Closing White Marubozu	0.5537	0.3728	0.5679	0.3790	0.5543	0.3755	0.5743	0.3642
Opening White Marubozu	0.5165	0.3778	0.5280	0.3850	0.5205	0.3911	0.5187	0.3770
Dragonfly Doji	0.6557	0.7624	0.6569	0.7616	0.6556	0.7592	0.6560	0.7514
White Paper Umbrella	0.5203	0.6221	0.5137	0.6320	0.5176	0.6277	0.5145	0.6166
Black Paper Umbrella	0.6215	0.6711	0.6123	0.6738	0.6130	0.6738	0.6127	0.6535
Panel B: Bullish Reversal Patterns								
Hammer	0.4435	0.4570	0.4388	0.4701	0.4175	0.4682	0.4453	0.4276
Bullish Engulfing	0.4408	0.3016	0.4324	0.3121	0.4455	0.2843	0.4394	0.2935
Piercing Line	0.5946	0.3054	0.5938	0.2745	0.6123	0.3850	0.6264	0.3258
Bullish Harami	0.5084	0.3364	0.5039	0.3437	0.5017	0.3560	0.4883	0.3300
Three Inside Up	0.5067	0.4444	0.4150	0.4654	0.5467	0.4133	0.4513	0.2697
Three Outside Up	0.5500	0.4091	0.5776	0.4353	0.5959	0.4571	0.5323	0.4627
Tweezer Bottom	0.4702	0.4513	0.4687	0.4642	0.4812	0.4255	0.4739	0.3945

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.3022	0.1391	0.3009	0.1387	0.3078	0.2038	0.2995	0.1610
Black Marubozu	0.4295	0.3164	0.4248	0.3324	0.4175	0.3192	0.4243	0.3127
Closing Black Marubozu	0.4040	0.2818	0.3941	0.2877	0.3959	0.2948	0.4004	0.2764
Opening Black Marubozu	0.4838	0.2534	0.4797	0.2561	0.4886	0.2732	0.4912	0.2560
Gravestone Doji	0.3872	0.8050	0.3842	0.8083	0.3962	0.7972	0.3853	0.7916
White Shooting Star	0.4815	0.6139	0.4780	0.6128	0.4769	0.6373	0.4693	0.6099
Black Shooting Star	0.4489	0.6216	0.4424	0.6237	0.4526	0.6219	0.4465	0.6177
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4808	0.4445	0.4806	0.4560	0.4762	0.4445	0.4886	0.4602
Bearish Engulfing	0.5078	0.3748	0.4967	0.3858	0.5022	0.3640	0.4947	0.3608
Dark Cloud Cover	0.5093	0.4029	0.5117	0.3890	0.5267	0.3858	0.5064	0.3702
Bearish Harami	0.4864	0.3371	0.4811	0.3477	0.4804	0.3266	0.4844	0.3342
Three Inside Down	0.4292	0.3540	0.4545	0.3557	0.4106	0.3333	0.3991	0.2661
Three Outside Down	0.3757	0.3039	0.3147	0.3553	0.4398	0.2530	0.3990	0.2798
Tweezer Top	0.4519	0.5152	0.4475	0.5168	0.4437	0.4749	0.4714	0.5015

The results presented in Tables 21 and 22 are similar to the equivalent results under previous scenarios. More specifically, the relative size of the bootstrap and original Dow stock series is generally consistent with the p-values displayed in Table 20. Bullish (bearish) single lines and patterns p-values greater (less) than 0.5 generally suggest that the means following an entry are higher (lower) on the bootstrapped series than on the original series.

The consistency of the standard deviation of returns on the bootstrapped series across the four null models (see Tables 21 and 22) provides further evidence of the robustness of the results to different specifications of the returns generation process. The Piercing Line bearish reversal patterns have standard deviations of returns of 0.0079, 0.0076, 0.0092, and 0.0081 for the random walk, AR(1), GARCH-M, and EGARCH null models respectively.

Table 21: Scenario E: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0001	0.0101	-0.0004	0.0105	0.0002	0.0101	-0.0004	0.0105
White Marubozu	0.0000	0.0078	-0.0004	0.0084	0.0001	0.0079	-0.0004	0.0084
Closing White Marubozu	0.0001	0.0088	-0.0005	0.0094	0.0001	0.0088	-0.0005	0.0094
Opening White Marubozu	0.0001	0.0094	-0.0003	0.0099	0.0002	0.0093	-0.0003	0.0099
Dragonfly Doji	0.0002	0.0097	-0.0007	0.0073	0.0002	0.0096	-0.0007	0.0073
White Paper Umbrella	0.0002	0.0093	-0.0005	0.0079	0.0002	0.0094	-0.0005	0.0079
Black Paper Umbrella	0.0002	0.0097	-0.0004	0.0082	0.0002	0.0097	-0.0004	0.0082
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0069	0.0013	0.0068	0.0002	0.0070	0.0013	0.0068
Bullish Engulfing	0.0002	0.0075	0.0011	0.0102	0.0002	0.0078	0.0011	0.0102
Piercing Line	0.0004	0.0079	-0.0012	0.0100	0.0009	0.0076	-0.0012	0.0100
Bullish Harami	0.0002	0.0069	0.0000	0.0096	0.0001	0.0074	0.0000	0.0096
Three Inside Up	0.0019	0.0040	-0.0003	0.0066	0.0003	0.0071	-0.0003	0.0066
Three Outside Up	-0.0007	0.0074	-0.0010	0.0073	0.0000	0.0075	-0.0010	0.0073
Tweezer Bottom	0.0001	0.0075	-0.0005	0.0079	0.0001	0.0076	-0.0005	0.0079

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0101	0.0010	0.0118	0.0002	0.0101	0.0010	0.0118
Black Marubozu	0.0001	0.0079	0.0014	0.0087	0.0003	0.0082	0.0014	0.0087
Closing Black Marubozu	0.0002	0.0088	0.0014	0.0107	0.0001	0.0088	0.0014	0.0107
Opening Black Marubozu	0.0001	0.0095	0.0003	0.0111	0.0001	0.0095	0.0003	0.0111
Gravestone Doji	0.0002	0.0097	0.0007	0.0070	0.0002	0.0097	0.0007	0.0070
White Shooting Star	0.0002	0.0097	0.0009	0.0084	0.0001	0.0098	0.0009	0.0084
Black Shooting Star	0.0002	0.0094	-0.0002	0.0082	0.0001	0.0094	-0.0002	0.0082
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0080	0.0002	0.0083	0.0003	0.0081	0.0002	0.0083
Bearish Engulfing	0.0003	0.0081	0.0003	0.0092	0.0003	0.0082	0.0003	0.0092
Dark Cloud Cover	0.0002	0.0086	0.0000	0.0096	-0.0001	0.0088	0.0000	0.0096
Bearish Harami	0.0003	0.0081	0.0006	0.0099	0.0003	0.0082	0.0006	0.0099
Three Inside Down	-0.0006	0.0073	0.0022	0.0093	0.0004	0.0080	0.0022	0.0093
Three Outside Down	0.0004	0.0076	0.0024	0.0104	-0.0004	0.0077	0.0024	0.0104
Tweezer Top	0.0002	0.0082	0.0005	0.0071	0.0001	0.0082	0.0005	0.0071

Table 22: Scenario E: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0105	-0.0004	0.0105	0.0002	0.0101	-0.0004	0.0105
White Marubozu	0.0003	0.0079	-0.0004	0.0084	0.0004	0.0078	-0.0004	0.0084
Closing White Marubozu	0.0001	0.0090	-0.0005	0.0094	0.0003	0.0086	-0.0005	0.0094
Opening White Marubozu	0.0001	0.0096	-0.0003	0.0099	0.0002	0.0093	-0.0003	0.0099
Dragonfly Doji	0.0002	0.0099	-0.0007	0.0073	0.0002	0.0097	-0.0007	0.0073
White Paper Umbrella	0.0002	0.0097	-0.0005	0.0079	0.0002	0.0095	-0.0005	0.0079
Black Paper Umbrella	0.0002	0.0102	-0.0004	0.0082	0.0002	0.0097	-0.0004	0.0082
Panel B: Bullish Reversal Patterns								
Hammer	0.0004	0.0075	0.0013	0.0068	0.0002	0.0065	0.0013	0.0068
Bullish Engulfing	0.0004	0.0075	0.0011	0.0102	0.0002	0.0075	0.0011	0.0102
Piercing Line	0.0004	0.0092	-0.0012	0.0100	0.0005	0.0081	-0.0012	0.0100
Bullish Harami	-0.0004	0.0076	0.0000	0.0096	-0.0003	0.0070	0.0000	0.0096
Three Inside Up	-0.0011	0.0068	-0.0003	0.0066	0.0018	0.0032	-0.0003	0.0066
Three Outside Up	0.0005	0.0078	-0.0010	0.0073	-0.0005	0.0063	-0.0010	0.0073
Tweezer Bottom	0.0003	0.0073	-0.0005	0.0079	0.0001	0.0070	-0.0005	0.0079

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0105	0.0010	0.0118	0.0002	0.0101	0.0010	0.0118
Black Marubozu	0.0002	0.0083	0.0014	0.0087	0.0002	0.0079	0.0014	0.0087
Closing Black Marubozu	0.0002	0.0091	0.0014	0.0107	0.0001	0.0087	0.0014	0.0107
Opening Black Marubozu	0.0002	0.0098	0.0003	0.0111	0.0002	0.0095	0.0003	0.0111
Gravestone Doji	0.0002	0.0101	0.0007	0.0070	0.0002	0.0097	0.0007	0.0070
White Shooting Star	0.0001	0.0102	0.0009	0.0084	0.0002	0.0098	0.0009	0.0084
Black Shooting Star	0.0002	0.0097	-0.0002	0.0082	0.0001	0.0095	-0.0002	0.0082
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0083	0.0002	0.0083	0.0003	0.0084	0.0002	0.0083
Bearish Engulfing	0.0001	0.0081	0.0003	0.0092	0.0001	0.0079	0.0003	0.0092
Dark Cloud Cover	0.0002	0.0090	0.0000	0.0096	-0.0002	0.0088	0.0000	0.0096
Bearish Harami	0.0003	0.0081	0.0006	0.0099	0.0002	0.0079	0.0006	0.0099
Three Inside Down	0.0002	0.0064	0.0022	0.0093	-0.0004	0.0065	0.0022	0.0093
Three Outside Down	0.0003	0.0061	0.0024	0.0104	0.0005	0.0066	0.0024	0.0104
Tweezer Top	0.0002	0.0080	0.0005	0.0071	0.0004	0.0081	0.0005	0.0071

4.3.6. Scenario F: Trade initiated at the Open Price on the Day after the Signal, a Five-Day Holding Period, a Ten-Day Exponential Moving Average to Determine Prior Trend, and all Candlestick Parameters Decreased by 20%

The possibility that the previous results are due to the candlestick specifications employed is considered in Sections 3.6 and 3.7. Practitioner books are very specific on certain elements of candlestick parameter definitions. For example, when a white single line must have similar open and low prices and similar close and high prices Morris (1995, p. 25) states that the difference "should be less than 10% of the open-close range." However, candlestick books point out that there is some flexibility in defining candlestick patterns, specifically the relationship between consecutive single lines required for a pattern.

In this section, the effect of decreasing all parameters by 20% is considered. This affects both single lines and patterns. Such a decrease will identify whether or not the lack of explanatory power of the candlesticks is due to having too broad a definition. This is the lower extreme of what might be considered as a reasonable specification based on the description of candlestick single lines and patterns in Nison (1991) and Morris (1995).

Evidence from the results displayed in Table 23 indicates a decline in the number of observations of each candlestick. For instance, in Scenario F there are 2,653 Long White single lines compared to 2,947 in Scenario C. The results are similar to those of Scenario C as the *t*-statistics of the bullish single lines and reversal patterns (Panels A and B respectively) are mostly negative. This indicates that the conditional means following a bullish signal are typically lower than the unconditional mean. A key difference is the levels of statistical significance. Under the Scenario C assumptions, the Long White, Opening White Marubozu, and Dragonfly Doji all led to returns that were statistically significantly less than the unconditional return. But under the Scenario F assumptions, none of the returns are statistically significant.

The bearish single lines and reversal patterns are even more similar to their Scenario C counterparts. Consistent with the Scenario C results (Table 11), all the conditional mean minus unconditional mean differences are positive, (except the Bearish Harami and Three Inside Down), and the Long Black, Black Marubozu, and Closing Black Marubozu are statistically significant at the 5% level.

Table 23: Scenario F: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2653	0.4760	0.0001	-1.524
White Marubozu	527	0.4581	0.0003	-0.124
Closing White Marubozu	1255	0.4744	0.0002	-0.654
Opening White Marubozu	1438	0.4693	0.0000	-1.896
Dragonfly Doji	277	0.4451	-0.0003	-1.936
White Paper Umbrella	518	0.4759	0.0005	0.588
Black Paper Umbrella	664	0.4672	0.0000	-1.334
Panel B: Bullish Reversal Patterns				
Hammer	62	0.4806	0.0002	-0.289
Bullish Engulfing	281	0.4847	0.0003	-0.209
Piercing Line	92	0.4707	-0.0002	-0.633
Bullish Harami	127	0.5047	0.0006	0.380
Three Inside Up	19	0.4789	0.0001	-0.218
Three Outside Up	65	0.4769	-0.0002	-0.731
Tweezer Bottom	388	0.4778	0.0003	-0.153

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2328	0.4934	0.0007	2.304*
Black Marubozu	470	0.4889	0.0011	2.487*
Closing Black Marubozu	870	0.4917	0.0011	3.192**
Opening Black Marubozu	1517	0.4868	0.0006	1.255
Gravestone Doji	191	0.4644	0.0009	1.301
White Shooting Star	484	0.4806	0.0004	0.034
Black Shooting Star	436	0.4851	0.0005	0.460
Panel D: Bearish Reversal Patterns				
Hanging Man	93	0.4957	0.0009	0.874
Bearish Engulfing	319	0.5034	0.0008	1.270
Dark Cloud Cover	150	0.4773	0.0006	0.574
Bearish Harami	384	0.4750	0.0002	-0.595
Three Inside Down	36	0.4806	-0.0013	-1.499
Three Outside Down	41	0.5341	0.0021	1.827
Tweezer Top	474	0.4793	0.0008	1.791

**statistically significant at the 1% level, *statistically significant at the 5% level

The results displayed in Table 24 have a similar trend to those in Table 23. The bootstrap mean proportions following buy (sell) signals are lower (higher) than their equivalents in Scenario C (Table 12). This is further confirmation that decreasing the parameter specification by 20% leads to candlestick trading rules being marginally closer to being statistically significant. However, the change is so slight that the rules are still a long way off being statistically significant.

Table 24: Scenario F: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5532	0.2381	0.5649	0.2442	0.5509	0.3415	0.5574	0.2878
White Marubozu	0.5168	0.4764	0.5073	0.4796	0.4899	0.4172	0.5098	0.4176
Closing White Marubozu	0.5090	0.3994	0.5144	0.3966	0.5108	0.3723	0.5229	0.3751
Opening White Marubozu	0.5438	0.3597	0.5459	0.3561	0.5522	0.3551	0.5660	0.3459
Dragonfly Doji	0.5994	0.8817	0.5903	0.8848	0.5959	0.8616	0.5906	0.8591
White Paper Umbrella	0.4654	0.6445	0.4644	0.6472	0.4665	0.6175	0.4601	0.6107
Black Paper Umbrella	0.5703	0.6962	0.5721	0.6924	0.5746	0.6673	0.5769	0.6569
Panel B: Bullish Reversal Patterns								
Hammer	0.5004	0.7154	0.5007	0.7265	0.4825	0.6475	0.4821	0.6035
Bullish Engulfing	0.4875	0.3478	0.4974	0.3625	0.4911	0.3011	0.5065	0.3017
Piercing Line	0.6120	0.3443	0.4561	0.4620	0.4890	0.4341	0.6022	0.4033
Bullish Harami	0.4683	0.2930	0.4576	0.3067	0.4484	0.3117	0.4741	0.2743
Three Inside Up	0.4513	0.3564	0.5165	0.3850	0.6154	0.3077	0.3321	0.5556
Three Outside Up	0.5351	0.3481	0.5082	0.3901	0.5208	0.3568	0.5552	0.3605
Tweezer Bottom	0.5031	0.5677	0.4953	0.5613	0.4942	0.4664	0.4828	0.4115
	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.3882	0.1197	0.3929	0.1145	0.3966	0.2255	0.3834	0.1647
Black Marubozu	0.4408	0.3740	0.4492	0.3958	0.4274	0.3444	0.4304	0.3681
Closing Black Marubozu	0.4234	0.2989	0.4232	0.2966	0.4186	0.3043	0.4244	0.2977
Opening Black Marubozu	0.4755	0.2122	0.4759	0.2128	0.4665	0.2585	0.4758	0.2372
Gravestone Doji	0.3421	0.7813	0.3402	0.7817	0.3442	0.7664	0.3331	0.7616
White Shooting Star	0.5299	0.5328	0.5310	0.5318	0.5373	0.5536	0.5242	0.5084
Black Shooting Star	0.4474	0.6677	0.4438	0.6727	0.4476	0.6346	0.4507	0.6245
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4776	0.5723	0.4647	0.5598	0.4688	0.5185	0.4732	0.5597
Bearish Engulfing	0.4793	0.4423	0.4860	0.4344	0.4816	0.3610	0.4884	0.3860
Dark Cloud Cover	0.4762	0.4074	0.4644	0.4070	0.4599	0.4328	0.4448	0.4073
Bearish Harami	0.5146	0.4333	0.5254	0.4472	0.5255	0.3810	0.5250	0.3946
Three Inside Down	0.5429	0.4000	0.5301	0.4211	0.5086	0.3265	0.5911	0.3574
Three Outside Down	0.3924	0.4525	0.3879	0.4788	0.3788	0.3909	0.3491	0.4214
Tweezer Top	0.4569	0.6193	0.4548	0.6171	0.4454	0.5085	0.4837	0.5515

The bootstrap mean and standard deviation results in Tables 25 and 26 for the random walk model further emphasise the consistency of results across the base case of Scenario C and Scenario F. The bullish single line results displayed in Table 13 indicate that the bootstrap means are all 0.0002 with the exception of the White Marubozu which is 0.0003. The equivalent mean returns for bullish single lines in Scenario F are all 0.0002. Moving to the standard deviations it is evident from Table 13 that the Long White, White Marubozu, Closing White Marubozu, Opening White Marubozu, Dragonfly Doji, White Paper Umbrella, and Black Paper Umbrella have standard deviations of 0.0103, 0.0096, 0.0099, 0.0099, 0.0098, 0.0097, and 0.0099 respectively, The corresponding standard deviations under Scenario F are 0.0102, 0.0097, 0.0100, 0.0100, 0.0098, 0.0098, and 0.0101 respectively.

Table 25: Scenario F: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0102	0.0001	0.0107	0.0002	0.0103	0.0001	0.0107
White Marubozu	0.0002	0.0097	0.0000	0.0089	0.0002	0.0096	0.0000	0.0089
Closing White Marubozu	0.0002	0.0100	0.0001	0.0101	0.0002	0.0099	0.0001	0.0101
Opening White Marubozu	0.0002	0.0100	-0.0001	0.0104	0.0001	0.0100	-0.0001	0.0104
Dragonfly Doji	0.0002	0.0098	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0098	0.0003	0.0086	0.0002	0.0098	0.0003	0.0086
Black Paper Umbrella	0.0002	0.0101	-0.0002	0.0091	0.0002	0.0100	-0.0002	0.0091
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0083	0.0000	0.0068	0.0002	0.0084	0.0000	0.0068
Bullish Engulfing	0.0001	0.0092	0.0001	0.0102	0.0001	0.0092	0.0001	0.0102
Piercing Line	0.0005	0.0109	-0.0002	0.0111	-0.0001	0.0120	-0.0002	0.0111
Bullish Harami	0.0002	0.0092	0.0004	0.0106	0.0002	0.0095	0.0004	0.0106
Three Inside Up	0.0013	0.0088	0.0002	0.0088	0.0006	0.0078	0.0002	0.0088
Three Outside Up	0.0001	0.0089	0.0000	0.0099	0.0002	0.0083	0.0000	0.0099
Tweezer Bottom	0.0001	0.0090	0.0002	0.0100	0.0001	0.0089	0.0002	0.0100

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0103	0.0004	0.0114	0.0002	0.0103	0.0004	0.0114
Black Marubozu	0.0001	0.0099	0.0004	0.0101	0.0002	0.0098	0.0004	0.0101
Closing Black Marubozu	0.0002	0.0101	0.0006	0.0108	0.0002	0.0100	0.0006	0.0108
Opening Black Marubozu	0.0002	0.0101	0.0002	0.0112	0.0002	0.0101	0.0002	0.0112
Gravestone Doji	0.0002	0.0100	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0100	-0.0002	0.0102	0.0002	0.0100	-0.0002	0.0102
Black Shooting Star	0.0002	0.0100	0.0000	0.0093	0.0001	0.0101	0.0000	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0093	0.0006	0.0083	0.0003	0.0093	0.0006	0.0083
Bearish Engulfing	0.0003	0.0095	0.0002	0.0098	0.0003	0.0096	0.0002	0.0098
Dark Cloud Cover	0.0001	0.0111	0.0005	0.0102	0.0003	0.0110	0.0005	0.0102
Bearish Harami	0.0002	0.0098	0.0001	0.0099	0.0002	0.0098	0.0001	0.0099
Three Inside Down	0.0001	0.0093	-0.0001	0.0099	0.0001	0.0096	-0.0001	0.0099
Three Outside Down	0.0002	0.0090	0.0012	0.0095	0.0002	0.0093	0.0012	0.0095
Tweezer Top	0.0002	0.0096	0.0003	0.0087	0.0002	0.0095	0.0003	0.0087

Table 26: Scenario F: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0106	0.0001	0.0107	0.0001	0.0103	0.0001	0.0107
White Marubozu	0.0002	0.0097	0.0000	0.0089	0.0002	0.0094	0.0000	0.0089
Closing White Marubozu	0.0001	0.0101	0.0001	0.0101	0.0002	0.0098	0.0001	0.0101
Opening White Marubozu	0.0002	0.0102	-0.0001	0.0104	0.0002	0.0099	-0.0001	0.0104
Dragonfly Doji	0.0002	0.0103	-0.0001	0.0076	0.0002	0.0099	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0102	0.0003	0.0086	0.0002	0.0098	0.0003	0.0086
Black Paper Umbrella	0.0002	0.0105	-0.0002	0.0091	0.0002	0.0101	-0.0002	0.0091
Panel B: Bullish Reversal Patterns								
Hammer	0.0003	0.0086	0.0000	0.0068	0.0001	0.0077	0.0000	0.0068
Bullish Engulfing	0.0002	0.0088	0.0001	0.0102	0.0001	0.0086	0.0001	0.0102
Piercing Line	0.0000	0.0116	-0.0002	0.0111	0.0001	0.0117	-0.0002	0.0111
Bullish Harami	0.0001	0.0099	0.0004	0.0106	0.0002	0.0094	0.0004	0.0106
Three Inside Up	0.0007	0.0084	0.0002	0.0088	0.0004	0.0083	0.0002	0.0088
Three Outside Up	0.0002	0.0085	0.0000	0.0099	0.0004	0.0084	0.0000	0.0099
Tweezer Bottom	0.0001	0.0088	0.0002	0.0100	0.0000	0.0082	0.0002	0.0100

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0004	0.0114	0.0002	0.0103	0.0004	0.0114
Black Marubozu	0.0001	0.0098	0.0004	0.0101	0.0001	0.0097	0.0004	0.0101
Closing Black Marubozu	0.0002	0.0101	0.0006	0.0108	0.0002	0.0100	0.0006	0.0108
Opening Black Marubozu	0.0002	0.0103	0.0002	0.0112	0.0002	0.0101	0.0002	0.0112
Gravestone Doji	0.0002	0.0103	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0104	-0.0002	0.0102	0.0002	0.0100	-0.0002	0.0102
Black Shooting Star	0.0002	0.0104	0.0000	0.0093	0.0002	0.0101	0.0000	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0094	0.0006	0.0083	0.0003	0.0096	0.0006	0.0083
Bearish Engulfing	0.0002	0.0093	0.0002	0.0098	0.0002	0.0093	0.0002	0.0098
Dark Cloud Cover	0.0002	0.0116	0.0005	0.0102	-0.0001	0.0112	0.0005	0.0102
Bearish Harami	0.0002	0.0096	0.0001	0.0099	0.0002	0.0094	0.0001	0.0099
Three Inside Down	0.0002	0.0085	-0.0001	0.0099	0.0003	0.0086	-0.0001	0.0099
Three Outside Down	0.0001	0.0083	0.0012	0.0095	0.0000	0.0084	0.0012	0.0095
Tweezer Top	0.0002	0.0092	0.0003	0.0087	0.0003	0.0093	0.0003	0.0087

4.3.7. Scenario G: Trade initiated at the Open Price on the Day after the Signal, a Five-Day Holding Period, a Ten-Day Exponential Moving Average to Determine Prior Trend and all Candlestick Parameters Increased by 20%

The results in Section 3.7 are based on increasing each parameter by 20%. This is the upper extreme of what might be considered a reasonable specification of a candlestick line and/or pattern. The results displayed in Table 27 make it clear that there are no major changes from those previously presented. As expected, the less strict specification results in more instances of each pattern. For example, in Scenario G there are 3,039 Long White single lines compared to 2,947 in Scenario C. All the bearish single lines and bullish reversal patterns have returns that are greater than zero less than 50% of the time, with the exception of the Bullish Harami and Three Inside Up. These results are the opposite to what candlestick technical analysis predicts, but are consistent with Scenario C.

Similarly, the proportion of returns following a sell signal that are greater than zero following a bearish single line and reversal patterns are all less than 50%, with the exception of the Bearish Engulfing. Again, these results are the opposite to those expected based on candlestick theory. The *t*-test results are also consistent with their Scenario C counterparts. The returns following Long Black, Black Marubozu, and Closing Black Marubozu bearish single lines are all greater than the unconditional return. In addition the majority of bullish single lines lead to returns that are less than the unconditional return. In line with Scenario C, these differences are statistically significant for the Long White and Dragonfly Doji lines.

Table 27: Scenario G: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	3039	0.4737	0.0000	-2.396*
White Marubozu	754	0.4626	0.0003	-0.150
Closing White Marubozu	1871	0.4698	0.0002	-0.949
Opening White Marubozu	1711	0.4713	0.0000	-1.887
Dragonfly Doji	268	0.4403	-0.0003	-2.072*
White Paper Umbrella	656	0.4788	0.0006	0.940
Black Paper Umbrella	824	0.4688	0.0003	-0.458
Panel B: Bullish Reversal Patterns				
Hammer	58	0.4879	0.0007	0.522
Bullish Engulfing	222	0.4914	0.0004	0.088
Piercing Line	156	0.4673	-0.0007	-1.933
Bullish Harami	93	0.5118	0.0009	0.770
Three Inside Up	14	0.5143	0.0013	0.613
Three Outside Up	45	0.4844	-0.0004	-0.755
Tweezer Bottom	323	0.4771	0.0002	-0.272

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2796	0.4912	0.0007	2.210*
Black Marubozu	669	0.4834	0.0009	2.233*
Closing Black Marubozu	1130	0.4901	0.0009	2.807**
Opening Black Marubozu	1886	0.4847	0.0006	1.405
Gravestone Doji	189	0.4630	0.0008	1.262
White Shooting Star	626	0.4834	0.0006	0.924
Black Shooting Star	554	0.4812	0.0005	0.523
Panel D: Bearish Reversal Patterns				
Hanging Man	88	0.4818	0.0007	0.560
Bearish Engulfing	264	0.5045	0.0009	1.375
Dark Cloud Cover	81	0.4741	-0.0005	-1.125
Bearish Harami	398	0.4751	0.0001	-0.657
Three Inside Down	32	0.4781	-0.0003	-0.640
Three Outside Down	33	0.5121	0.0020	1.475
Tweezer Top	368	0.4761	0.0009	1.848

**statistically significant at the 1% level, *statistically significant at the 5% level

The bootstrap results for each candlestick are consistent with their *t*-test counterparts. For both the bullish single lines and bullish reversal patterns those lines and patterns with negative *t*-statistics have higher bootstrap *p*-values. In other words, for lines and patterns that have lower conditional than unconditional returns there is more likelihood of there being higher profitability on the randomly generated bootstrapped series than on the original series. This result is invariant to the null model used to generate the simulated series.

There is also consistency between the *t*-test and bootstrap result for the bearish single lines and reversal patterns. For instance, the Dark Cloud Cover pattern, which has a negative *t*-statistic, indicating lower conditional than unconditional returns, has a simulated *p*-value that is greater than 0.5 for each of the null models. So, this pattern is more profitable on the randomly generated series than on the original more than

50% of the time. Conversely, the Tweezer Top pattern has a positive *t*-statistic and a *p*-value of less than 0.5 across all four null models.

Table 28: Scenario G: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5963	0.3595	0.5930	0.3622	0.6012	0.4380	0.6009	0.3874
White Marubozu	0.5097	0.5343	0.5098	0.5282	0.5036	0.4742	0.5180	0.4782
Closing White Marubozu	0.5323	0.4864	0.5377	0.4841	0.5316	0.4397	0.5408	0.4475
Opening White Marubozu	0.5532	0.4814	0.5522	0.4837	0.5570	0.4550	0.5650	0.4452
Dragonfly Doji	0.6066	0.8822	0.6065	0.8842	0.6091	0.8597	0.6152	0.8546
White Paper Umbrella	0.4485	0.7196	0.4504	0.7233	0.4477	0.6662	0.4546	0.6560
Black Paper Umbrella	0.5413	0.8017	0.5440	0.8037	0.5489	0.7816	0.5456	0.7689
Panel B: Bullish Reversal Patterns								
Hammer	0.4454	0.6160	0.4563	0.6041	0.4412	0.5235	0.4484	0.5156
Bullish Engulfing	0.4850	0.3576	0.4880	0.3726	0.4824	0.3165	0.4921	0.2971
Piercing Line	0.5909	0.3201	0.5967	0.3201	0.5922	0.3387	0.6178	0.3800
Bullish Harami	0.4816	0.3194	0.4340	0.3656	0.4634	0.3098	0.4394	0.3208
Three Inside Up	0.4657	0.6267	0.5641	0.3563	0.4754	0.5013	0.4916	0.3810
Three Outside Up	0.4593	0.3333	0.4508	0.4836	0.4769	0.3769	0.3967	0.3141
Tweezer Bottom	0.4914	0.6007	0.4852	0.5823	0.4872	0.4713	0.4782	0.4251
	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.4216	0.1906	0.4124	0.1867	0.4277	0.3135	0.4107	0.2381
Black Marubozu	0.4525	0.4606	0.4549	0.4625	0.4603	0.4239	0.4585	0.4170
Closing Black Marubozu	0.4478	0.3633	0.4419	0.3685	0.4435	0.3560	0.4465	0.3469
Opening Black Marubozu	0.4619	0.2956	0.4601	0.3032	0.4638	0.3419	0.4580	0.3163
Gravestone Doji	0.3428	0.7766	0.3386	0.7806	0.3487	0.7680	0.3372	0.7604
White Shooting Star	0.4568	0.6344	0.4555	0.6373	0.4624	0.6300	0.4544	0.6013
Black Shooting Star	0.4639	0.7908	0.4647	0.7877	0.4628	0.7094	0.4621	0.7187
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4786	0.6092	0.4728	0.6129	0.4702	0.5421	0.4741	0.5883
Bearish Engulfing	0.4759	0.4226	0.4768	0.4284	0.4757	0.3536	0.4650	0.3631
Dark Cloud Cover	0.5428	0.4275	0.5287	0.4795	0.5089	0.4122	0.5229	0.4314
Bearish Harami	0.5183	0.4673	0.5088	0.4593	0.5191	0.3910	0.5162	0.4160
Three Inside Down	0.5432	0.4198	0.5333	0.3926	0.5319	0.3475	0.5241	0.3655
Three Outside Down	0.3814	0.3814	0.4071	0.4956	0.3636	0.3455	0.4202	0.3445
Tweezer Top	0.4538	0.5945	0.4579	0.6051	0.4472	0.4806	0.4750	0.5400

The results displayed in Tables 29 and 30 indicate that the robustness of results to different null model specifications that is evident in the results reported previously also hold for the Scenario G assumptions. This is typified by the standard deviation of returns for the Long Black bearish single line. This is 0.0102, 0.0102, 0.0107, and 0.0103 for the random walk, AR(1), GARCH-M and EAGRCH null model respectively.

Table 29: Scenario G: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
LongWhite	0.0001	0.0102	0.0000	0.0102	0.0002	0.0102	0.0000	0.0102
White Marubozu	0.0003	0.0094	0.0000	0.0082	0.0002	0.0094	0.0000	0.0082
Closing White Marubozu	0.0002	0.0096	0.0000	0.0095	0.0002	0.0097	0.0000	0.0095
Opening White Marubozu	0.0002	0.0100	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0098	-0.0001	0.0076	0.0002	0.0099	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0096	0.0004	0.0083	0.0002	0.0096	0.0004	0.0083
Black Paper Umbrella	0.0002	0.0100	-0.0004	0.0087	0.0002	0.0100	-0.0004	0.0087
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0083	0.0005	0.0075	0.0002	0.0081	0.0005	0.0075
Bullish Engulfing	0.0001	0.0090	0.0001	0.0102	0.0001	0.0091	0.0001	0.0102
Piercing Line	0.0001	0.0097	-0.0004	0.0108	-0.0001	0.0095	-0.0004	0.0108
Bullish Harami	0.0004	0.0089	0.0005	0.0105	-0.0001	0.0093	0.0005	0.0105
Three Inside Up	-0.0029	0.0090	0.0005	0.0088	-0.0002	0.0090	0.0005	0.0088
Three Outside Up	-0.0004	0.0088	-0.0002	0.0102	0.0001	0.0091	-0.0002	0.0102
Tweezer Bottom	0.0001	0.0088	0.0003	0.0098	0.0002	0.0087	0.0003	0.0098

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0102	0.0003	0.0108	0.0002	0.0102	0.0003	0.0108
Black Marubozu	0.0001	0.0095	0.0003	0.0094	0.0002	0.0095	0.0003	0.0094
Closing Black Marubozu	0.0002	0.0097	0.0006	0.0102	0.0002	0.0096	0.0006	0.0102
Opening Black Marubozu	0.0002	0.0100	0.0001	0.0106	0.0002	0.0100	0.0001	0.0106
Gravestone Doji	0.0002	0.0099	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0100	0.0000	0.0097	0.0002	0.0099	0.0000	0.0097
Black Shooting Star	0.0002	0.0096	0.0001	0.0083	0.0002	0.0096	0.0001	0.0083
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0091	0.0005	0.0081	0.0003	0.0091	0.0005	0.0081
Bearish Engulfing	0.0002	0.0094	0.0003	0.0097	0.0001	0.0095	0.0003	0.0097
Dark Cloud Cover	0.0004	0.0096	-0.0002	0.0097	0.0004	0.0102	-0.0002	0.0097
Bearish Harami	0.0002	0.0094	0.0001	0.0095	0.0002	0.0094	0.0001	0.0095
Three Inside Down	0.0003	0.0083	-0.0001	0.0088	0.0002	0.0086	-0.0001	0.0088
Three Outside Down	0.0002	0.0089	0.0012	0.0099	0.0003	0.0099	0.0012	0.0099
Tweezer Top	0.0002	0.0092	0.0004	0.0083	0.0002	0.0093	0.0004	0.0083

Table 30: Scenario G: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0107	0.0000	0.0102	0.0001	0.0102	0.0000	0.0102
White Marubozu	0.0001	0.0096	0.0000	0.0082	0.0001	0.0093	0.0000	0.0082
Closing White Marubozu	0.0003	0.0099	0.0000	0.0095	0.0002	0.0095	0.0000	0.0095
Opening White Marubozu	0.0002	0.0102	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0102	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0099	0.0004	0.0083	0.0002	0.0095	0.0004	0.0083
Black Paper Umbrella	0.0002	0.0104	-0.0004	0.0087	0.0002	0.0101	-0.0004	0.0087
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0081	0.0005	0.0075	0.0002	0.0075	0.0005	0.0075
Bullish Engulfing	0.0002	0.0088	0.0001	0.0102	0.0001	0.0085	0.0001	0.0102
Piercing Line	0.0001	0.0102	-0.0004	0.0108	0.0003	0.0097	-0.0004	0.0108
Bullish Harami	0.0003	0.0086	0.0005	0.0105	0.0000	0.0085	0.0005	0.0105
Three Inside Up	0.0030	0.0063	0.0005	0.0088	-0.0002	0.0047	0.0005	0.0088
Three Outside Up	-0.0002	0.0089	-0.0002	0.0102	-0.0005	0.0083	-0.0002	0.0102
Tweezer Bottom	0.0002	0.0083	0.0003	0.0098	0.0001	0.0079	0.0003	0.0098

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0003	0.0108	0.0001	0.0103	0.0003	0.0108
Black Marubozu	0.0001	0.0095	0.0003	0.0094	0.0002	0.0094	0.0003	0.0094
Closing Black Marubozu	0.0002	0.0097	0.0006	0.0102	0.0002	0.0095	0.0006	0.0102
Opening Black Marubozu	0.0002	0.0102	0.0001	0.0106	0.0001	0.0100	0.0001	0.0106
Gravestone Doji	0.0002	0.0102	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0104	0.0000	0.0097	0.0002	0.0100	0.0000	0.0097
Black Shooting Star	0.0002	0.0098	0.0001	0.0083	0.0002	0.0097	0.0001	0.0083
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0092	0.0005	0.0081	0.0003	0.0092	0.0005	0.0081
Bearish Engulfing	0.0002	0.0091	0.0003	0.0097	0.0001	0.0090	0.0003	0.0097
Dark Cloud Cover	0.0001	0.0101	-0.0002	0.0097	0.0001	0.0097	-0.0002	0.0097
Bearish Harami	0.0002	0.0091	0.0001	0.0095	0.0002	0.0090	0.0001	0.0095
Three Inside Down	0.0000	0.0076	-0.0001	0.0088	0.0002	0.0081	-0.0001	0.0088
Three Outside Down	-0.0001	0.0080	0.0012	0.0099	0.0003	0.0084	0.0012	0.0099
Tweezer Top	0.0002	0.0088	0.0004	0.0083	0.0003	0.0091	0.0004	0.0083

4.3.8. Scenario H: Trade initiated at the Open Price on the Day after the Signal, a Five-Day Holding Period, and a Five-Day Exponential Moving Average to Determine Prior Trend

As their names suggest, bullish and bearish reversal patterns indicate a change in prior trend. Therefore pattern tests require the prior trend to be specified. Morris (1995) advocates the use of a ten-day exponential moving average, so it is used in the base scenario. In Section 3.8 the question of whether or not the previous results are specific to this moving average specification is investigated. Specifically, a five-day exponential average is investigated.

This change does not affect the single line results as single lines are not based on a moving average. Nevertheless, these results are included for completeness. The results displayed in Table 31 indicate that changing the moving average from ten to five days does not have a significant bearing on the bullish or bearish reversal results. More of the bullish reversal patterns have positive *t*-statistics indicating that the means conditional on a buy signal are larger than is the unconditional return in Scenario C (five versus four). This is consistent with candlestick theory, but none of these differences are statistically significantly different from zero. Three of the seven bearish reversal patterns have negative *t*-statistics, compared to two under the Scenario C assumptions. However, none of these are statistically significant.

Table 31: Scenario H: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2947	0.4760	0.0000	-2.131*
White Marubozu	642	0.4581	0.0004	0.028
Closing White Marubozu	1565	0.4726	0.0002	-0.540
Opening White Marubozu	1611	0.4703	0.0000	-2.054*
Dragonfly Doji	270	0.4419	-0.0003	-2.084*
White Paper Umbrella	567	0.4771	0.0005	0.659
Black Paper Umbrella	727	0.4670	0.0002	-0.814
Panel B: Bullish Reversal Patterns				
Hammer	60	0.5083	0.0011	1.025
Bullish Engulfing	274	0.4938	0.0005	0.358
Piercing Line	151	0.4702	-0.0005	-1.534
Bullish Harami	117	0.5060	0.0009	0.728
Three Inside Up	18	0.4833	0.0007	0.232
Three Outside Up	60	0.5017	0.0006	0.306
Tweezer Bottom	379	0.4694	-0.0001	-1.358

Candlestick	N(Sell)	Sell>0	Mean	*T*-Stat
Panel C: Bearish Single Lines				
Long Black	2661	0.4919	0.0007	2.499*
Black Marubozu	557	0.4867	0.0011	2.503*
Closing Black Marubozu	1022	0.4877	0.0009	2.485*
Opening Black Marubozu	1737	0.4856	0.0005	1.064
Gravestone Doji	191	0.4644	0.0009	1.301
White Shooting Star	520	0.4829	0.0005	0.579
Black Shooting Star	465	0.4884	0.0005	0.778
Panel D: Bearish Reversal Patterns				
Hanging Man	83	0.4699	0.0004	0.056
Bearish Engulfing	279	0.4993	0.0006	0.817
Dark Cloud Cover	123	0.4683	-0.0004	-1.158
Bearish Harami	406	0.4808	0.0003	-0.284
Three Inside Down	39	0.4872	-0.0001	-0.556
Three Outside Down	36	0.5056	0.0013	0.985
Tweezer Top	398	0.4771	0.0007	1.330

**statistically significant at the 1% level, *statistically significant at the 5% level

The bootstrap results displayed in Table 32 are consistent with their *t*-statistic counterparts. None of the reversal pattern bootstrap results are greater than 0.95 or less than 0.05 - which indicates that none of the candlestick patterns are statistically significant at the 5% level. This result, which is consistent with that for each of the previous scenarios, confirms that candlestick reversal patterns do not have predictive power for DJIA stocks for the period of this study.

Table 32: Scenario H: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5798	0.2825	0.5818	0.2842	0.5906	0.3877	0.5915	0.3267
White Marubozu	0.4984	0.5099	0.4996	0.5136	0.5075	0.4465	0.5070	0.4560
Closing White Marubozu	0.5248	0.4488	0.5163	0.4577	0.5105	0.4102	0.5316	0.4158
Opening White Marubozu	0.5485	0.4286	0.5533	0.4270	0.5534	0.4119	0.5590	0.4047
Dragonfly Doji	0.6058	0.8906	0.6035	0.8864	0.6041	0.8606	0.6048	0.8585
White Paper Umbrella	0.4587	0.6709	0.4476	0.6728	0.4532	0.6444	0.4563	0.6310
Black Paper Umbrella	0.5536	0.7673	0.5495	0.7637	0.5607	0.7395	0.5536	0.7209
Panel B: Bullish Reversal Patterns								
Hammer	0.4474	0.6330	0.4425	0.6361	0.4435	0.5578	0.4419	0.5335
Bullish Engulfing	0.4911	0.3658	0.4760	0.3636	0.4862	0.3243	0.4922	0.3190
Piercing Line	0.6032	0.3512	0.5761	0.4158	0.5842	0.4711	0.5789	0.4240
Bullish Harami	0.4796	0.2579	0.4623	0.2500	0.4813	0.2522	0.4875	0.2194
Three Inside Up	0.4454	0.4664	0.6521	0.2320	0.6215	0.2565	0.5641	0.2056
Three Outside Up	0.4850	0.3820	0.4564	0.4232	0.4380	0.3554	0.4615	0.3291
Tweezer Bottom	0.5287	0.5831	0.5008	0.5888	0.5170	0.4815	0.5176	0.4227

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.4021	0.1483	0.3911	0.1471	0.4068	0.2729	0.3771	0.2073
Black Marubozu	0.4387	0.4207	0.4306	0.4254	0.4331	0.3854	0.4364	0.3872
Closing Black Marubozu	0.4563	0.3419	0.4489	0.3525	0.4479	0.3324	0.4621	0.3304
Opening Black Marubozu	0.4761	0.2535	0.4777	0.2520	0.4836	0.2951	0.4738	0.2692
Gravestone Doji	0.3369	0.7749	0.3368	0.7791	0.3455	0.7686	0.3413	0.7599
White Shooting Star	0.4823	0.6081	0.4802	0.6068	0.4833	0.5926	0.4793	0.5552
Black Shooting Star	0.4428	0.6963	0.4430	0.6920	0.4468	0.6545	0.4407	0.6407
Panel D: Bearish Reversal Patterns								
Hanging Man	0.5396	0.5964	0.5349	0.5886	0.5345	0.5442	0.5473	0.5840
Bearish Engulfing	0.4928	0.4298	0.4995	0.4270	0.4986	0.3598	0.4894	0.3723
Dark Cloud Cover	0.5528	0.3595	0.5879	0.3748	0.5529	0.3788	0.5557	0.3852
Bearish Harami	0.5077	0.4434	0.5015	0.4321	0.5157	0.3740	0.5053	0.4038
Three Inside Down	0.4466	0.3932	0.4917	0.4167	0.4940	0.3147	0.4591	0.3735
Three Outside Down	0.4286	0.4400	0.3839	0.4777	0.4301	0.4247	0.4340	0.4623
Tweezer Top	0.4741	0.6149	0.4675	0.6164	0.4695	0.5040	0.4865	0.5465

The results displayed in Tables 33 and 34 further reinforce the fact that the profitability (or lack thereof) of candlestick charting is invariant to assumption changes. The mean buy returns on the bootstrap series for the AR(1) model are 0.0001, 0.0001, 0.0001, 0.0000, 0.0010, 0.0003 and 0.0001 for the Hammer, Bullish Engulfing, Piercing Line, Bullish Harami, Three Inside Up, Three Outside Up, and Tweezer Bottom respectively. The corresponding returns under Scenario C are 0.0001, 0.0002, 0.0001, 0.0000, 0.0008, 0.0005 and 0.0002 respectively.

Table 33: Scenario H: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0103	0.0000	0.0104	0.0001	0.0102	0.0000	0.0104
White Marubozu	0.0001	0.0095	0.0000	0.0085	0.0001	0.0095	0.0000	0.0085
Closing White Marubozu	0.0002	0.0098	0.0000	0.0098	0.0002	0.0098	0.0000	0.0098
Opening White Marubozu	0.0001	0.0100	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0099	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0097	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0099	-0.0002	0.0089	0.0002	0.0099	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0082	0.0005	0.0078	0.0001	0.0082	0.0005	0.0078
Bullish Engulfing	0.0001	0.0091	0.0003	0.0101	0.0001	0.0090	0.0003	0.0101
Piercing Line	0.0003	0.0105	-0.0004	0.0104	0.0001	0.0104	-0.0004	0.0104
Bullish Harami	0.0002	0.0090	0.0004	0.0114	0.0000	0.0093	0.0004	0.0114
Three Inside Up	-0.0012	0.0086	0.0004	0.0083	0.0010	0.0096	0.0004	0.0083
Three Outside Up	0.0000	0.0087	0.0007	0.0101	0.0003	0.0089	0.0007	0.0101
Tweezer Bottom	0.0002	0.0089	0.0003	0.0099	0.0001	0.0089	0.0003	0.0099

Candlestick	RW Bootstrap Sell	σ_s	RW Dow Sell	σ_s	AR(1) Bootstrap Sell	σ_s	AR(1) Dow Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0103	0.0003	0.0110	0.0002	0.0103	0.0003	0.0110
Black Marubozu	0.0002	0.0097	0.0004	0.0097	0.0001	0.0096	0.0004	0.0097
Closing Black Marubozu	0.0002	0.0098	0.0005	0.0104	0.0002	0.0100	0.0005	0.0104
Opening Black Marubozu	0.0001	0.0100	0.0002	0.0109	0.0002	0.0100	0.0002	0.0109
Gravestone Doji	0.0002	0.0099	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0100	-0.0002	0.0100	0.0001	0.0100	-0.0002	0.0100
Black Shooting Star	0.0002	0.0099	-0.0002	0.0093	0.0002	0.0100	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0093	0.0002	0.0081	0.0002	0.0092	0.0002	0.0081
Bearish Engulfing	0.0002	0.0095	0.0001	0.0097	0.0002	0.0094	0.0001	0.0097
Dark Cloud Cover	0.0004	0.0100	-0.0006	0.0112	0.0004	0.0103	-0.0006	0.0112
Bearish Harami	0.0002	0.0097	0.0001	0.0098	0.0002	0.0095	0.0001	0.0098
Three Inside Down	0.0003	0.0091	0.0004	0.0090	0.0003	0.0087	0.0004	0.0090
Three Outside Down	0.0000	0.0092	0.0008	0.0093	0.0001	0.0095	0.0008	0.0093
Tweezer Top	0.0002	0.0094	0.0003	0.0082	0.0002	0.0094	0.0003	0.0082

Table 34: Scenario H: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

Candlestick	GARCH-M Bootstrap Buy	σ_b	GARCH-M Dow Buy	σ_b	EGARCH Bootstrap Buy	σ_b	EGARCH Dow Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0107	0.0000	0.0104	0.0002	0.0103	0.0000	0.0104
White Marubozu	0.0002	0.0095	0.0000	0.0085	0.0002	0.0094	0.0000	0.0085
Closing White Marubozu	0.0002	0.0098	0.0000	0.0098	0.0002	0.0096	0.0000	0.0098
Opening White Marubozu	0.0001	0.0103	-0.0002	0.0100	0.0002	0.0099	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0102	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0100	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0103	-0.0002	0.0089	0.0002	0.0100	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0004	0.0084	0.0005	0.0078	0.0001	0.0077	0.0005	0.0078
Bullish Engulfing	0.0002	0.0089	0.0003	0.0101	0.0001	0.0088	0.0003	0.0101
Piercing Line	0.0004	0.0115	-0.0004	0.0104	0.0003	0.0103	-0.0004	0.0104
Bullish Harami	0.0004	0.0087	0.0004	0.0114	0.0002	0.0087	0.0004	0.0114
Three Inside Up	0.0012	0.0065	0.0004	0.0083	0.0004	0.0074	0.0004	0.0083
Three Outside Up	0.0005	0.0086	0.0007	0.0101	0.0000	0.0081	0.0007	0.0101
Tweezer Bottom	0.0001	0.0085	0.0003	0.0099	0.0001	0.0080	0.0003	0.0099

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0003	0.0110	0.0001	0.0103	0.0003	0.0110
Black Marubozu	0.0001	0.0097	0.0004	0.0097	0.0002	0.0095	0.0004	0.0097
Closing Black Marubozu	0.0002	0.0100	0.0005	0.0104	0.0002	0.0097	0.0005	0.0104
Opening Black Marubozu	0.0002	0.0103	0.0002	0.0109	0.0002	0.0100	0.0002	0.0109
Gravestone Doji	0.0002	0.0102	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0104	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Black Shooting Star	0.0002	0.0102	-0.0002	0.0093	0.0001	0.0100	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0093	0.0002	0.0081	0.0003	0.0094	0.0002	0.0081
Bearish Engulfing	0.0002	0.0092	0.0001	0.0097	0.0001	0.0091	0.0001	0.0097
Dark Cloud Cover	0.0003	0.0104	-0.0006	0.0112	0.0000	0.0106	-0.0006	0.0112
Bearish Harami	0.0002	0.0093	0.0001	0.0098	0.0001	0.0093	0.0001	0.0098
Three Inside Down	0.0005	0.0077	0.0004	0.0090	0.0003	0.0085	0.0004	0.0090
Three Outside Down	0.0004	0.0080	0.0008	0.0093	-0.0002	0.0092	0.0008	0.0093
Tweezer Top	0.0002	0.0090	0.0003	0.0082	0.0003	0.0091	0.0003	0.0082

4.3.9. Scenario I: Trade initiated at the Open Price on the Day after the Signal, a Five-Day Holding Period, and a Fifteen-Day Exponential Moving Average to Determine Prior Trend

The final section of results are the outcome of investigation into the impact of increasing the moving average to determine whether or not a prior trend exists. This change is made to determine whether or not the moving average length is the major driver of the results. Fifteen days is the maximum length that could be considered reasonable for trend determination given the short-term nature of candlestick technical analysis.

Table 35: Scenario I: *T*-Test Results

Candlestick	N(Buy)	Buy>0	Mean	*T*-Stat
Panel A: Bullish Single Lines				
Long White	2947	0.4760	0.0000	-2.131*
White Marubozu	642	0.4581	0.0004	0.028
Closing White Marubozu	1565	0.4726	0.0002	-0.540
Opening White Marubozu	1611	0.4703	0.0000	-2.054*
Dragonfly Doji	270	0.4419	-0.0003	-2.084*
White Paper Umbrella	567	0.4771	0.0005	0.659
Black Paper Umbrella	727	0.4670	0.0002	-0.814
Panel B: Bullish Reversal Patterns				
Hammer	54	0.5000	0.0010	0.907
Bullish Engulfing	234	0.4906	0.0005	0.318
Piercing Line	134	0.4687	-0.0005	-1.312
Bullish Harami	111	0.5099	0.0008	0.582
Three Inside Up	17	0.5059	0.0013	0.643
Three Outside Up	55	0.4945	-0.0001	-0.486
Tweezer Bottom	333	0.4691	-0.0001	-1.011
Candlestick	**N(Sell)**	**Sell>0**	**Mean**	***T*-Stat**
Panel C: Bearish Single Lines				
Long Black	2661	0.4919	0.0007	2.499*
Black Marubozu	557	0.4867	0.0011	2.503*
Closing Black Marubozu	1022	0.4877	0.0009	2.485*
Opening Black Marubozu	1737	0.4856	0.0005	1.064
Gravestone Doji	191	0.4644	0.0009	1.301
White Shooting Star	520	0.4829	0.0005	0.579
Black Shooting Star	465	0.4884	0.0005	0.778
Panel D: Bearish Reversal Patterns				
Hanging Man	83	0.4807	0.0007	0.579
Bearish Engulfing	306	0.4971	0.0006	0.769
Dark Cloud Cover	123	0.4732	0.0006	0.371
Bearish Harami	405	0.4674	0.0000	-1.064
Three Inside Down	34	0.4676	-0.0011	-1.410
Three Outside Down	37	0.5081	0.0020	1.669
Tweezer Top	401	0.4756	0.0007	1.228

**statistically significant at the 1% level, *statistically significant at the 5% level

As mentioned previously, single lines are not related to the prior trend so their results are not affected by the change in moving average specification. It is clear that, as expected, increasing the moving average length reduces the number of patterns. For instance, the number of Hammer and Bullish Engulfing patterns drops from 57 and 252 under Scenario C to 54 and 234 respectively under Scenario I. The results displayed in Table 35 Panels B and D indicate that changing the moving average specification to fifteen days has very little effect on the results. For instance, all the bullish reversal patterns (except the Piercing Line, Three Outside Down, and Tweezer Bottom) have positive *t*-statistics, indicating that the returns following these patterns are, on average, higher than the unconditional return. However, none of these differences are statistically significant.

Table 36: Scenario I: Bootstrap Proportions for all Null Models

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.5867	0.2801	0.5892	0.2819	0.5841	0.3825	0.5911	0.3183
White Marubozu	0.5042	0.5097	0.5089	0.5158	0.4985	0.4478	0.5133	0.4506
Closing White Marubozu	0.5159	0.4463	0.5211	0.4499	0.5134	0.4112	0.5293	0.4181
Opening White Marubozu	0.5529	0.4211	0.5480	0.4278	0.5524	0.4190	0.5568	0.4100
Dragonfly Doji	0.6078	0.8833	0.6059	0.8863	0.6059	0.8616	0.6024	0.8605
White Paper Umbrella	0.4569	0.6744	0.4538	0.6780	0.4623	0.6371	0.4584	0.6326
Black Paper Umbrella	0.5557	0.7659	0.5496	0.7705	0.5547	0.7392	0.5554	0.7239
Panel B: Bullish Reversal Patterns								
Hammer	0.4741	0.6971	0.4690	0.6875	0.4729	0.6225	0.4609	0.6076
Bullish Engulfing	0.4844	0.3680	0.4799	0.3519	0.4727	0.3127	0.4864	0.2991
Piercing Line	0.5755	0.3476	0.5515	0.3733	0.5162	0.3894	0.6239	0.3456
Bullish Harami	0.4809	0.2438	0.4355	0.2823	0.4879	0.2666	0.4456	0.2663
Three Inside Up	0.4654	0.5671	0.4123	0.2851	0.4286	0.2857	0.5714	0.2429
Three Outside Up	0.5375	0.3676	0.4961	0.3217	0.4960	0.3306	0.4706	0.3394
Tweezer Bottom	0.5097	0.5671	0.5140	0.5683	0.5124	0.4625	0.4928	0.4137

	RW		AR(1)		GARCH-M		EGARCH	
Candlestick	**Sell**	**σ_s**	**Sell**	**σ_s**	**Sell**	**σ_s**	**Sell**	**σ_s**
Panel C: Bearish Single Lines								
Long Black	0.4006	0.1470	0.3930	0.1506	0.4034	0.2717	0.3844	0.2061
Black Marubozu	0.4413	0.4276	0.4203	0.4302	0.4367	0.3892	0.4303	0.3997
Closing Black Marubozu	0.4522	0.3402	0.4468	0.3474	0.4503	0.3373	0.4502	0.3414
Opening Black Marubozu	0.4751	0.2532	0.4807	0.2593	0.4771	0.2930	0.4813	0.2774
Gravestone Doji	0.3384	0.7805	0.3316	0.7784	0.3460	0.7640	0.3319	0.7635
White Shooting Star	0.4837	0.6027	0.4886	0.6088	0.4892	0.5962	0.4839	0.5611
Black Shooting Star	0.4456	0.6940	0.4494	0.6951	0.4450	0.6461	0.4464	0.6442
Panel D: Bearish Reversal Patterns								
Hanging Man	0.4988	0.6189	0.4970	0.6192	0.4911	0.5726	0.5151	0.5970
Bearish Engulfing	0.4975	0.4298	0.4865	0.4243	0.4902	0.3477	0.4855	0.3760
Dark Cloud Cover	0.4702	0.4331	0.4519	0.4114	0.4928	0.4692	0.5031	0.4130
Bearish Harami	0.5172	0.4546	0.5229	0.4612	0.5198	0.3934	0.5145	0.4038
Three Inside Down	0.5922	0.4000	0.5789	0.3522	0.5550	0.3158	0.5726	0.3361
Three Outside Down	0.3900	0.4400	0.3939	0.4040	0.3695	0.3744	0.4372	0.3767
Tweezer Top	0.4790	0.6206	0.4715	0.6256	0.4708	0.5086	0.4987	0.5618

The bootstrap results displayed in Table 36 are also very similar to their Scenario C counterparts (Table 12). Both the bullish and bearish reversal pattern results are divided relatively evenly between being above and below 0.5. None are close to being statistically significant. This is added confirmation that there is no evidence that candlestick single lines or patterns signal abnormal returns for the DJIA stocks for the period studied.

Table 37: Scenario I: Bootstrap and Raw Series Means and Standard Deviations for Random Walk and AR(1) Null Models

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0102	0.0000	0.0104	0.0002	0.0102	0.0000	0.0104
White Marubozu	0.0002	0.0095	0.0000	0.0085	0.0003	0.0097	0.0000	0.0085
Closing White Marubozu	0.0002	0.0098	0.0000	0.0098	0.0002	0.0098	0.0000	0.0098
Opening White Marubozu	0.0002	0.0099	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0098	-0.0001	0.0076	0.0002	0.0098	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0097	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0099	-0.0002	0.0089	0.0002	0.0099	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0002	0.0083	0.0003	0.0070	0.0002	0.0082	0.0003	0.0070
Bullish Engulfing	0.0002	0.0091	0.0002	0.0102	0.0002	0.0090	0.0002	0.0102
Piercing Line	0.0002	0.0102	-0.0003	0.0103	-0.0001	0.0102	-0.0003	0.0103
Bullish Harami	0.0003	0.0091	0.0005	0.0108	0.0002	0.0091	0.0005	0.0108
Three Inside Up	-0.0002	0.0103	0.0006	0.0085	-0.0002	0.0080	0.0006	0.0085
Three Outside Up	0.0002	0.0085	0.0001	0.0100	0.0002	0.0087	0.0001	0.0100
Tweezer Bottom	0.0002	0.0088	0.0001	0.0101	0.0001	0.0088	0.0001	0.0101

	RW				AR(1)			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0102	0.0003	0.0110	0.0002	0.0103	0.0003	0.0110
Black Marubozu	0.0002	0.0097	0.0004	0.0097	0.0001	0.0097	0.0004	0.0097
Closing Black Marubozu	0.0002	0.0098	0.0005	0.0104	0.0002	0.0099	0.0005	0.0104
Opening Black Marubozu	0.0001	0.0100	0.0002	0.0109	0.0002	0.0100	0.0002	0.0109
Gravestone Doji	0.0002	0.0099	0.0006	0.0075	0.0002	0.0099	0.0006	0.0075
White Shooting Star	0.0002	0.0100	-0.0002	0.0100	0.0002	0.0100	-0.0002	0.0100
Black Shooting Star	0.0001	0.0099	-0.0002	0.0093	0.0002	0.0100	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0002	0.0092	0.0003	0.0080	0.0003	0.0093	0.0003	0.0080
Bearish Engulfing	0.0003	0.0096	0.0002	0.0099	0.0002	0.0095	0.0002	0.0099
Dark Cloud Cover	0.0004	0.0105	0.0002	0.0097	0.0000	0.0102	0.0002	0.0097
Bearish Harami	0.0002	0.0096	0.0001	0.0096	0.0002	0.0096	0.0001	0.0096
Three Inside Down	0.0002	0.0092	-0.0002	0.0098	-0.0001	0.0091	-0.0002	0.0098
Three Outside Down	0.0005	0.0090	0.0011	0.0097	0.0005	0.0091	0.0011	0.0097
Tweezer Top	0.0002	0.0094	0.0002	0.0083	0.0002	0.0095	0.0002	0.0083

Once again, the bootstrap means are very consistent across null models. This is further evidence of the strength of the results. The mean returns following a Hammer pattern is 0.0002 for the Random Walk and AR(1) null models and 0.083 and 0.0003 and 0.0001 for the GARCH-M and EGARCH models respectively.

Table 38: Scenario I: Bootstrap and Raw Series Means and Standard Deviations for GARCH-M and EGARCH Null Models

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Buy	σ_b	Buy	σ_b	Buy	σ_b	Buy	σ_b
Panel A: Bullish Single Lines								
Long White	0.0002	0.0107	0.0000	0.0104	0.0001	0.0103	0.0000	0.0104
White Marubozu	0.0002	0.0095	0.0000	0.0085	0.0001	0.0094	0.0000	0.0085
Closing White Marubozu	0.0002	0.0098	0.0000	0.0098	0.0001	0.0097	0.0000	0.0098
Opening White Marubozu	0.0002	0.0102	-0.0002	0.0100	0.0002	0.0099	-0.0002	0.0100
Dragonfly Doji	0.0002	0.0102	-0.0001	0.0076	0.0002	0.0099	-0.0001	0.0076
White Paper Umbrella	0.0002	0.0100	0.0002	0.0085	0.0002	0.0097	0.0002	0.0085
Black Paper Umbrella	0.0002	0.0103	-0.0002	0.0089	0.0002	0.0100	-0.0002	0.0089
Panel B: Bullish Reversal Patterns								
Hammer	0.0003	0.0085	0.0003	0.0070	0.0001	0.0079	0.0003	0.0070
Bullish Engulfing	0.0001	0.0089	0.0002	0.0102	0.0002	0.0085	0.0002	0.0102
Piercing Line	0.0000	0.0102	-0.0003	0.0103	0.0004	0.0107	-0.0003	0.0103
Bullish Harami	0.0004	0.0090	0.0005	0.0108	0.0002	0.0089	0.0005	0.0108
Three Inside Up	0.0002	0.0088	0.0006	0.0085	0.0012	0.0068	0.0006	0.0085
Three Outside Up	-0.0001	0.0088	0.0001	0.0100	0.0000	0.0085	0.0001	0.0100
Tweezer Bottom	0.0001	0.0085	0.0001	0.0101	0.0000	0.0080	0.0001	0.0101

	GARCH-M				EGARCH			
	Bootstrap		Dow		Bootstrap		Dow	
Candlestick	Sell	σ_s	Sell	σ_s	Sell	σ_s	Sell	σ_s
Panel C: Bearish Single Lines								
Long Black	0.0002	0.0107	0.0003	0.0110	0.0002	0.0103	0.0003	0.0110
Black Marubozu	0.0001	0.0097	0.0004	0.0097	0.0001	0.0096	0.0004	0.0097
Closing Black Marubozu	0.0002	0.0100	0.0005	0.0104	0.0001	0.0098	0.0005	0.0104
Opening Black Marubozu	0.0002	0.0103	0.0002	0.0109	0.0002	0.0101	0.0002	0.0109
Gravestone Doji	0.0002	0.0103	0.0006	0.0075	0.0002	0.0100	0.0006	0.0075
White Shooting Star	0.0002	0.0104	-0.0002	0.0100	0.0002	0.0101	-0.0002	0.0100
Black Shooting Star	0.0002	0.0102	-0.0002	0.0093	0.0002	0.0099	-0.0002	0.0093
Panel D: Bearish Reversal Patterns								
Hanging Man	0.0003	0.0094	0.0003	0.0080	0.0003	0.0094	0.0003	0.0080
Bearish Engulfing	0.0002	0.0092	0.0002	0.0099	0.0002	0.0091	0.0002	0.0099
Dark Cloud Cover	0.0002	0.0110	0.0002	0.0097	0.0003	0.0103	0.0002	0.0097
Bearish Harami	0.0002	0.0094	0.0001	0.0096	0.0002	0.0093	0.0001	0.0096
Three Inside Down	0.0005	0.0081	-0.0002	0.0098	0.0003	0.0083	-0.0002	0.0098
Three Outside Down	0.0000	0.0084	0.0011	0.0097	0.0001	0.0087	0.0011	0.0097
Tweezer Top	0.0002	0.0090	0.0002	0.0083	0.0003	0.0093	0.0002	0.0083

4.4. Conclusion

There is strong evidence that candlestick technical trading strategies on DJIA stocks for the 1992 – 2002 period do not have value. The only statistically significant results are contrary to candlestick theory. Single lines and reversal patterns that are said to be bullish (i.e. indicators of future price increases) are actually found to signal lower than average returns. Similarly, bearish single lines and reversal patterns are found to signal higher than average returns.

However, caution should be exercised when interpreting these results as these findings are specific to the *t*-test methodology. The more sophisticated bootstrapping methodology, which accounts for well known *t*-test assumption violations, shows no evidence of statistical significance.

These results are robust to numerous methodology assumption changes. They are found to be consistent across a range of implementation scenarios after a signal is generated a range of holding periods, and different definitions of a prior trend.

Chapter Five: Conclusions

In this thesis the profitability of candlestick trading strategies, the oldest known form of technical analysis, in the U.S. equity market is investigated. In contrast to traditional technical analysis, candlestick technical analysis involves analysis of open, high, low, and close prices within a day and over successive days.

Numerous surveys of foreign exchange and equity market participants and financial journalists have been conducted to determine the relative importance of fundamental and technical analysis to these market participants (e.g. Carter and Van Auken, 1990; Allen and Taylor, 1992; Lui and Mole, 1998; and Oberlechner, 2001). This literature consistently shows that the shorter the forecasting horizon the greater the emphasis which these individuals place on technical analysis. More specifically, respondents place approximately twice as much weight on technical analysis for a horizon of a week as they do for a horizon of a year. Fundamental analysis is seen to be more important for horizons of 3 months and over.

Despite market participants ascribing the most value to short-term technical analysis, the academic literature has focused on testing the profitability of long-term technical trading rules. Most studies test rules based around 50 to 200 days of historical data, which generate trading signals relatively infrequently. In contrast, the candlestick trading rules examined in this thesis examines rely on one to three days of historical data and positions are held for ten days. For this reason, these rules are very popular with market participants. Nison (2004, p. 22) comments "since its introduction to the

Western world candlestick technical analysis has become ubiquitous, available in almost every software and online charting package."

The results in this research indicate that the use of candlestick trading strategies is not profitable for DJIA stocks in the U.S. equity market over the 1992-2002 period. The majority of previous traditional technical analysis studies have found that technical analysis has value before transaction costs and risk adjustment, but that these two factors erode profitability. This finding is consistent with the broader definition of the efficient market hypothesis. Candlestick technical analysis is, however, shown to be unprofitable even before any adjustment is made for trading costs and risk.

The choice of candlestick technical analysis and the choice of data make this study a very robust test of technical analysis. It is less susceptible to the criticism of data snooping than are many other technical analysis studies. Candlestick technical analysis was developed by Japanese rice traders in the 1700s, therefore testing the technique using DJIA component stock data is an out-of-sample test. The use of stock data which are able to be traded in their own right overcomes the criticism that the profits of technical analysis documented on nontraded indices are purely hypothetical. Individual stock data also overcome any bias introduced by nonsynchronous trading within an index.

By limiting the analysis to the actively traded DJIA stocks, prices that would have been able to be obtained by proponents of candlestick technical analysis are used. The market microstructure of the NYSE means orders would be able to be filled at the prices used in this thesis. Finally, the time frame of the study, 1992-2002, was carefully selected to ensure that market participants would have been aware of candlestick technical analysis and would have had the ability to implement it during this time. This is an important consideration, as the challenge to market efficiency from recently developed complex trading rules that are reliant on massive computer power and that are tested on data 50-100 years old is dubious at best.

The profitability of candlestick technical analysis was tested using two methodologies. The *t*-test methodology is standard, but the bootstrapping involves an extension to the conventional methodology to allow the generation of random open, high, low, and close prices. In previous research a bootstrapping methodology that focuses solely on close prices has been adopted. This approach was the first step in this thesis. Null models, such as the random walk, AR(1), GARCH-M, and EGARCH were fitted to the original close price series for each stock. The residuals were then resampled and used to generate a return and price series for each stock that had the same time-series properties as the original series, but was random.

Once a randomly generated close series had been formed, vectors of the original (high – close)/close and (close-low)/close percentage differences were created. A random sample from these percentage difference vectors was then taken. Next, these high-close (close-low) percentage differences were added (subtracted) to (from) the simulated close price to form simulated high and low prices. A similar process was used to generate simulated open prices. To ensure that the resampled open price was never higher than the high nor lower than the low the close-open percentage differences were resampled if this situation arose.

The less robust t-statistic methodology shows evidence that some bullish rules indicate lower than average returns and some bearish rules indicate higher than average returns, the exact opposite of what the practitioner candlestick literature suggests. However, these results may be due to violations of the t-test assumptions in the data. The more robust bootstrap methodology shows that there is no evidence of candlesticks having predictive power. The returns following candlestick signals are shown not to be statistically significantly different from the returns on the random series generated based on the four null models. Moreover, the standard deviation of returns following candlestick signals is not statistically significantly different on the original or random series.

This result was thoroughly checked to ensure that it is not specific to some of the assumptions adopted. Nine separate scenarios were considered to determine if specific assumptions were driving the results. These scenarios involved varying the entry day from the closing price on the day of the signal to the opening and closing prices on the day following a signal. The number of days a position was kept open following a signal was also varied from five days to two and ten days. Finally, the specification of the variables that define candlestick single lines and patterns, and the definition of the prior trend were varied. The results are very robust of the full range of this sensitivity analysis.

In summary, this research shows that trading on the signals generated by candlestick technical analysis does not add value for the major stocks traded in the U.S. market. This evidence is consistent with market efficiency. While it may be rational for brokerage firms to include candlestick technical analysis in advice offered to clients if this analysis leads to increased turnover, investors who base their decisions on candlestick technical analysis are shown not to benefit from it.

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Appendix One: Candlestick Single Lines and Reversal Patterns

Appendix One contains a graphical depiction and explanation of each of the candlestick single lines and patterns tested in this thesis. The description is based around that in leading candlestick practitioner books.[7] The Appendix is divided into four sections. Sections 1 and 2 contain bullish and bearish single lines respectively while Sections 3 and 4 contain bullish and bearish reversal patterns respectively.

A.1.1. Bullish Single Lines

The single lines displayed below are all bullish lines. Each bullish line has a bearish counterpart.

Long White Candle

A Long White Candle, which has a close well above the open towards the high of the day, indicates positive sentiment towards a stock suggesting that the price can be expected to rise in the future.

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[7] These books include: Bigalow (2002), Fischer and Fischer (2003), Morris (1995), Nison (1991, 1994), Pring (2002), Wagner & Matheny (1993).

White Marubozu

A White Marubozu is a long white body with no shadows at either end. This is an extremely strong line as prices have risen throughout the day and closed at their high. It is often the first part of a bullish continuation or bullish reversal candle pattern.

Closing White Marubozu

A Closing Marubozu has no shadow extending from the close end of the body, indicating that prices have closed at their highs. It therefore has similar strength to a Marubozu.

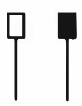
Opening White Marubozu

The Opening Marubozu has no shadow extending from the open price end of the body. The Opening Marubozu is similar to a Long White Candle and not as strong as the Closing Marabozu.

Dragonfly Doji

The Dragonfly Doji occurs when the open and close are at the high of the day. The price declines during the day, but then rallies to close at, or near, the opening price.

White and Black Paper Umbrella



The Paper Umbrella is similar to the Dragonfly Doji. A White Paper Umbrella is the stronger of the two as it indicates declining prices throughout the day and then a rally with a close above the opening price. A Black Paper Umbrella is also considered a bullish line as prices have declined throughout the day, but then rallied to close well above their lows. A Black Paper Umbrella is the only black candle that is considered bullish.

A.1.2. Bearish Single Lines

The single lines displayed below are all bearish lines.

Long Black Candle

A Long Black Candle, which has a close well below the open towards the low of the day, indicates negative sentiment towards a stock, suggesting that the price can be expected to fall in the future.

Black Marubozu

A Black Marubozu is a long black body with no shadows at either end. This is an extremely weak line as prices have fallen throughout the day and closed at their low. It is often the first part of a bearish continuation or bearish reversal candle pattern.

Closing Black Marubozu

A Closing Marubozu has no shadow extending from the close end of the body, indicating that prices have closed at their lows. It therefore has similar strength to a Marubozu.

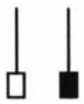
Opening Black Marubozu

The Opening Marubozu has no shadow extending from the open price end of the body. The Opening Marubozu is similar to a Long Black Candle and not as strong as the Closing Marabozu.

Gravestone Doji

The Gravestone Doji occurs when the open and close are at the low of the day. The price rallies during the day, but then declines to close at, or near, the opening price.

White and Black Shooting Star

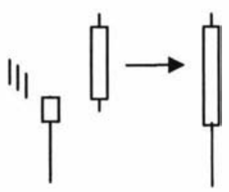


The Shooting Star is similar to the Gravestone Doji. A Black Shooting Star is the weaker of the two as it indicates rising prices throughout the day and then a decline with a close below the opening price. A White Shooting Star is also considered a bearish line as prices have risen throughout the day, but then declined to close well below their highs. A White Shooting Star is the only white candle that is considered bearish.

A.1.3. Bullish Reversal Patterns

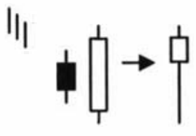
Bullish patterns are defined as *those that reduce a bullish single line* (i.e., a white candle with a short upper line or a black paper umbrella). *Bearish patterns* are defined as *those that reduce a bearish single line* (i.e., a black candle with a short upper line or a white shooting star).

Hammer



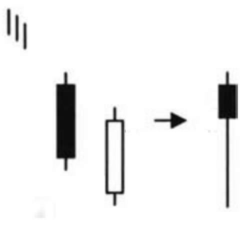
The Hammer involves a sell off after a decline to a new intra-day low. Prices then rally to close above the open. Prices on the following day close higher still indicating a reversal has occurred. Nison (1991, p. 29) stated that the lower shadow should be twice the height of the real body and it should have no, or a very short, upper shadow.

Bullish Engulfing



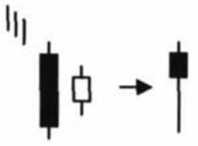
A downtrend must be underway and the first day's body colour reflects the trend. The second day opens lower, and then closes above the open of the first day, indicating a change in sentiment. The Bullish Engulfing pattern reduces to a Hammer which fully supports its interpretation. The Bullish Engulfing pattern is also the first two days of the Three Outside Up pattern.

Piercing Line



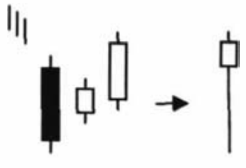
The Piercing Line indicates a situation where the market is declining. Following a down day the market opens lower, then rallies throughout the day and closes above the mid-point of the previous day. This action causes concern to bears and indicates that a potential bottom has been made. The Piercing Line is similar to, but not as strong as, the Bullish Engulfing Pattern.

Bullish Harami



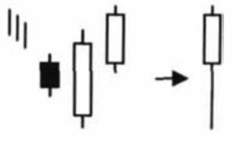
Harami is a Japanese word for *pregnant* or *body within*. In a Bullish Harami, a long black day perpetuates the downtrend. The next day, prices open higher, which shocks many complacent bears and many short positions are covered causing prices to rise further. This is said to be the first day in a trend reversal.

Three Inside Up



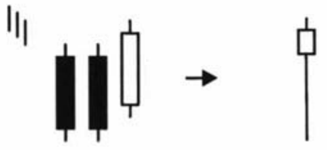
This pattern is a confirmation for the Bullish Harami. Therefore the psychology is the same as that behind the Harami with the added strength that the trend has changed.

Three Outside Up



The Three Outside Up is confirmation for the Bullish Engulfing Pattern.

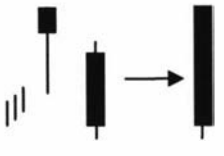
Tweezer Bottom



Tweezer Bottoms are two or more candlesticks with matching lows. The fact that price is unable to penetrate a given level on successive days indicates that there is good buying support at that level and that the downtrend is likely to reverse.

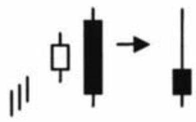
A.1.4. Bearish Reversal Patterns

Hanging Man



The Hanging Man involves an intra-day decline following an uptrend. Prices then rally, but fail to close above the open. Prices on the following day move lower still, indicating a reversal has occurred. Nison (1991, p. 29) stated that the lower shadow should be twice the height of the real body and it should have no, or a very short, upper shadow.

Bearish Engulfing

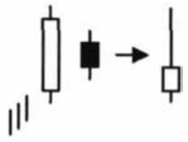


An uptrend must be underway and the first day's body colour reflects the trend. The second day opens higher, and then closes below the open of the first day, indicating a change in sentiment. The Bearish Engulfing pattern is also the first two days of the Three Outside Down pattern.

Dark Cloud Cover

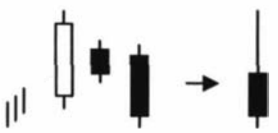
The Dark Cloud Cover is a bearish reversal pattern and the counterpart of the Piercing Line pattern. The more penetration of the black body into the prior white body, the greater the chance for a top reversal.

Bearish Harami



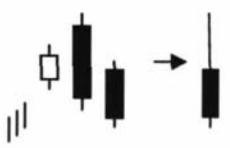
In a Bearish Harami, a long white day perpetuates the uptrend. The next day, prices open lower, which shocks many complacent bulls and many longs are closed causing prices to fall further. This is said to be the first day in a trend reversal.

Three Inside Down



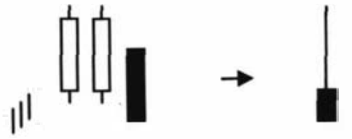
This pattern is a confirmation for the Harami. Therefore the psychology is the same as that behind the Harami with the added strength that the trend has changed.

Three Outside Down



The Three Outside Down is confirmation for the Bearish Engulfing Pattern. The combined pattern reduces to a shooting star which fully supports its interpretation.

Tweezer Top



Tweezer Tops are two or more candlesticks with matching highs. The fact that price is unable to penetrate a given level on successive days indicates that there is good selling resistance at that level and that the down trend is likely to reverse.

Appendix Two: Dow Stocks

Appendix Two contains a list of the companies that are included in the data set. There were several changes to the composition of the Dow Jones Industrial Index (DJIA) over the 1992 – 2002 period so an explanation of each change is provided. Start (End) date is the first (last) data a stock's data are included in this research.

Ticker	Company Name	Start Date	End Date	Note
AA	Alcoa Inc.	1/01/1992	31/12/2002	1
T	AT&T Corp	1/01/1992	31/12/2002	
BS	Bethlehem Steel	1/01/1992	16/03/1997	2
DD	The Goodyear Tire & Rubber Co	1/01/1992	31/12/2002	
EK	Eastman Kodak Co.	1/01/1992	31/12/2002	
GE	General Electric Co.	1/01/1992	31/12/2002	
GM	General Motors Corp.	1/01/1992	31/12/2002	
GT	The Goodyear Tire & Rubber Co	1/01/1992	31/10/1999	3
IP	International Paper Co.	1/01/1992	31/12/2002	
PG	Procter & Gamble Co.	1/01/1992	31/12/2002	
S	Sears Roebuck & Co.	1/01/1992	31/10/1999	4
CVX	ChevronTexaco Corp	1/01/1992	31/10/1999	5
XOM	Exxon Mobil Co.	1/01/1992	31/12/2002	6
DOW	Dow Chemical Co.	1/01/1992	31/10/1999	7
UTX	United Technologies Corp.	1/01/1992	31/12/2002	
MMM	3M Co	1/01/1992	31/12/2002	8
IBM	International Business Machines Corp	1/01/1992	31/12/2002	
MRK	Merck & Co Inc	1/01/1992	31/12/2002	
AXP	American Express Co.	1/01/1992	31/12/2002	
MCD	McDonald's Corp.	1/01/1992	31/12/2002	
MO	Altria Group Inc	1/01/1992	31/12/2002	9
BA	The Boeing Co	1/01/1992	31/12/2002	
KO	Coca-Cola Co.	1/01/1992	31/12/2002	
JPM	JPMorgan Chase and Co	1/01/1992	31/12/2002	10
CAT	Caterpillar Inc.	1/01/1992	31/12/2002	
DIS	The Walt Disney Co.	1/01/1992	31/12/2002	
JNJ	Johnson & Johnson Inc	17/03/1997	31/12/2002	11
HPQ	Hewlett-Packard Co.	1/01/1992	31/12/2002	12
C	CitiGroup Inc	1/01/1992	31/12/2002	13
WMT	Wal-Mart Stores Inc	1/01/1992	31/12/2002	14
INTC	Intel Corp.	1/11/1999	31/12/2002	15
HD	Home Depot Inc.	1/11/1999	31/12/2002	16
MSFT	Microsoft Corp.	1/11/1999	31/12/2002	17
SBC	SBC Communications Inc.	1/11/1999	31/12/2002	
HON	Honeywell International Inc	1/01/1992	31/12/2002	18

Note	
1	Was called Aluminium Co. of America prior to Jan 4 1999
2	Replaced with Johnson & Johnson on Mar 17 1997
3	Replaced with Intel Corp on Nov 1 1999
4	Replaced with Home Depot Inc. on Nov 1 1999
5	Replaced with Microsoft on Nov 1 1999
6	Was called Exxon prior to Dec 1 1999.
7	Was called Union Carbide prior to Feb 6 2001. Replaced with SBC Communications on Nov 1 1999.
8	Was called Minnesota Mining & Manufacturing prior to Apr 8 2002
9	Was called Philip Morris Companies prior to 27 Jan 2003
10	Was called J.P. Morgan prior to 1 Feb 2001
11	Replaced Bethlehem Steel on Mar 17 1997
12	Replaced Texaco Inc. on May 17 1997. No Texaco data were avaliable so HPQ was included for entire period
13	Called Travelers Group prior to Oct 19 1998. Replaced Westinghouse Electric on May 17 1997. No Westinghouse Electric data were avaliable so C was included for the entire period
14	Replaced Woolworth in Mar 17 1997. No Woolworth data so WMT was included for the entire period
15	Replaced The Goodyear Tire & Rubber Co on Nov 1 1999
16	Replaced Sears Roebuck & Co. on Nov 1 1999
17	Replaced ChevronTexaco Corp on Nov 1 1999
18	Was called Allied Signal in Dow prior to Honeywell merger on 2 Dec 1999

Appendix Three: Matlab Code

The MATLAB code that was written to conduct the tests required to produce the empirical results of this thesis is included in Appendix Three.

Candlestick Single Lines			**Candlestick Reversal Patterns**		
Name	**Type**	**Abbreviation**	**Name**	**Type**	**Abbreviation**
Long White Candle	Bullish	lw	Hammer	Bullish	hammer
White Marubozu	Bullish	wm	Bullish Engulfing	Bullish	bulleng
Closing White Marubozu	Bullish	cwm	Piercing Line	Bullish	pieline
Opening White Marubozu	Bullish	owm	Bullish Harami	Bullish	bullhar
Dragonfly Doji	Bullish	dd	Three Inside Up	Bullish	thriup
White Paper Umbrella	Bullish	wpu	Three Outside Up	Bullish	throup
Black Paper Umbrella	Bullish	bpu	Tweezer Bottom	Bullish	twbot
Long Black Candle	Bearish	lb	Hanging Man	Bearish	hangman
Black Marubozu	Bearish	bm	Bearish Engulfing	Bearish	beareng
Closing Black Marubozu	Bearish	cbm	Dark Cloud Cover	Bearish	dcc
Opening Black Marubozu	Bearish	obm	Bearish Harami	Bearish	bearhar
Gravestone Doji	Bearish	gd	Three Inside Down	Bearish	thridn
White Shooting Star	Bearish	wss	Three Outside Down	Bearish	throdn
Black Shooting Star	Bearish	bss	Tweezer Top	Bearish	twtop

Throughout the code each candlestick is referred to by an abbreviation as defined in the table displayed above. The first section of this appendix contains the code that defines each candlestick. This code was stored separately in individual files but is presented as one file here to conserve space. The next section contains the code used to conduct *t*-tests. This was done separately for each stock for each candlestick. The *t*-test code refers to two embedded functions which are presented separately. The first of these, the EMA code is used to define the prior trend. uttest, is used to calculate the *t*-statistics. The random walk bootstrap code is then presented. This code, together with the other null model bootstrap code, was modified and run nine separate times depending on the scenario being tested. Only Scenario C code is presented in this appendix to conserve space. The entire bootstrap code uses an embedded function to conduct that bootstrap resampling step. This function, which is called *resample*, is also presented. This is followed by the bootstrap code for the AR1, GARCH-M, and EGARCH models. This code is the same as the random walk bootstrap code apart from the code specific to the fitting of the respective null models. The GARCH-M and EGARCH functions were written as separate functions so these are also presented.

A.3.1. Candlestick Functions

```
%LW

function signals = lw(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) > (1+w)*o(i) & l(i) < (1-t)*o(i) & l(i) > (o(i)-y*(c(i)-o(i))) & h(i) > (1+t)*c(i) & h(i) < (c(i)+y*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;


%WM

function signals = wm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) > (1+w)*o(i) & h(i) <= (1+t)*c(i) & l(i) >= (1-t)*o(i)
            signals(i) = 1;
        end;
end;


%CWM

function signals = cwm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) > (1+w)*o(i) & h(i) <= (1+t)*c(i) & l(i) < (1-t)*o(i) & l(i) > (o(i)-y*(c(i)-o(i)))
            signals(i) = 1;
        end;
```

```
end;


%OWM

function signals = owm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) > (1+w)*o(i) & h(i) > (1+t)*c(i) & h(i) < (c(i)+y*(c(i)-o(i))) & l(i) >= (1-t)*o(i)
            signals(i) = 1;
        end;
end;


%DD

function signals = dd(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if o(i) > (1-t)*h(i) & o(i) < (1+t)*h(i) &  o(i) > (1-t)*c(i) & o(i) < (1+t)*c(i) & l(i) < (1-v)*c(i)
            signals(i) = 1;
        end;
end;


%WPU

function signals = lw(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if h(i) < (c(i)+x*(c(i)-o(i))) & c(i) > (1+t)*o(i) & c(i) < (1+u)*o(i) & l(i) < (o(i)-zz*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;
```

```
%BPU

function signals = bpu(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
        if h(i) < (o(i)+x*(o(i)-c(i))) & c(i) < (1-t)*o(i) & c(i) > (1-u)*o(i) & l(i) < (c(i)-zz*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;


%HAMMER

function signals = hammer(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)
        if h(i-1) < (c(i-1)+x*(c(i-1)-o(i-1))) & c(i-1) > (1+t)*o(i-1) & c(i-1) < (1+u)*o(i-1) & l(i-1) < (o(i-1)-zz*(c(i-1)-o(i-1))) & o(i) > l(i-1) & c(i) > o(i) & c(i) > c(i-1) & h(i) < (c(i)+y*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;


%BULLENG

function signals = bulleng(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)
        if c(i-1) < (1-t)*o(i-1) & o(i) < c(i-1) & c(i) > o(i-1) & l(i) < l(i-1) & l(i) > (o(i)-y*(c(i)-o(i))) & h(i) < (c(i)+y*(c(i)-o(i))) & h(i) > h(i-1)
            signals(i) = 1;
        end;
end;
```

```
%PIELINE

function signals = pieline(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)
        if c(i-1) < (1-w)*o(i-1) & l(i-1) > (c(i-1)-y*(o(i-1)-c(i-1))) & h(i-1) < (o(i-1)+y*(o(i-1)-c(i-1))) & c(i) > (c(i-1)+y*(o(i-1)-c(i-1))) & c(i) < o(i-1) & o(i) < c(i-1) & h(i) < (c(i)+y*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;


%BULLHAR

function signals = bullhar(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)

            signals(i) = 1;
        end;
end;


%THRIUP

function signals = thriup(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=3:length(c)

            signals(i) = 1;
        end;
end;
```

```
%THROUP

function signals = throup(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=3:length(c)
         if c(i-2) < (1-t)*o(i-2) & o(i-1) < c(i-2) & c(i-1) > o(i-2) & l(i-1) < l(i-2) & l(i-1) > (o(i-1)-y*(c(i-1)-o(i-1))) & h(i-1) < (c(i-1)+y*(c(i-1)-o(i-1))) & h(i-1) > h(i-2) & o(i) > o(i-1) & c(i) > c(i-1) & h(i) < (c(i) + y*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;


%TWBOT

function signals = twbot(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=3:length(c)

            signals(i) = 1;
        end;
end;


%LB

function signals = lb(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) < (1-w)*o(i) & l(i) < (1-t)*c(i) & l(i) > (c(i)-y*(o(i)-c(i))) & h(i) > (1+t)*o(i) & h(i) < (o(i)+y*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;
```

```
%BM

function signals = bm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) < (1-w)*o(i) & h(i) <= (1+t)*o(i) & l(i) >= (1-t)*c(i)
            signals(i) = 1;
        end;
end;


%CBM

function signals = cbm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) < (1-w)*o(i) & h(i) > (1+t)*o(i) & h(i) < (o(i)+y*(o(i)-c(i))) & l(i) >= (1-t)*c(i)
            signals(i) = 1;
        end;
end;


%OBM

function signals = obm(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
         if c(i) < (1-w)*o(i) & h(i) <= (1+t)*o(i) & l(i) < (1-t)*c(i) & l(i) > (c(i)-y*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;


%GD

function signals = gd(o,h,l,c,t,u,v,w,x,y,zz);
```

```
signals = zeros(size(c));
for i=1:length(c)
         if o(i) > (1-t)*l(i) & o(i) < (1+t)*l(i) &  o(i) > (1-t)*c(i) & o(i) < (1+t)*c(i) & h(i) > (1+v)*c(i)
            signals(i) = 1;
        end;
end;


%WSS

function signals = wss(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
        if h(i) > (c(i)+zz*(c(i)-o(i))) & c(i) > (1+t)*o(i) & c(i) < (1+u)*o(i) & l(i) > (o(i)-x*(c(i)-o(i)))
            signals(i) = 1;
        end;
end;


%BSS

function signals = bss(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=1:length(c)
        if h(i) > (o(i)+zz*(o(i)-c(i))) & c(i) > (1-u)*o(i) & c(i) < (1-t)*o(i) & l(i) > (c(i)-x*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;


%HANGMAN

function signals = hangman(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)
```

```
		if h(i-1) < (o(i-1)+x*(o(i-1)-c(i-1))) & c(i-1) < (1-t)*o(i-1) & c(i-1) > (1-u)*o(i-1) & l(i-1) < (c(i-1)-zz*(o(i-1)-c(i-1))) & o(i) < h(i-1) & c(i) < o(i) & c(i) < c(i-1) & l(i) > (c(i)-y*(o(i)-c(i)))
			signals(i) = 1;
		end;
end;


%BEARENG

function signals = beareng(o,h,l,c,t,u,v,w,x,y,z);
signals = zeros(size(c));
for i=2:length(c)
		if c(i-1) > (1+t)*o(i-1) & o(i) > c(i-1) & c(i) < o(i-1) & l(i) < l(i-1) & l(i) > (c(i)-y*(o(i)-c(i))) & h(i) > h(i-1) & h(i) < (o(i)+y*(o(i)-c(i)))
			signals(i) = 1;
		end;
end;


%DCC

function signals = dcc(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=2:length(c)
		if c(i-1) > (1+w)*o(i-1) & l(i-1) > (o(i-1)-y*(c(i-1)-o(i-1))) & h(i-1) < (c(i-1)+y*(c(i-1)-o(i-1))) & c(i) < (o(i-1)+y*(c(i-1)-o(i-1))) & c(i) > o(i-1) & o(i) > c(i-1) & l(i) > (c(i)-y*(o(i)-c(i)))
			signals(i) = 1;
		end;
end;


%BEARHAR

function signals = bearhar(o,h,l,c,t,u,v,w,x,y,z);
signals = zeros(size(c));
for i=2:length(c)
```

```
        if c(i-1) > (1+w)*o(i-1) & l(i-1) > (o(i-1)-y*(c(i-1)-o(i-1))) & h(i-1) < (c(i-1)+y*(c(i-1)-o(i-1))) & o(i) < c(i-1) & c(i) > o(i-1) & c(i) < o(i) & l(i) > l(i-1) & h(i) < h(i-1)
            signals(i) = 1;
        end;
end;


%THRIDN

function signals = thridn(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=3:length(c)
        if c(i-2) > (1+w)*o(i-2) & l(i-2) > (o(i-2)-y*(c(i-2)-o(i-2))) & h(i-2) < (c(i-2)+y*(c(i-2)-o(i-2))) & o(i-1) < c(i-2) & c(i-1) > o(i-2) & c(i-1) < o(i-1) & l(i-1) > l(i-2) & h(i-1) < h(i-2) & o(i) < c(i-2) & o(i) > o(i-2) & c(i) < o(i-2) & l(i) > (c(i)-y*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;


%THRODN

function signals = throdn(o,h,l,c,t,u,v,w,x,y,zz);
signals = zeros(size(c));
for i=3:length(c)
        if c(i-2) > (1+t)*o(i-2) & o(i-1) > c(i-2) & c(i-1) < o(i-2) & l(i-1) < l(i-2) & l(i-1) > (c(i-1)-y*(o(i-1)-c(i-1))) & h(i-1) > h(i-2) & h(i-1) < (o(i-1)+y*(o(i-1)-c(i-1))) & o(i) > c(i-1) & o(i) < o(i-1) & c(i) < c(i-1) & l(i) > (c(i)-y*(o(i)-c(i)))
            signals(i) = 1;
        end;
end;


%TWTOP

function signals = twtop(o,h,l,c,t,u,v,w,x,y,zz);
```

```
signals = zeros(size(c));
for i=3:length(c)

            signals(i) = 1;
        end;
end;
```

A.3.2. *T*-Test

```
%TTEST

%THINGS TO CHECK

%Is the buy return array picking up the correct returns (open v close)?
%Is the buy return array positive for long rules and negative for short rules?
%Is the tlag correct?
%Is the number of bootstraps correct?
%Is the number of rules correct?
%Is the emaf correct?
%Is the HP correct?
%Are the CS parameters correct?
%Is the output labelled correctly

tickers = char('xom','wmt','utx','t','sbc','s','pg','msft','mrk','mo','mmm','mcd','ko','jpm','jnj','ipl','aa','intc','ibm','hon','hd','gt','gm','ge','ek','dow','dis','dd','cat','ba','axp','bhmsq','cvx','hpq','c');
%tickers = char('spytest');

format long

%Parameters

tlag = 2;
HP = 10;
emaf = 10;
numRules = 28;

% t = 0.0005;
% u = 0.005;
% v = 0.001;
% w = 0.01;
% x = 0.1;
```

```
% y = 0.5;
% z = 2;

t = 0.0005;
u = 0.0075;
v = 0.001;
w = 0.015;
x = 0.1;
y = 0.5;
zz = 2;

%Start program

for z=1:numRules

          output = zeros(size(tickers,1)+1,5);
          dowReturns = [];
          dowBuyReturns = [];
          dowSellReturns = [];
          dowBuyCounter = 0;
          dowSellCounter = 0;
          dowBuys = 0;
          dowSells = 0;

          errorFlag = zeros(size(tickers,1),1);

          for m=1:size(tickers,1)

        ticker = strcat('input\',tickers(m,:),'.csv');

                    M = csvread(ticker,1,0);
                    open = M(:,2);
                    high = M(:,3);
                    low = M(:,4);
                    close = M(:,5);

```

```
        %returns = [0; diff(log(close))];
        returns = [0; diff(log(open))];

                lwSig = lw(open,high,low,close,t,u,v,w,x,y,zz);
                wmSig = wm(open,high,low,close,t,u,v,w,x,y,zz);
                cwmSig = cwm(open,high,low,close,t,u,v,w,x,zz);
                owmSig = owm(open,high,low,close,t,u,v,w,x,y,zz);
                ddSig = dd(open,high,low,close,t,u,v,w,x,y,zz);
                wpuSig = wpu(open,high,low,close,t,u,v,w,x,y,zz);
                bpuSig = bpu(open,high,low,close,t,u,v,w,x,y,zz);
                hammerSig = hammer(open,high,low,close,t,u,v,w,x,y,zz);
                bullengSig = bulleng(open,high,low,close,t,u,v,w,x,y,zz);
                pielineSig = pieline(open,high,low,close,t,u,v,w,x,y,zz);
                bullharSig = bullhar(open,high,low,close,t,u,v,w,x,y,zz);
                thriupSig = thriup(open,high,low,close,t,u,v,w,x,y,zz);
                throupSig = throup(open,high,low,close,t,u,v,w,x,y,zz);
                twbotSig = twbot(open,high,low,close,t,u,v,w,x,y,zz);
                lbSig = lb(open,high,low,close,t,u,v,w,x,y,zz);
                bmSig = bm(open,high,low,close,t,u,v,w,x,y,zz);
                cbmSig = cbm(open,high,low,close,t,u,v,w,x,y,zz);
                obmSig = obm(open,high,low,close,t,u,v,w,x,y,zz);
                gdSig = gd(open,high,low,close,t,u,v,w,x,y,zz);
                wssSig = wss(open,high,low,close,t,u,v,w,x,y,zz);
                bssSig = bss(open,high,low,close,t,u,v,w,x,y,zz);
                    hangmanSig = hangman(open,high,low,close,t,u,v,w,x,y,zz);
                bearengSig = beareng(open,high,low,close,t,u,v,w,x,y,zz);
                dccSig = dcc(open,high,low,close,t,u,v,w,x,y,zz);
                bearharSig = bearhar(open,high,low,close,t,u,v,w,x,y,zz);
                thridnSig = thridn(open,high,low,close,t,u,v,w,x,y,zz);
                throdnSig = throdn(open,high,low,close,t,u,v,w,x,y,zz);
                twtopSig = twtop(open,high,low,close,t,u,v,w,x,y,zz);
                expma = ema(close,emaf);

                    T = length(open);
        signalArray = zeros(T,1);

```

```
   %%%%%%%%%% RULES %%%%%%%%%%

 if z==1 %Rule 1.
      rule(z) = 1;
      for i=2:T-2
          if lwSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==2 %Rule 2.
      rule(z) = 2;
      for i=2:T-2
         if wmSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
if z==3 %Rule 3.
      rule(z) = 3;
      for i=2:T-2
          if cwmSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==4 %Rule 4.
      rule(z) = 4;
      for i=2:T-2
         if owmSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==5 %Rule 5.
      rule(z) = 5;
```

```
        for i=2:T-2
            if ddSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==6 %Rule 6.
        rule(z) = 6;
        for i=2:T-2
           if wpuSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==7 %Rule 7.
        rule(z) = 7;
        for i=2:T-2
            if bpuSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==8 %Rule 8.
        rule(z) = 8;
        for i=3:T-3
            if close(i-2) < expma(i-2) & hammerSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==9 %Rule 9.
        rule(z) = 9;
        for i=3:T-3
            if close(i-2) < expma(i-2) & bullengSig(i)
                signalArray(i+tlag) = 1;
            end;
```

```
            end;
        end;
        if z==10 %Rule 10.
            rule(z) = 10;
            for i=3:T-3
                if close(i-2) < expma(i-2) & pielineSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
       end;
       if z==11 %Rule 11.
            rule(z) = 11;
            for i=3:T-3
                if close(i-2) < expma(i-2) & bu11harSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
       end;
      if z==12 %Rule 12.
            rule(z) = 12;
            for i=4:T-4
                if close(i-3) < expma(i-3) & thriupSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
       end;
       if z==13 %Rule 13.
            rule(z) = 13;
            for i=4:T-4
                if close(i-3) < expma(i-3) & throupSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
       end;
       if z==14 %Rule 14.
            rule(z) = 14;
```

```
   for i=4:T-4
     if close(i-3) < expma(i-3) & twbotSig(i)
       signalArray(i+tlag) = 1;
     end;
   end;
 end;
  if z==15 %Rule 15.
   rule(z) = 15;
   for i=2:T-2
     if lbSig(i)
       signalArray(i+tlag) = 1;
     end;
   end;
 end;
 if z==16 %Rule 16.
   rule(z) = 16;
   for i=2:T-2
    if bmSig(i)
       signalArray(i+tlag) = 1;
     end;
   end;
 end;
if z==17 %Rule 17.
   rule(z) = 17;
   for i=2:T-2
     if cbmSig(i)
       signalArray(i+tlag) = 1;
     end;
   end;
 end;
if z==18 %Rule 18.
   rule(z) = 18;
   for i=2:T-2
    if obmSig(i)
       signalArray(i+tlag) = 1;
     end;
```

```
            end;
        end;
      if z==19 %Rule 19.
            rule(z) = 19;
            for i=2:T-2
                if gdSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==20 %Rule 20.
            rule(z) = 20;
            for i=2:T-2
               if wssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==21 %Rule 21.
            rule(z) = 21;
            for i=2:T-2
                if bssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==22 %Rule 22.
            rule(z) = 22;
            for i=3:T-3
                if close(i-2) > expma(i-2) & hangmanSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==23 %Rule 23.
            rule(z) = 23;
```

```
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearengSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==24 %Rule 24.
            rule(z) = 24;
            for i=3:T-3
                if close(i-2) > expma(i-2) & dccSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==25 %Rule 25.
            rule(z) = 25;
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearharSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==26 %Rule 26.
            rule(z) = 26;
            for i=4:T-4
                if close(i-3) > expma(i-3) & thridnSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==27 %Rule 27.
            rule(z) = 27;
            for i=4:T-4
                if close(i-3) > expma(i-3) & throdnSig(i)
                    signalArray(i+tlag) = 1;
                end;
```

```
            end;
        end;
        if z==28 %Rule 28.
            rule(z) = 28;
            for i=4:T-4
                if close(i-3) > expma(i-3) & twtopSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;


         %Reprocess to remove double signals

         for i=HP+1:T-HP+1
             if signalArray(i) == 1 & max(signalArray(i-HP:i-1)) == 1
                 signalArray(i) = 0;
             end;
         end;

         %Profit calcs

         %Iterate through buy/sell points calculating profit.

         buys = 0;
         sells = 0;

         buyRetArray = [];
         sellRetArray = [];


         for i=1:T-HP-1

             %Calculate buy profit

             if signalArray(i) == 1
```

```
                %Write all returns into array for sigma calc.
                 buyRetArray = [buyRetArray; returns(i:i+HP-1)];%*
                 buys = buys + 1;

             end;

             %*Change for open or close returns.

         end;

         [char('----------------') tickers(m,:) char('----------------')]

         if buys == 0
             errorFlag(m) = 1;
         else
             [p,buyTstat] = uttest(buyRetArray, returns);
             buyProp = length(buyRetArray(buyRetArray>0))/length(buyRetArray);
             output(m+1,:) = [buys mean(buyRetArray) buyTstat p buyProp ];  %N.B. First row is total Dow.

             dowBuys = dowBuys + buys;
             dowBuyReturns = [dowBuyReturns; buyRetArray];
             dowReturns = [dowReturns; returns];
         end;


           end;

           [p,buyTstat] = uttest(dowBuyReturns, dowReturns);
           buyProp = length(dowBuyReturns(dowBuyReturns>0))/length(dowBuyReturns);
           output(1,:) = [dowBuys mean(dowBuyReturns) buyTstat p buyProp];  %N.B. First row is total Dow.

           %csvwrite(strcat('output\dow_',model,'.csv'),output);

           if rule(z) < 10
               fid = fopen(strcat('output\c_ttest_rule',char(rule(z)+48),'.csv'),'w'); %Changed this line 10
```

```
Jan 04
    else
        fid =
fopen(strcat('output\c_ttest_rule',char(floor(rule(z)/10)+48),char(mod(rule(z),10)+48),'.csv'),'w'); %Changed
this line 10 Jan 04
    end;
          fprintf(fid,'%s\n\n','T-TEST:');
          fprintf(fid,'%s\n',',buy N,buy mean,buy t,buy p,buy binomial');
          fprintf(fid,'%s,%f,%f,%f,%f,%f\n','DOW',output(1,:));
          for i=2:size(output,1)
        if errorFlag(i-1) == 0
            fprintf(fid,'%s,%f,%f,%f,%f,%f\n',tickers(i-1,:),output(i,:));
        else
            fprintf(fid,'%s,%s\n',tickers(i-1,:),'Error: No signals.');
        end;
          end;

end;
```

A.3.3. EMA

```
function expma = ema(price,L)

expma = zeros(size(price));
factor = 2/(L+1);
for i=2:length(price)
    expma(i) = price(i)*factor + expma(i-1)*(1-factor);
end;
```

A.3.4. Uttest

```
function [p, t, df] = uttest(d1, d2)
%UTTEST Student's t-test for unequal variances.
%       UTTEST(X1, X2) gives the probability that Student's t
%       calculated on data X1 and X2, sampled from distributions
%       with different variances, is higher than observed, i.e.
%       the "significance" level.  This is used to test whether
%       two sample have significantly different means.
%       [P, T] = UTTEST(X1, X2) gives this probability P and the
%       value of Student's t in T. The smaller P is, the more
%       significant the difference between the means.
%       E.g. if P = 0.05 or 0.01, it is very likely that the
%       two sets are sampled from distributions with different
%       means.
%
%       This works if the samples are drawn from distributions with
%       DIFFERENT VARIANCE. Otherwise, use TTEST.
%
%See also: TTEST, PTTEST.
[l1 c1] = size(d1) ;
n1 = l1 * c1 ;
x1 = reshape(d1, l1 * c1, 1) ;
[l2 c2] = size(d2) ;
n2 = l2 * c2 ;
x2 = reshape(d2, l2 * c2, 1) ;
[a1 v1] = avevar(x1) ;
[a2 v2] = avevar(x2) ;
df = (v1 / n1 + v2 / n2) * (v1 / n1 + v2 / n2) / ...
     ( (v1 / n1) * (v1 / n1) / (n1 - 1) + (v2 / n2) * (v2 / n2) / (n2 -1) ) ;
t = (a1 - a2) / sqrt( v1 / n1 + v2 / n2 ) ;
p = betainc( df / (df + t*t), df/2, 0.5) ;
```

A.3.5. Random Walk Bootstrap

```
%BOOTSTRAP RANDOM WALK

%THINGS TO CHECK

%Are the output descriptions correct?
%Is the buy return array picking up the correct returns (open v close)?
%Is the tlag correct?
%Is the number of bootstraps correct?
%Is the number of rules correct?
%Is the emaf correct?
%Is the HP correct?
%Are the CS parameters correct?


%Generates random walk bootstrapped series.

format long

%Parameters

tlag = 2;                %Time lag on return calculations, e.g. set to 2 for close t+2.
N = 501;                 %Number of bootstrap iterations + 1 (first block holds original series).
numRules = 30;            %Number of trading rules to test.
emaf = 10;
HP = 10;
rule = zeros(numRules,1);

% t = 0.0005;
% u = 0.005;
% v = 0.001;
% w = 0.01;
% x = 0.1;
```

```
% y = 0.5;
% zz = 2;

t = 0.0005;
u = 0.0075;
v = 0.001;
w = 0.015;
x = 0.1;
y = 0.5;
zz = 2;

%Input

tickers = char('xom','wmt','utx','t','sbc','s','pg','msft','mrk','mo','mmm','mcd','ko','jpm','jnj','ipl','aa','intc','ibm','hon','hd','gt','gm','ge','ek','dow','dis','dd','cat','ba','axp','bhmsq','cvx','hpq','c');

%tickers = char('xom','wmt');

%First column holds buyArray mean for each stock. Second column holds
%market return for each stock.

bootstrapMeans = zeros(size(tickers,1)*(N-1),2);%%
origMeans = zeros(size(tickers,1),2,numRules);
output = zeros(size(tickers,1),3,numRules);
convergence = zeros(N,2,numRules,size(tickers,1));

%%%NEW AGGREGATE CODE%%%
aggregate = zeros(size(tickers,1),2,numRules);
%%%%%%%%%%%%%%%%%%%%%%%%

errorFlag = zeros(size(tickers,1),numRules);   %Set to 1 if no signals on original series

for l=1:size(tickers,1);

    tickers(l,:)
```

```
ticker = strcat('input\',tickers(1,:),'.csv');

      M = csvread(ticker,1,0);
      open = M(:,6);
      high = M(:,7);
      low = M(:,8);
      close = M(:,9);
      adj_open = M(:,2);
      adj_high = M(:,3);
      adj_low = M(:,4);
      adj_close = M(:,5);

%%%%%%%%%%TEMP%%%%%%%%%%%%%%
open = adj_open;
high = adj_high;
low = adj_low;
close = adj_close;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%

      T = length(close);



%Initialize big output array

M = zeros(T*N,4);

      %Get original return series

      open_returns = [0; diff(log(open))];
      high_returns = [0; diff(log(high))];
      low_returns = [0; diff(log(low))];
      close_returns = [0; diff(log(close))];

      %Bootstrap step starts.
```

```
        for n=1:N

      %Resample each return series and create new open, high, low, close
      %series

      if n==1;

          new_open_returns = open_returns;
          new_high_returns = high_returns;
          new_low_returns = low_returns;
          new_close_returns = close_returns;

          %Now recreate price series

          new_open = open;
                      new_high = high;
                            new_low = low;
                            new_close = close;

      else

          %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
          %8. RESAMPLE CLOSE, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
          %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

%           h_c_diff = (high-close)./close;
%           c_l_diff = (close-low)./close;
%           o_c_diff = (open-close)./close;
%
%           h_c = resample(h_c_diff);
%           c_l = resample(c_l_diff);
%           o_c = resample(o_c_diff);
%
%           %Now generate new close using random walk.
%
```

```
%               new_close_returns = resample(close_returns);
%               new_close = cumprod([close(1); exp(new_close_returns(2:end))]);
%
%               new_high = new_close + new_close.*h_c;
%               new_low = new_close - new_close.*c_l;
%               new_open = new_close + new_close.*o_c;
%
%               %Correct days where series are out of order
%
%               %Get indexes of days that are wrong.
%
%               wrong_high = find(new_high < max(new_low,new_open));
%               wrong_low = find(new_low > min(new_high,new_open));
%
%               for k=1:length(wrong_high);
%                   index = wrong_high(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
%               end;
%
%               for k=1:length(wrong_low);
%                   index = wrong_low(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
```

```
%              end;

             %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

             %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
             %8. RESAMPLE OPEN, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
             %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

             h_c_diff = (high-open)./open;
             c_l_diff = (open-low)./open;
             o_c_diff = (close-open)./open;

             h_c = resample(h_c_diff);
             c_l = resample(c_l_diff);
             o_c = resample(o_c_diff);

             %Now generate new open using random walk.

             new_open_returns = resample(open_returns);
             new_open = cumprod([open(1); exp(new_open_returns(2:end))]);

             new_high = new_open + new_open.*h_c;
             new_low = new_open - new_open.*c_l;
             new_close = new_open + new_open.*o_c;

             %Correct days where series are out of order

             %Get indexes of days that are wrong.

             wrong_high = find(new_high < max(new_low,new_close));
             wrong_low = find(new_low > min(new_high,new_close));

             for k=1:length(wrong_high);
                 index = wrong_high(k);
                 j = 0;
                 while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) >
```

```
min([new_high(index) new_close(index)]) );
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

            for k=1:length(wrong_low);
                index = wrong_low(k);
                j = 0;
                while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) >
min([new_high(index) new_close(index)]) );
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

%           REMEMBER TO CHANGE BUY RETURN ARRAY TO OPEN RETURNS

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

        end;

        M((n-1)*T+1:n*T,:) = [new_open new_high new_low new_close];

    end;

    %%%%%% START TRADING RULE STEP %%%%%%

    for z=1:numRules    %Rule loop.

                    %Initialize the grandiosely named indicator functions, which are just glorified counters
:)
```

```
            I_buy = 0;
            I_buySigma = 0;

            counter = 0; %Count number of times no buy periods found.

            %Bootstrap step starts.

            for n=1:N

        new_open = M(T*(n-1)+1:T*n,1);
                new_high = M(T*(n-1)+1:T*n,2);
                new_low = M(T*(n-1)+1:T*n,3);
                new_close = M(T*(n-1)+1:T*n,4);

        new_close_returns = [0; diff(log(new_close))];
        new_open_returns = [0; diff(log(new_open))];
        new_high_returns = [0; diff(log(new_high))];
        new_low_returns = [0; diff(log(new_low))];

        signalArray = zeros(T,1);

        lwSig = lw(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        wmSig = wm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        cwmSig = cwm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        owmSig = owm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        ddSig = dd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        wpuSig = wpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        bpuSig = bpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        hammerSig = hammer(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        bullengSig = bulleng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        pielineSig = pieline(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        bullharSig = bullhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        thriupSig = thriup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        throupSig = throup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
        twbotSig = twbot(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
```

```
            lbSig = lb(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bmSig = bm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            cbmSig = cbm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            obmSig = obm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            gdSig = gd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wssSig = wss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bssSig = bss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
              hangmanSig = hangman(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bearengSig = beareng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            dccSig = dcc(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bearharSig = bearhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            thridnSig = thridn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            throdnSig = throdn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            twtopSig = twtop(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            expma = ema(new_close,emaf);

          %%%%%%%%%% RULES %%%%%%%%%%

     if z==1 %Rule 1.
            rule(z) = 1;
            for i=2:T-2
                if lwSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
      end;
      if z==2 %Rule 2.
            rule(z) = 2;
            for i=2:T-2
               if wmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
      end;
    if z==3 %Rule 3.
            rule(z) = 3;
```

```
            for i=2:T-2
                if cwmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==4 %Rule 4.
            rule(z) = 4;
            for i=2:T-2
               if owmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==5 %Rule 5.
            rule(z) = 5;
            for i=2:T-2
                if ddSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==6 %Rule 6.
            rule(z) = 6;
            for i=2:T-2
               if wpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==7 %Rule 7.
            rule(z) = 7;
            for i=2:T-2
                if bpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
```

```
            end;
    end;
    if z==8 %Rule 8.
        rule(z) = 8;
        for i=3:T-3
            if close(i-2) < expma(i-2) & hammerSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==9 %Rule 9.
        rule(z) = 9;
        for i=3:T-3
            if close(i-2) < expma(i-2) & bullengSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==10 %Rule 10.
        rule(z) = 10;
        for i=3:T-3
            if close(i-2) < expma(i-2) & pielineSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==11 %Rule 11.
        rule(z) = 11;
        for i=3:T-3
            if close(i-2) < expma(i-2) & bullharSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;
    if z==12 %Rule 12.
        rule(z) = 12;
```

```
            for i=4:T-4
                if close(i-3) < expma(i-3) & thriupSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==13 %Rule 13.
            rule(z) = 13;
            for i=4:T-4
                if close(i-3) < expma(i-3) & throupSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==14 %Rule 14.
            rule(z) = 14;
            for i=4:T-4
                if close(i-3) < expma(i-3) & twbotSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
           if z==15 %Rule 15.
            rule(z) = 15;
            for i=2:T-2
                if lbSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
         if z==16 %Rule 16.
            rule(z) = 16;
            for i=2:T-2
               if bmSig(i)
                    signalArray(i+tlag) = 1;
                end;
```

```
            end;
        end;
      if z==17 %Rule 17.
            rule(z) = 17;
            for i=2:T-2
                if cbmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
      if z==18 %Rule 18.
            rule(z) = 18;
            for i=2:T-2
               if obmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
      if z==19 %Rule 19.
            rule(z) = 19;
            for i=2:T-2
                if gdSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==20 %Rule 20.
            rule(z) = 20;
            for i=2:T-2
               if wssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==21 %Rule 21.
            rule(z) = 21;
```

```
            for i=2:T-2
                if bssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==22 %Rule 22.
            rule(z) = 22;
            for i=3:T-3
                if close(i-2) > expma(i-2) & hangmanSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==23 %Rule 23.
            rule(z) = 23;
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearengSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==24 %Rule 24.
            rule(z) = 24;
            for i=3:T-3
                if close(i-2) > expma(i-2) & dccSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==25 %Rule 25.
            rule(z) = 25;
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearharSig(i)
                    signalArray(i+tlag) = 1;
                end;
```

```
              end;
         end;
        if z==26 %Rule 26.
              rule(z) = 26;
              for i=4:T-4
                  if close(i-3) > expma(i-3) & thridnSig(i)
                      signalArray(i+tlag) = 1;
                  end;
              end;
         end;
         if z==27 %Rule 27.
              rule(z) = 27;
              for i=4:T-4
                  if close(i-3) > expma(i-3) & throdnSig(i)
                      signalArray(i+tlag) = 1;
                  end;
              end;
         end;
         if z==28 %Rule 28.
              rule(z) = 28;
              for i=4:T-4
                  if close(i-3) > expma(i-3) & twtopSig(i)
                      signalArray(i+tlag) = 1;
                  end;
              end;
         end;

              %Reprocess to remove double signals
              for i=HP+1:T-HP+1
                  if signalArray(i) == 1 & max(signalArray(i-HP:i-1)) == 1
                      signalArray(i) = 0;
                  end;
              end;

              %%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```
        %Profit calcs

        %Iterate through buy/sell points calculating profit.

        buys = 0;

        buyCounter = 0;

        buyRetArray = [];

        for i=1:T-HP-1

            %Calculate buy profit

            if signalArray(i) == 1

                %Write all returns into array for sigma calc.
                buyRetArray = [buyRetArray; new_open_returns(i:i+HP-1)];%*
                buys = buys + 1;

            end;

        end;

        %plot(new_close)
        %hold on
        numBuys(n) = buys;

        if buys==0
            if n==1
                errorFlag(1,z) = 1;
                break;
            end;
            convergence(n,:,z,1) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
            counter = counter + 1;
            continue;
```

```
            end;


            buySigma = std(buyRetArray);
            buyRet = mean(buyRetArray);


            if n==1     %First time through record profit as original Dow profit.
                origBuyRet = buyRet;
                origBuySigma = buySigma;
            end;

            %Compare returns to original

            if buyRet > origBuyRet & n~=1
                I_buy = I_buy + 1;
            end;

           if buySigma > origBuySigma & n~=1
                I_buySigma = I_buySigma + 1;
            end;

            %%
            if n~=1
                convergence(n,:,z,1) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
                bootstrapMeans(1*(n-1),:,z) =  [buyRet buySigma];
            end;
            %%

                    end;

                    if n~=1
            if errorFlag(1,z) == 0
                                        probability_buy = I_buy/(N-1-counter);      %N-1 correction since
first time through gets Dow result.
                                        probability_buySigma = I_buySigma/(N-1-counter);
```

```
                output(l,:,z) = [probability_buy probability_buySigma N-1-counter];

                origMeans(l,:,z) = [origBuyRet origBuySigma];

                %%%%NEW AGGREGATE CODE%%%%

                aggregate(l,:,z) = [I_buy I_buySigma];

                %%%%%%%%%%%%%%%%%%%%%%%%%%

            end;
                    end;

    end;

end;

for z=1:numRules

   if rule(z) < 10
              fid = fopen(strcat('output\c_rw_rule',char(rule(z)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    else
        fid = fopen(strcat('output\c_rw_rule',char(floor(rule(z)/10)+48),char(mod(rule(z),10)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    end;

          fprintf(fid,'%s\n\n','BOOTSTRAP RESULTS:');
          fprintf(fid,'%s\n',',buy,sigma buy,num bootstraps');
          for i=1:size(output,1)
        if errorFlag(i,z) == 0
            fprintf(fid,'%s,%f,%f,%f\n',tickers(i,:),output(i,:,z));
        else
            fprintf(fid,'%s,%s\n',tickers(i,:),'Error: No signal on original series.');
```

```
            end;
              end;

         %%%NEW AGGREGATE CODE%%%%
        fprintf(fid,'\n%s\n\n','AGGREGATE RESULTS:');
        fprintf(fid,'\n%s,%f,%f,%f\n\n','Aggregate',sum(aggregate(:,:,z))/sum(output(:,3,z)));
        %%%%%%%%%%%%%%%%%%%%%%%%%

        bsMean = bootstrapMeans(:,:,z);%%
        oMean = origMeans(:,:,z);%%
              averages = [sum(bsMean)/length(bsMean(bsMean~=0)); sum(oMean)/length(oMean(oMean~=0))];%%

        %averages = [mean(bootstrapMeans(:,:,z)); mean(origMeans(:,:,z))];

              fprintf(fid,'\n%s\n\n','AVERAGES:');
        fprintf(fid,'%s\n',',buy,sigma buy');
        fprintf(fid,'%s,%f,%f\n','mean',averages(1,1),averages(1,2));
        fprintf(fid,'%s,%f,%f\n','dow',averages(2,1),averages(2,2));
              fclose(fid);

    end;

    %%%%%% CONVERGENCE OUTPUT %%%%%%
    fid = fopen('output\c_rw_convergence.csv','w');
    fprintf(fid,'Rule,');
    for l = 1:size(tickers,1)-1
        fprintf(fid,'Ticker,P_b,P_sigmab, ,');
    end;
    fprintf(fid,'Ticker,P_b,P_sigma_b\n');
    for z = 1:numRules
        for n=1:N
            fprintf(fid, '%f,', z);
            for l = 1:size(tickers,1)-1
                fprintf(fid, '%s,%f,%f, ,', tickers(l,:), convergence(n,1,z,l), convergence(n,2,z,l));
            end;
            fprintf(fid, '%s,%f,%f\n', tickers(size(tickers,1),:), convergence(n,1,z,size(tickers,1)),
```

```
convergence(n,2,z,size(tickers,1)));
    end;
    fprintf(fid, '\n');
end;
fclose(fid);
```

A.3.6. Resample Function

```
function new_sample = resample(v)
%RESAMPLE Resamples a column vector v with replacement
%   RESAMPLE(v) resamples v with replacement and returns a new vector of
%   size(v) with elements randomly drawn from v with replacement.

index_vector = fix(rand(size(v))*length(v))+1;
new_sample = v(index_vector);
```

A.3.7. AR1 Bootstrap

```
%BOOTSTRAP AR(1)

%THINGS TO CHECK

%Are the output descriptions correct?
%Is the buy return array picking up the correct returns (open v close)?
%Is the tlag correct?
%Is the number of bootstraps correct?
%Is the number of rules correct?
%Is the emaf correct?
%Is the HP correct?
%Are the CS parameters correct?


%Generates AR(1) bootstrapped series.

format long

%Parameters

tlag = 2;                %Time lag on return calculations, e.g. set to 2 for close t+2.
N = 501;                 %Number of bootstrap iterations + 1 (first block holds original series).
numRules = 30;            %Number of trading rules to test.
emaf = 10;
HP = 10;
rule = zeros(numRules,1);

% t = 0.0005;
% u = 0.005;
% v = 0.001;
% w = 0.01;
```

```
% x = 0.1;
% y = 0.5;
% zz = 2;

t = 0.0005;
u = 0.0075;
v = 0.001;
w = 0.015;
x = 0.1;
y = 0.5;
zz = 2;

%Input

tickers =
char('xom','wmt','utx','t','sbc','s','pg','msft','mrk','mo','mmm','mcd','ko','jpm','jnj','ipl','aa','intc','i
bm','hon','hd','gt','gm','ge','ek','dow','dis','dd','cat','ba','axp','bhmsq','cvx','hpq','c');
%tickers = char('xom','wmt');

%First column holds buyArray mean for each stock. Second column holds
%market return for each stock.

bootstrapMeans = zeros(size(tickers,1)*(N-1),2);%%
origMeans = zeros(size(tickers,1),2,numRules);
output = zeros(size(tickers,1),3,numRules);
Tstats = zeros(size(tickers,1)+1,3);
convergence = zeros(N,2,numRules,size(tickers,1));

%%%NEW AGGREGATE CODE%%%
aggregate = zeros(size(tickers,1),2,numRules);
%%%%%%%%%%%%%%%%%%%%%%%%

errorFlag = zeros(size(tickers,1),numRules);   %Set to 1 if no signals on original series

for l=1:size(tickers,1);

```

```
tickers(l,:)

ticker = strcat('input\',tickers(l,:),'.csv');

      M = csvread(ticker,1,0);
      open = M(:,6);
      high = M(:,7);
      low = M(:,8);
      close = M(:,9);
adj_open = M(:,2);
      adj_high = M(:,3);
      adj_low = M(:,4);
      adj_close = M(:,5);

%%%%%%%%%%%TEMP%%%%%%%%%%%%%
open = adj_open;
high = adj_high;
low = adj_low;
close = adj_close;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

      T = length(close);

%Initialize big output array

M = zeros(T*N,4);

      %Get original return series

      open_returns = [0; diff(log(open))];
      high_returns = [0; diff(log(high))];
      low_returns = [0; diff(log(low))];
      close_returns = [0; diff(log(close))];

%Carry out OLS regression for each series.

```

```
            ret = open_returns(2:end);
            retLagged = open_returns(1:end-1);
            X = [retLagged.^0 retLagged.^1];
            a = regress(ret,X);
            [a_open,bint,open_residuals,rint,stats] = regress(ret,X);

      covB = inv(X'*X)*(sum(open_residuals.^2)/(T-2));
      Tstats(1,:) = [a_open(1)/sqrt(covB(1,1)) a_open(2)/sqrt(covB(2,2)) tinv(0.975,T-2)];    %Confidence
  intervals for constant and slope

            %Bootstrap step starts.

            for n=1:N

          %Resample each return series and create new open, high, low, close
          %series

          if n==1;

              new_open_returns = open_returns;
              new_high_returns = high_returns;
              new_low_returns = low_returns;
              new_close_returns = close_returns;

              %Now recreate price series

              new_open = open;
                          new_high = high;
                                new_low = low;
                                new_close = close;

          else

  %             %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
  %             %8. RESAMPLE CLOSE, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
  %             %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.
```

```
%
%            h_c_diff = (high-close)./close;
%            c_l_diff = (close-low)./close;
%            o_c_diff = (open-close)./close;
%
%            h_c = resample(h_c_diff);
%            c_l = resample(c_l_diff);
%            o_c = resample(o_c_diff);
%
%            %Now generate new close using random walk.
%
%            new_close_residuals = [0; resample(close_residuals)];
%            for k=2:length(close_returns)
%                new_close_returns(k) = a_close(1) + a_close(2)*new_close_returns(k-1) + new_close_residuals(k);
%            end;
%            new_close = cumprod([close(1); exp(new_close_returns(2:end))]);
%
%            new_high = new_close + new_close.*h_c;
%            new_low = new_close - new_close.*c_l;
%            new_open = new_close + new_close.*o_c;
%
%            %Correct days where series are out of order
%
%            %Get indexes of days that are wrong.
%
%            wrong_high = find(new_high < max(new_low,new_open));
%            wrong_low = find(new_low > min(new_high,new_open));
%
%            for k=1:length(wrong_high);
%                index = wrong_high(k);
%                j = 0;
%                while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                    new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                    new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
```

```
%                   new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                   j = j + 1;
%               end;
%           end;
%
%           for k=1:length(wrong_low);
%               index = wrong_low(k);
%               j = 0;
%               while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                   new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                   new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                   new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                   j = j + 1;
%               end;
%           end;

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
            %8. RESAMPLE OPEN, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
            %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

            h_c_diff = (high-open)./open;
            c_l_diff = (open-low)./open;
            o_c_diff = (close-open)./open;

            h_c = resample(h_c_diff);
            c_l = resample(c_l_diff);
            o_c = resample(o_c_diff);

            %Now generate new open using AR(1).

            new_open_residuals = [0; resample(open_residuals)];
            for k=2:length(open_returns)
                new_open_returns(k) = a_open(1) + a_open(2)*new_open_returns(k-1) + new_open_residuals(k);
```

```
end;
new_open = cumprod([open(1); exp(new_open_returns(2:end))]);

new_high = new_open + new_open.*h_c;
new_low = new_open - new_open.*c_l;
new_close = new_open + new_open.*o_c;

%Correct days where series are out of order

%Get indexes of days that are wrong.

wrong_high = find(new_high < max(new_low,new_close));
wrong_low = find(new_low > min(new_high,new_close));

for k=1:length(wrong_high);
    index = wrong_high(k);
    j = 0;
    while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
        new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
        new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
        new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
        j = j + 1;
    end;
end;

for k=1:length(wrong_low);
    index = wrong_low(k);
    j = 0;
    while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
        new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
        new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
        new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
        j = j + 1;
    end;
```

```
                end;

%               REMEMBER TO CHANGE BUY RETURN ARRAY TO OPEN RETURNS

                %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            end;

            M((n-1)*T+1:n*T,:) = [new_open new_high new_low new_close];

        end;

        %%%%%% START TRADING RULE STEP %%%%%%

        for z=1:numRules    %Rule loop.

                        %Initialize the grandiosely named indicator functions, which are just glorified counters :)

                        I_sell = 0;
                        I_buy = 0;
                        I_bs = 0;
                        I_buySigma = 0;
                        I_sellSigma = 0;

                        counter = 0; %Count number of times no buy periods found.

                        %Bootstrap step starts.

                        for n=1:N

                new_open = M(T*(n-1)+1:T*n,1);
                            new_high = M(T*(n-1)+1:T*n,2);
                            new_low = M(T*(n-1)+1:T*n,3);
                            new_close = M(T*(n-1)+1:T*n,4);
```

```
            new_close_returns = [0; diff(log(new_close))];
            new_open_returns = [0; diff(log(new_open))];
            new_high_returns = [0; diff(log(new_high))];
            new_low_returns = [0; diff(log(new_low))];

            signalArray = zeros(T,1);

            lwSig = lw(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wmSig = wm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            cwmSig = cwm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            owmSig = owm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            ddSig = dd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wpuSig = wpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bpuSig = bpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            hammerSig = hammer(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bullengSig = bulleng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            pielineSig = pieline(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bullharSig = bullhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            thriupSig = thriup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            throupSig = throup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            twbotSig = twbot(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            lbSig = lb(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bmSig = bm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            cbmSig = cbm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            obmSig = obm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            gdSig = gd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wssSig = wss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bssSig = bss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
              hangmanSig = hangman(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bearengSig = beareng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            dccSig = dcc(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bearharSig = bearhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            thridnSig = thridn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            throdnSig = throdn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            twtopSig = twtop(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            expma = ema(new_close,emaf);
```

```
%%%%%%%%%% RULES %%%%%%%%%%

  if z==1 %Rule 1.
       rule(z) = 1;
       for i=2:T-2
           if lwSig(i)
               signalArray(i+tlag) = 1;
           end;
       end;
   end;
   if z==2 %Rule 2.
       rule(z) = 2;
       for i=2:T-2
          if wmSig(i)
               signalArray(i+tlag) = 1;
           end;
       end;
   end;
 if z==3 %Rule 3.
       rule(z) = 3;
       for i=2:T-2
           if cwmSig(i)
               signalArray(i+tlag) = 1;
           end;
       end;
   end;
   if z==4 %Rule 4.
       rule(z) = 4;
       for i=2:T-2
          if owmSig(i)
               signalArray(i+tlag) = 1;
           end;
       end;
   end;
   if z==5 %Rule 5.
```

```
            rule(z) = 5;
            for i=2:T-2
                if ddSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==6 %Rule 6.
            rule(z) = 6;
            for i=2:T-2
               if wpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==7 %Rule 7.
            rule(z) = 7;
            for i=2:T-2
                if bpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==8 %Rule 8.
            rule(z) = 8;
            for i=3:T-3
                if close(i-2) < expma(i-2) & hammerSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==9 %Rule 9.
            rule(z) = 9;
            for i=3:T-3
                if close(i-2) < expma(i-2) & bullengSig(i)
                    signalArray(i+tlag) = 1;
```

```
              end;
          end;
      end;
      if z==10 %Rule 10.
          rule(z) = 10;
          for i=3:T-3
              if close(i-2) < expma(i-2) & pielineSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
     end;
     if z==11 %Rule 11.
          rule(z) = 11;
          for i=3:T-3
              if close(i-2) < expma(i-2) & bullharSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
     end;
    if z==12 %Rule 12.
          rule(z) = 12;
          for i=4:T-4
              if close(i-3) < expma(i-3) & thriupSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
     end;
     if z==13 %Rule 13.
          rule(z) = 13;
          for i=4:T-4
              if close(i-3) < expma(i-3) & throupSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
     end;
     if z==14 %Rule 14.
```

```
          rule(z) = 14;
          for i=4:T-4
              if close(i-3) < expma(i-3) & twbotSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
      end;
        if z==15 %Rule 15.
          rule(z) = 15;
          for i=2:T-2
              if lbSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
      end;
      if z==16 %Rule 16.
          rule(z) = 16;
          for i=2:T-2
             if bmSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
      end;
    if z==17 %Rule 17.
          rule(z) = 17;
          for i=2:T-2
              if cbmSig(i)
                  signalArray(i+tlag) = 1;
              end;
          end;
      end;
    if z==18 %Rule 18.
          rule(z) = 18;
          for i=2:T-2
             if obmSig(i)
                  signalArray(i+tlag) = 1;
```

```
                end;
            end;
        end;
      if z==19 %Rule 19.
            rule(z) = 19;
            for i=2:T-2
                if gdSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==20 %Rule 20.
            rule(z) = 20;
            for i=2:T-2
               if wssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==21 %Rule 21.
            rule(z) = 21;
            for i=2:T-2
                if bssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==22 %Rule 22.
            rule(z) = 22;
            for i=3:T-3
                if close(i-2) > expma(i-2) & hangmanSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==23 %Rule 23.
```

```
            rule(z) = 23;
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearengSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==24 %Rule 24.
            rule(z) = 24;
            for i=3:T-3
                if close(i-2) > expma(i-2) & dccSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==25 %Rule 25.
            rule(z) = 25;
            for i=3:T-3
                if close(i-2) > expma(i-2) & bearharSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==26 %Rule 26.
            rule(z) = 26;
            for i=4:T-4
                if close(i-3) > expma(i-3) & thridnSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==27 %Rule 27.
            rule(z) = 27;
            for i=4:T-4
                if close(i-3) > expma(i-3) & throdnSig(i)
                    signalArray(i+tlag) = 1;
```

```
            end;
        end;
    end;
    if z==28 %Rule 28.
        rule(z) = 28;
        for i=4:T-4
            if close(i-3) > expma(i-3) & twtopSig(i)
                signalArray(i+tlag) = 1;
            end;
        end;
    end;


        %Reprocess to remove double signals
        for i=HP+1:T-HP+1
            if signalArray(i) == 1 & max(signalArray(i-HP:i-1)) == 1
                signalArray(i) = 0;
            end;
        end;

        %%%%%%%%%%%%%%%%%%%%%%%%%%%

        %Profit calcs

        %Iterate through buy/sell points calculating profit.

        buys = 0;

        buyCounter = 0;

        buyRetArray = [];

        for i=1:T-HP-1

            %Calculate buy profit

```

```
            if signalArray(i) == 1

                %Write all returns into array for sigma calc.
                buyRetArray = [buyRetArray; new_open_returns(i:i+HP-1)];%*
                buys = buys + 1;

            end;

        end;

        %plot(new_close)
        %hold on
        numBuys(n) = buys;

        if buys==0
            if n==1
                errorFlag(1,z) = 1;
                break;
            end;
            convergence(n,:,z,1) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
            counter = counter + 1;
            continue;
        end;


        buySigma = std(buyRetArray);
        buyRet = mean(buyRetArray);


        if n==1     %First time through record profit as original Dow profit.
            origBuyRet = buyRet;
            origBuySigma = buySigma;
        end;

        %Compare returns to original

```

```
            if buyRet > origBuyRet & n~=1
                I_buy = I_buy + 1;
            end;

           if buySigma > origBuySigma & n~=l
                I_buySigma = I_buySigma + 1;
            end;

            %%
            if n~=1
                convergence(n,:,z,l) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
                bootstrapMeans(l*(n-1),:,z) =  [buyRet buySigma];
            end;
            %%

                    end;

                    if n~=1
            if errorFlag(l,z) == 0
                                        probability_buy = I_buy/(N-1-counter);      %N-1 correction since first time through gets Dow result.
                                        probability_buySigma = I_buySigma/(N-1-counter);

                output(l,:,z) = [probability_buy probability_buySigma N-1-counter];

                origMeans(l,:,z) = [origBuyRet origBuySigma];

                %%%%NEW AGGREGATE CODE%%%%

                aggregate(l,:,z) = [I_buy I_buySigma];

                %%%%%%%%%%%%%%%%%%%%%%%%%%

            end;
                    end;

```

```
    end;

end;

for z=1:numRules

   if rule(z) < 10
              fid = fopen(strcat('output\c_ar1_rule',char(rule(z)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    else
        fid = fopen(strcat('output\c_ar1_rule',char(floor(rule(z)/10)+48),char(mod(rule(z),10)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    end;

    fprintf(fid,'%s\n\n','BOOTSTRAP RESULTS:');
    fprintf(fid,'%s\n',',buy,sigma buy,num bootstraps');
          for i=1:size(output,1)
        if errorFlag(i,z) == 0
            fprintf(fid,'%s,%f,%f,%f\n',tickers(i,:),output(i,:,z));
        else
            fprintf(fid,'%s,%s\n',tickers(i,:),'Error: No signal on original series.');
        end;
          end;

           %%%NEW AGGREGATE CODE%%%%
    fprintf(fid,'\n%s\n\n','AGGREGATE RESULTS:');
    fprintf(fid,'\n%s,%f,%f,%f\n\n','Aggregate',sum(aggregate(:,:,z))/sum(output(:,3,z)));
    %%%%%%%%%%%%%%%%%%%%%%%%%

    bsMean = bootstrapMeans(:,:,z);%%
    oMean = origMeans(:,:,z);%%
          averages = [sum(bsMean)/length(bsMean(bsMean~=0)); sum(oMean)/length(oMean(oMean~=0))];%%

    %averages = [mean(bootstrapMeans(:,:,z)); mean(origMeans(:,:,z))];

```

```
    fprintf(fid,'\n%s\n\n','AVERAGES:');
    fprintf(fid,'%s\n',',buy,sigma buy');
    fprintf(fid,'%s,%f,%f\n','mean',averages(1,1),averages(1,2));
    fprintf(fid,'%s,%f,%f\n','dow',averages(2,1),averages(2,2));

    %T-stat count

          tCount = zeros(1,2);
          for i=1:size(tickers,1)
       tCount = tCount +  (abs(Tstats(i,1:end-1)) > Tstats(i,end));
          end
          Tstats(end,1:end-1) = tCount;

          fprintf(fid,'\n%s\n\n','PARAMETER SIGNIFICANCE COUNT:');
          fprintf(fid,'%s\n',',constant,slope,Tc');
          for i=1:size(Tstats,1)-1
        fprintf(fid,'%s,%f,%f,%f\n',tickers(i,:),Tstats(i,:));
          end;
          fprintf(fid,'%s,%f,%f\n','COUNT',tCount);

    fclose(fid);

end;

%%%%%% CONVERGENCE OUTPUT %%%%%%
fid = fopen('output\c_ar1_convergence.csv','w');
fprintf(fid,'Rule,');
for l = 1:size(tickers,1)-1
    fprintf(fid,'Ticker,P_b,P_sigmab, ,');
end;
fprintf(fid,'Ticker,P_b,P_sigma_b\n');
for z = 1:numRules
    for n=1:N
        fprintf(fid, '%f,', z);
        for l = 1:size(tickers,1)-1
            fprintf(fid, '%s,%f,%f, ,', tickers(l,:), convergence(n,1,z,l), convergence(n,2,z,l));
```

```
            end;
            fprintf(fid, '%s,%f,%f\n', tickers(size(tickers,1),:), convergence(n,1,z,size(tickers,1)),
convergence(n,2,z,size(tickers,1)));
        end;
        fprintf(fid, '\n');
end;
fclose(fid);
```

A.3.8. GARCH-M Bootstrap

```
%BOOTSTRAP GARCHM

%THINGS TO CHECK

%Are the output descriptions correct?
%Is the buy return array picking up the correct returns (open v close)?
%Is the GARCH fit picking up the correct returns (open v close)?
%Is the tlag correct?
%Is the number of bootstraps correct?
%Is the number of rules correct?
%Is the emaf correct?
%Is the HP correct?
%Are the CS parameters correct?


%Generates garchm bootstrapped series.

format long

%Parameters

tlag = 2;                   %Time lag on return calculations, e.g. set to 2 for close t+2.
N = 501;                    %Number of bootstrap iterations + 1 (first block holds original series).
numRules = 30;               %Number of trading rules to test.
emaf = 10;
HP = 10;
rule = zeros(numRules,1);

% t = 0.0005;
% u = 0.005;
% v = 0.001;
% w = 0.01;
```

```
% x = 0.1;
% y = 0.5;
% zz = 2;

t = 0.0005;
u = 0.0075;
v = 0.001;
w = 0.015;
x = 0.1;
y = 0.5;
zz = 2;


%Input

tickers = char('xom','wmt','utx','t','sbc','s','pg','msft','mrk','mo','mmm','mcd','ko','jpm','jnj','ipl','aa','intc','ibm','hon','hd','gt','gm','ge','ek','dow','dis','dd','cat','ba','axp','bhmsq','cvx','hpq','c');
%tickers = char('xom','wmt');

%First column holds buyArray mean for each stock. Second column holds
%market return for each stock.

bootstrapMeans = zeros(size(tickers,1)*(N-1),2);
origMeans = zeros(size(tickers,1),2,numRules);
output = zeros(size(tickers,1),3,numRules);
Tstats = zeros(size(tickers,1)+1,7);
convergence = zeros(N,2,numRules,size(tickers,1));

%%%NEW AGGREGATE CODE%%%
aggregate = zeros(size(tickers,1),2,numRules);
%%%%%%%%%%%%%%%%%%%%%%%%

errorFlag = zeros(size(tickers,1),numRules);   %Set to 1 if no signals on original series

for l=1:size(tickers,1);
```

```
       tickers(1,:)

       ticker = strcat('input\',tickers(1,:),'.csv');

             M = csvread(ticker,1,0);
             open = M(:,6);
             high = M(:,7);
             low = M(:,8);
             close = M(:,9);
       adj_open = M(:,2);
             adj_high = M(:,3);
             adj_low = M(:,4);
             adj_close = M(:,5);

       %%%%%%%%%%%TEMP%%%%%%%%%%%%%%
       open = adj_open;
       high = adj_high;
       low = adj_low;
       close = adj_close;
       %%%%%%%%%%%%%%%%%%%%%%%%%%%%%

             T = length(close);



       %Initialize big output array

       M = zeros(T*N,4);

             %Get original return series

             open_returns = [0; diff(log(open))];
             high_returns = [0; diff(log(high))];
             low_returns = [0; diff(log(low))];
             close_returns = [0; diff(log(close))];
```

```
    %Fit garchm

    spec = garchset('VarianceModel', 'GARCH-M', 'P', 1, 'Q', 1, 'R', 0, 'M', 1, 'Display', 'off');
          [coeff, errors, LLF, innovations, sigma, summary] = garchfit(spec, open_returns);
          garchdisp(coeff, errors);

    %Write t-stats to array

    Tstats(1,:) = [coeff.C/errors.C coeff.MA(1)/errors.MA(1) coeff.InMean/errors.InMean  coeff.K/errors.K
coeff.GARCH(1)/errors.GARCH(1) coeff.ARCH(1)/errors.ARCH(1) tinv(0.975,T-6)];


          %Bootstrap step starts.

          for n=1:N


        %Resample each return series and create new open, high, low, close
        %series

        if n==1;

            new_open_returns = open_returns;
            new_high_returns = high_returns;
            new_low_returns = low_returns;
            new_close_returns = close_returns;

            %Now recreate price series

            new_open = open;
                        new_high = high;
                              new_low = low;
                              new_close = close;

        else
```

```
                %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
                %8. RESAMPLE CLOSE, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
                %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

%               h_c_diff = (high-close)./close;
%               c_l_diff = (close-low)./close;
%               o_c_diff = (open-close)./close;
%
%               h_c = resample(h_c_diff);
%               c_l = resample(c_l_diff);
%               o_c = resample(o_c_diff);
%
%               h_c = h_c_diff;
%               c_l = c_l_diff;
%               o_c = o_c_diff;
%
%               %Now generate new close using garchm.
%
%               new_close_returns = garchm_function(1,close_returns,innovations./sigma,coeff.C,coeff.MA(1),coeff.InMean,coeff.K,coeff.GARCH(1),coeff.ARCH(1),sigma);
%               new_close = cumprod([close(1); exp(new_close_returns(2:end))]);
%
%               new_high = new_close + new_close.*h_c;
%               new_low = new_close - new_close.*c_l;
%               new_open = new_close + new_close.*o_c;
%
%               %Correct days where series are out of order
%
%               %Get indexes of days that are wrong.
%
%               wrong_high = find(new_high < max(new_low,new_open));
%               wrong_low = find(new_low > min(new_high,new_open));
%
%               for k=1:length(wrong_high);
```

```
%                   index = wrong_high(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
%               end;
%
%               for k=1:length(wrong_low);
%                   index = wrong_low(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
%               end;
%
            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
            %8. RESAMPLE OPEN, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
            %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

            h_c_diff = (high-open)./open;
            c_l_diff = (open-low)./open;
            o_c_diff = (close-open)./open;

            h_c = resample(h_c_diff);
            c_l = resample(c_l_diff);
            o_c = resample(o_c_diff);
```

```
            %Now generate new open using garchm.

            new_open_returns = garchm_function(1,open_returns,innovations./sigma,coeff.C,coeff.MA(1),coeff.InMean,coeff.K,coeff.GARCH(1),coeff.ARCH(1),sigma);
            new_open = cumprod([open(1); exp(new_open_returns(2:end))]);

            new_high = new_open + new_open.*h_c;
            new_low = new_open - new_open.*c_l;
            new_close = new_open + new_open.*o_c;

            %Correct days where series are out of order

            %Get indexes of days that are wrong.

            wrong_high = find(new_high < max(new_low,new_close));
            wrong_low = find(new_low > min(new_high,new_close));

            for k=1:length(wrong_high);
                index = wrong_high(k);
                j = 0;
                while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

            for k=1:length(wrong_low);
                index = wrong_low(k);
                j = 0;
                while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
```

```
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

%           % REMEMBER TO CHANGE BUY RETURN ARRAY TO OPEN RETURNS

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

        end;

        M((n-1)*T+1:n*T,:) = [new_open new_high new_low new_close];

    end;

    %%%%%% START TRADING RULE STEP %%%%%%

    for z=1:numRules    %Rule loop.

                %Initialize the grandiosely named indicator functions, which are just glorified counters :)

                I_buy = 0;
                I_buySigma = 0;

                counter = 0; %Count number of times no buy periods found.

                %Bootstrap step starts.

                for n=1:N

            new_open = M(T*(n-1)+1:T*n,1);
                    new_high = M(T*(n-1)+1:T*n,2);
                    new_low = M(T*(n-1)+1:T*n,3);
```

```
            new_close = M(T*(n-1)+1:T*n,4);

    new_close_returns = [0; diff(log(new_close))];
    new_open_returns = [0; diff(log(new_open))];
    new_high_returns = [0; diff(log(new_high))];
    new_low_returns = [0; diff(log(new_low))];

    signalArray = zeros(T,1);

    lwSig = lw(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    wmSig = wm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    cwmSig = cwm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    owmSig = owm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    ddSig = dd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    wpuSig = wpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bpuSig = bpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    hammerSig = hammer(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bullengSig = bulleng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    pielineSig = pieline(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bullharSig = bullhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    thriupSig = thriup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    throupSig = throup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    twbotSig = twbot(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    lbSig = lb(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bmSig = bm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    cbmSig = cbm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    obmSig = obm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    gdSig = gd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    wssSig = wss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bssSig = bss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
      hangmanSig = hangman(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bearengSig = beareng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    dccSig = dcc(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    bearharSig = bearhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    thridnSig = thridn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
    throdnSig = throdn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
```

```
            twtopSig = twtop(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            expma = ema(new_close,emaf);

        %%%%%%%%%% RULES %%%%%%%%%%

         if z==1 %Rule 1.
            rule(z) = 1;
            for i=2:T-2
                if lwSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
          end;
          if z==2 %Rule 2.
            rule(z) = 2;
            for i=2:T-2
               if wmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
          end;
        if z==3 %Rule 3.
            rule(z) = 3;
            for i=2:T-2
                if cwmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
          end;
          if z==4 %Rule 4.
            rule(z) = 4;
            for i=2:T-2
               if owmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
```

```
        end;
        if z==5 %Rule 5.
            rule(z) = 5;
            for i=2:T-2
                if ddSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==6 %Rule 6.
            rule(z) = 6;
            for i=2:T-2
                if wpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==7 %Rule 7.
            rule(z) = 7;
            for i=2:T-2
                if bpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==8 %Rule 8.
            rule(z) = 8;
            for i=3:T-3
                if close(i-2) < expma(i-2) & hammerSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==9 %Rule 9.
            rule(z) = 9;
            for i=3:T-3
```

```
          if close(i-2) < expma(i-2) & bullengSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==10 %Rule 10.
      rule(z) = 10;
      for i=3:T-3
          if close(i-2) < expma(i-2) & pielineSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==11 %Rule 11.
      rule(z) = 11;
      for i=3:T-3
          if close(i-2) < expma(i-2) & bullharSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
if z==12 %Rule 12.
      rule(z) = 12;
      for i=4:T-4
          if close(i-3) < expma(i-3) & thriupSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==13 %Rule 13.
      rule(z) = 13;
      for i=4:T-4
          if close(i-3) < expma(i-3) & throupSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
```

```
        end;
        if z==14 %Rule 14.
            rule(z) = 14;
            for i=4:T-4
                if close(i-3) < expma(i-3) & twbotSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
           if z==15 %Rule 15.
            rule(z) = 15;
            for i=2:T-2
                if lbSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
         if z==16 %Rule 16.
            rule(z) = 16;
            for i=2:T-2
               if bmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
       if z==17 %Rule 17.
            rule(z) = 17;
            for i=2:T-2
                if cbmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
         end;
       if z==18 %Rule 18.
            rule(z) = 18;
            for i=2:T-2
```

```
                if obmSig(i)
                     signalArray(i+tlag) = 1;
                 end;
             end;
         end;
       if z==19 %Rule 19.
             rule(z) = 19;
             for i=2:T-2
                 if gdSig(i)
                     signalArray(i+tlag) = 1;
                 end;
             end;
         end;
         if z==20 %Rule 20.
             rule(z) = 20;
             for i=2:T-2
                if wssSig(i)
                     signalArray(i+tlag) = 1;
                 end;
             end;
         end;
         if z==21 %Rule 21.
             rule(z) = 21;
             for i=2:T-2
                 if bssSig(i)
                     signalArray(i+tlag) = 1;
                 end;
             end;
         end;
         if z==22 %Rule 22.
             rule(z) = 22;
             for i=3:T-3
                 if close(i-2) > expma(i-2) & hangmanSig(i)
                     signalArray(i+tlag) = 1;
                 end;
             end;
```

```
  end;
  if z==23 %Rule 23.
      rule(z) = 23;
      for i=3:T-3
          if close(i-2) > expma(i-2) & bearengSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==24 %Rule 24.
      rule(z) = 24;
      for i=3:T-3
          if close(i-2) > expma(i-2) & dccSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==25 %Rule 25.
      rule(z) = 25;
      for i=3:T-3
          if close(i-2) > expma(i-2) & bearharSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
if z==26 %Rule 26.
      rule(z) = 26;
      for i=4:T-4
          if close(i-3) > expma(i-3) & thridnSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==27 %Rule 27.
      rule(z) = 27;
      for i=4:T-4
```

```
                if close(i-3) > expma(i-3) & throdnSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==28 %Rule 28.
            rule(z) = 28;
            for i=4:T-4
                if close(i-3) > expma(i-3) & twtopSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;


            %Reprocess to remove double signals
            for i=HP+1:T-HP+1
                if signalArray(i) == 1 & max(signalArray(i-HP:i-1)) == 1
                    signalArray(i) = 0;
                end;
            end;

            %%%%%%%%%%%%%%%%%%%%%%%%%%%

            %Profit calcs

            %Iterate through buy/sell points calculating profit.

            buys = 0;

            buyCounter = 0;

            buyRetArray = [];

           for i=1:T-HP-1

```

```
            %Calculate buy profit

            if signalArray(i) == 1

                %Write all returns into array for sigma calc.
                buyRetArray = [buyRetArray; new_open_returns(i:i+HP-1)];%*
                buys = buys + 1;

            end;

        end;

        %plot(new_close)
        %hold on
        numBuys(n) = buys;

      if buys==0
            if n==1
                errorFlag(1,z) = 1;
                break;
            end;
            convergence(n,:,z,1) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
            counter = counter + 1;
            continue;
        end;


        buySigma = std(buyRetArray);
        buyRet = mean(buyRetArray);


        if n==1     %First time through record profit as original Dow profit.
            origBuyRet = buyRet;
            origBuySigma = buySigma;
        end;

```

```
            %Compare returns to original

            if buyRet > origBuyRet & n~=1
                I_buy = I_buy + 1;
            end;

           if buySigma > origBuySigma & n~=1
                I_buySigma = I_buySigma + 1;
            end;

            %%
            if n~=1
                convergence(n,:,z,l) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
                bootstrapMeans(l*(n-1),:,z) =  [buyRet buySigma];
            end;
            %%

                    end;

                    if n~=1
            if errorFlag(l,z) == 0
                                        probability_buy = I_buy/(N-1-counter);      %N-1 correction since first time through gets Dow result.
                                        probability_buySigma = I_buySigma/(N-1-counter);

                output(l,:,z) = [probability_buy probability_buySigma N-1-counter];

                origMeans(l,:,z) = [origBuyRet origBuySigma];

                %%%%NEW AGGREGATE CODE%%%%

                aggregate(l,:,z) = [I_buy I_buySigma];

                %%%%%%%%%%%%%%%%%%%%%%%%%%

            end;
```

```
                    end;

        end;

end;

for z=1:numRules

    if rule(z) < 10
                fid = fopen(strcat('output\c_garchm_rule',char(rule(z)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    else
        fid = fopen(strcat('output\c_garchm_rule',char(floor(rule(z)/10)+48),char(mod(rule(z),10)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    end;

    fprintf(fid,'%s\n\n','BOOTSTRAP RESULTS:');
    fprintf(fid,'%s\n',',buy,sigma buy,num bootstraps');
          for i=1:size(output,1)
        if errorFlag(i,z) == 0
            fprintf(fid,'%s,%f,%f,%f\n',tickers(i,:),output(i,:,z));
        else
            fprintf(fid,'%s,%s\n',tickers(i,:),'Error: No signal on original series.');
        end;
          end;

             %%%NEW AGGREGATE CODE%%%%
    fprintf(fid,'\n%s\n\n','AGGREGATE RESULTS:');
    fprintf(fid,'\n%s,%f,%f,%f\n\n','Aggregate',sum(aggregate(:,:,z))/sum(output(:,3,z)));
    %%%%%%%%%%%%%%%%%%%%%%%%%


    bsMean = bootstrapMeans(:,:,z);%%
    oMean = origMeans(:,:,z);%%
          averages = [sum(bsMean)/length(bsMean(bsMean~=0)); sum(oMean)/length(oMean(oMean~=0))];%%
```

```
    %averages = [mean(bootstrapMeans(:,:,z)); mean(origMeans(:,:,z))];

    fprintf(fid,'\n%s\n\n','AVERAGES:');
    fprintf(fid,'%s\n',',buy,sigma buy');
    fprintf(fid,'%s,%f,%f\n','mean',averages(1,1),averages(1,2));
    fprintf(fid,'%s,%f,%f\n','dow',averages(2,1),averages(2,2));

    %T-stat count

         tCount = zeros(1,6);
         for i=1:size(tickers,1)
       tCount = tCount +  (abs(Tstats(i,1:end-1)) > Tstats(i,end));
         end
         Tstats(end,1:end-1) = tCount;

         fprintf(fid,'\n%s\n\n','PARAMETER SIGNIFICANCE COUNT:');
         fprintf(fid,'%s\n',',C,MA,InMean,K,GARCH,ARCH');
         for i=1:size(Tstats,1)-1
        fprintf(fid,'%s,%f,%f,%f,%f,%f,%f,%f\n',tickers(i,:),Tstats(i,:));
         end;
         fprintf(fid,'%s,%f,%f,%f,%f,%f,%f\n','COUNT',Tstats(end,:));

    fclose(fid);

end;

%%%%%% CONVERGENCE OUTPUT %%%%%%
fid = fopen('output\c_gm_convergence.csv','w');
fprintf(fid,'Rule,');
for l = 1:size(tickers,1)-1
    fprintf(fid,'Ticker,P_b,P_sigmab, ,');
end;
fprintf(fid,'Ticker,P_b,P_sigma_b\n');
for z = 1:numRules
    for n=1:N
```

```
        fprintf(fid, '%f,', z);
        for l = 1:size(tickers,1)-1
            fprintf(fid, '%s,%f,%f, ,', tickers(l,:), convergence(n,1,z,l), convergence(n,2,z,l));
        end;
        fprintf(fid, '%s,%f,%f\n', tickers(size(tickers,1),:), convergence(n,1,z,size(tickers,1)),
convergence(n,2,z,size(tickers,1)));
    end;
    fprintf(fid, '\n');
end;
fclose(fid);
```

A.3.9. GARCH-M Function

```
function R = garchm_function(N,returns,residuals,C,MA,InMean,K,GARCH,ARCH,sigma)
%GARCHM_BOOTSTRAP bootstraps a garch-m model.
%Input is residuals and fitted parameters from original garch-m model. N is
%the number of realisations to create. Returns a T by N matrix of N return
%series of length T.
%Note the parameter match with Blake is as follows:
%   C = a
%   MA = b
%   InMean = gamma
%   K = alpha0
%   GARCH = beta
%   ARCH = alpha1

lead = 1000; %Lead in period to minimize transient effects.

T = length(residuals);
R = zeros(T+lead,N);

for n=1:N

    epsilon = resample([residuals; residuals; residuals]); %Need a longer residual series for lead period.
    %epsilon = randn([T*3,1]);
    ht = std(residuals.*sigma)^2;
    R(1,n) = 0;

    for t=2:T+lead

        old_ht = ht;
        ht = K + ARCH*(epsilon(t-1)*sqrt(old_ht))^2 + GARCH*old_ht;
        R(t,n) = C + InMean*ht + MA*(epsilon(t-1)*sqrt(old_ht)) +epsilon(t)*sqrt(ht);

%         old_ht = ht;
```

```
%          ht = K + ARCH*(epsilon(t-1))^2 + GARCH*old_ht;
%          R(t,n) = C + InMean*ht + MA*(epsilon(t-1))+epsilon(t);

    end;

end;
```

A.3.10. EGARCH Bootstrap

```
%BOOTSTRAP EGARCH

%THINGS TO CHECK

%Are the output descriptions correct?
%Is the buy return array picking up the correct returns (open v close)?
%Is the GARCH fit picking up the correct returns (open v close)?
%Is the tlag correct?
%Is the number of bootstraps correct?
%Is the number of rules correct?
%Is the emaf correct?
%Is the HP correct?
%Are the CS parameters correct?


%Generates egarch bootstrapped series.

format long

%Parameters

tlag = 2;                %Time lag on return calculations, e.g. set to 2 for close t+2.
N = 501;                 %Number of bootstrap iterations + 1 (first block holds original series).
numRules = 30;            %Number of trading rules to test.
emaf = 10;
HP = 10;
rule = zeros(numRules,1);

% t = 0.0005;
% u = 0.005;
% v = 0.001;
% w = 0.01;
```

```
% x = 0.1;
% y = 0.5;
% zz = 2;

t = 0.0005;
u = 0.0075;
v = 0.001;
w = 0.015;
x = 0.1;
y = 0.5;
zz = 2;


%Input

tickers = char('xom','wmt','utx','t','sbc','s','pg','msft','mrk','mo','mmm','mcd','ko','jpm','jnj','ipl','aa','intc','ibm','hon','hd','gt','gm','ge','ek','dow','dis','dd','cat','ba','axp','bhmsq','cvx','hpq','c');
%tickers = char('xom','wmt');

%First column holds buyArray mean for each stock. Second column holds
%market return for each stock.

bootstrapMeans = zeros(size(tickers,1)*(N-1),2);%%
origMeans = zeros(size(tickers,1),2,numRules);
output = zeros(size(tickers,1),3,numRules);
Tstats = zeros(size(tickers,1)+1,8);
convergence = zeros(N,2,numRules,size(tickers,1));

%%%NEW AGGREGATE CODE%%%
aggregate = zeros(size(tickers,1),2,numRules);
%%%%%%%%%%%%%%%%%%%%%%%%

errorFlag = zeros(size(tickers,1),numRules);   %Set to 1 if no signals on original series

for l=1:size(tickers,1);
```

```
tickers(1,:)
ticker = strcat('input\',tickers(1,:),'.csv');
      M = csvread(ticker,1,0);
      open = M(:,6);
      high = M(:,7);
      low = M(:,8);
      close = M(:,9);
adj_open = M(:,2);
      adj_high = M(:,3);
      adj_low = M(:,4);
      adj_close = M(:,5);
%%%%%%%%%%%TEMP%%%%%%%%%%%%%%
open = adj_open;
high = adj_high;
low = adj_low;
close = adj_close;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
      T = length(close);
%Initialize big output array
M = zeros(T*N,4);
      %Get original return series
      open_returns = [0; diff(log(open))];
      high_returns = [0; diff(log(high))];
      low_returns = [0; diff(log(low))];
      close_returns = [0; diff(log(close))];
```

```
                %Fit egarch

    spec = garchset('VarianceModel', 'EGARCH', 'P', 1, 'Q', 1, 'R', 1, 'M', 1, 'Display', 'off');
          [coeff, errors, LLF, innovations, sigma, summary] = garchfit(spec, open_returns);
          garchdisp(coeff, errors);

    %Write t-stats to array

    Tstats(1,:) = [coeff.C/errors.C coeff.MA(1)/errors.MA(1) coeff.AR(1)/errors.AR(1) coeff.K/errors.K
coeff.GARCH(1)/errors.GARCH(1) coeff.ARCH(1)/errors.ARCH(1) coeff.Leverage(1)/errors.Leverage(1)
tinv(0.975,T-7)];

          %Bootstrap step starts.

          for n=1:N

        %Resample each return series and create new open, high, low, close
        %series

        if n==1;

            new_open_returns = open_returns;
            new_high_returns = high_returns;
            new_low_returns = low_returns;
            new_close_returns = close_returns;

            %Now recreate price series

            new_open = open;
                        new_high = high;
                              new_low = low;
                              new_close = close;

        else
```

```
              %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%             %8. RESAMPLE CLOSE, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
%             %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.
%
%             h_c_diff = (high-close)./close;
%             c_l_diff = (close-low)./close;
%             o_c_diff = (open-close)./close;
%
%             h_c = resample(h_c_diff);
%             c_l = resample(c_l_diff);
%             o_c = resample(o_c_diff);
%
%             h_c = h_c_diff;
%             c_l = c_l_diff;
%             o_c = o_c_diff;
%
%             %Now generate new close using egarch.
%
%             new_close_returns = egarch_function(1,close_returns,innovations./sigma,coeff.C,coeff.MA(1),coeff.AR(1),coeff.K,coeff.GARCH(1),coeff.ARCH(1),coeff.Leverage(1),sigma);
%             new_close = cumprod([close(1); exp(new_close_returns(2:end))]);
%
%             new_high = new_close + new_close.*h_c;
%             new_low = new_close - new_close.*c_l;
%             new_open = new_close + new_close.*o_c;
%
%             %Correct days where series are out of order
%
%             %Get indexes of days that are wrong.
%
%             wrong_high = find(new_high < max(new_low,new_open));
%             wrong_low = find(new_low > min(new_high,new_open));
%
%             for k=1:length(wrong_high);
```

```
%                   index = wrong_high(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
%               end;
%
%               for k=1:length(wrong_low);
%                   index = wrong_low(k);
%                   j = 0;
%                   while j<1000 & ( new_high(index) < max([new_low(index) new_open(index)])| new_low(index) > min([new_high(index) new_open(index)]) );
%                       new_low(index) = new_close(index) - new_close(index)*c_l_diff(fix(rand*T)+1);
%                       new_open(index) = new_close(index) + new_close(index)*o_c_diff(fix(rand*T)+1);
%                       new_high(index) = new_close(index) + new_close(index)*h_c_diff(fix(rand*T)+1);
%                       j = j + 1;
%                   end;
%               end;
%
            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
            %8. RESAMPLE OPEN, RECREATE OTHER SERIES RANDOMLY FROM HIGH-CLOSE,
            %OPEN-CLOSE AND CLOSE-LOW RESAMPLED, SCALED DIFFERENCE VECTORS.

            h_c_diff = (high-open)./open;
            c_l_diff = (open-low)./open;
            o_c_diff = (close-open)./open;

            h_c = resample(h_c_diff);
            c_l = resample(c_l_diff);
            o_c = resample(o_c_diff);
```

```
            %Now generate new open using egarch

            new_open_returns = egarch_function(1,open_returns,innovations./sigma,coeff.C,coeff.MA(1),coeff.AR(1),coeff.K,coeff.GARCH(1),coeff.ARCH(1),coeff.Leverage(1),sigma);
            new_open = cumprod([open(1); exp(new_open_returns(2:end))]);

            new_high = new_open + new_open.*h_c;
            new_low = new_open - new_open.*c_l;
            new_close = new_open + new_open.*o_c;

            %Correct days where series are out of order

            %Get indexes of days that are wrong.

            wrong_high = find(new_high < max(new_low,new_close));
            wrong_low = find(new_low > min(new_high,new_close));

            for k=1:length(wrong_high);
                index = wrong_high(k);
                j = 0;
                while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

            for k=1:length(wrong_low);
                index = wrong_low(k);
                j = 0;
                while j<1000 & ( new_high(index) < max([new_low(index) new_close(index)])| new_low(index) > min([new_high(index) new_close(index)]) );
```

```
                    new_low(index) = new_open(index) - new_open(index)*c_l_diff(fix(rand*T)+1);
                    new_close(index) = new_open(index) + new_open(index)*o_c_diff(fix(rand*T)+1);
                    new_high(index) = new_open(index) + new_open(index)*h_c_diff(fix(rand*T)+1);
                    j = j + 1;
                end;
            end;

%           REMEMBER TO CHANGE BUY RETURN ARRAY TO OPEN RETURNS

            %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

        end;

        M((n-1)*T+1:n*T,:) = [new_open new_high new_low new_close];

    end;

    %%%%%% START TRADING RULE STEP %%%%%%

    for z=1:numRules    %Rule loop.

                    %Initialize the grandiosely named indicator functions, which are just glorified counters
:)

                    I_buy = 0;
                    I_buySigma = 0;

                    counter = 0; %Count number of times no buy periods found.

                    %Bootstrap step starts.

                    for n=1:N

            new_open = M(T*(n-1)+1:T*n,1);
                        new_high = M(T*(n-1)+1:T*n,2);
                        new_low = M(T*(n-1)+1:T*n,3);
```

```
                    new_close = M(T*(n-1)+1:T*n,4);

            new_close_returns = [0; diff(log(new_close))];
            new_open_returns = [0; diff(log(new_open))];
            new_high_returns = [0; diff(log(new_high))];
            new_low_returns = [0; diff(log(new_low))];

            signalArray = zeros(T,1);

              lwSig = lw(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wmSig = wm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            cwmSig = cwm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            owmSig = owm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            ddSig = dd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wpuSig = wpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bpuSig = bpu(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            hammerSig = hammer(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bullengSig = bulleng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            pielineSig = pieline(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bullharSig = bullhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            thriupSig = thriup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            throupSig = throup(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            twbotSig = twbot(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            lbSig = lb(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bmSig = bm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            cbmSig = cbm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            obmSig = obm(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            gdSig = gd(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            wssSig = wss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bssSig = bss(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
              hangmanSig = hangman(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            beareng Sig = beareng(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            dccSig = dcc(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            bearharSig = bearhar(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            thridnSig = thridn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            throdnSig = throdn(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
```

```
            twtopSig = twtop(new_open,new_high,new_low,new_close,t,u,v,w,x,y,zz);
            expma = ema(new_close,emaf);

      %%%%%%%%%% RULES %%%%%%%%%%

       if z==1 %Rule 1.
            rule(z) = 1;
            for i=2:T-2
                if lwSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==2 %Rule 2.
            rule(z) = 2;
            for i=2:T-2
               if wmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
      if z==3 %Rule 3.
            rule(z) = 3;
            for i=2:T-2
                if cwmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==4 %Rule 4.
            rule(z) = 4;
            for i=2:T-2
               if owmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
```

```
        end;
        if z==5 %Rule 5.
            rule(z) = 5;
            for i=2:T-2
                if ddSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==6 %Rule 6.
            rule(z) = 6;
            for i=2:T-2
               if wpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==7 %Rule 7.
            rule(z) = 7;
            for i=2:T-2
                if bpuSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==8 %Rule 8.
            rule(z) = 8;
            for i=3:T-3
                if close(i-2) < expma(i-2) & hammerSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==9 %Rule 9.
            rule(z) = 9;
            for i=3:T-3
```

```
          if close(i-2) < expma(i-2) & bullengSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==10 %Rule 10.
      rule(z) = 10;
      for i=3:T-3
          if close(i-2) < expma(i-2) & pielineSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==11 %Rule 11.
      rule(z) = 11;
      for i=3:T-3
          if close(i-2) < expma(i-2) & bullharSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
if z==12 %Rule 12.
      rule(z) = 12;
      for i=4:T-4
          if close(i-3) < expma(i-3) & thriupSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==13 %Rule 13.
      rule(z) = 13;
      for i=4:T-4
          if close(i-3) < expma(i-3) & throupSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
```

```
 end;
 if z==14 %Rule 14.
      rule(z) = 14;
      for i=4:T-4
          if close(i-3) < expma(i-3) & twbotSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
    if z==15 %Rule 15.
      rule(z) = 15;
      for i=2:T-2
          if lbSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==16 %Rule 16.
      rule(z) = 16;
      for i=2:T-2
         if bmSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
if z==17 %Rule 17.
      rule(z) = 17;
      for i=2:T-2
          if cbmSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
if z==18 %Rule 18.
      rule(z) = 18;
      for i=2:T-2
```

```
                if obmSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==19 %Rule 19.
            rule(z) = 19;
            for i=2:T-2
                if gdSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==20 %Rule 20.
            rule(z) = 20;
            for i=2:T-2
                if wssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==21 %Rule 21.
            rule(z) = 21;
            for i=2:T-2
                if bssSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==22 %Rule 22.
            rule(z) = 22;
            for i=3:T-3
                if close(i-2) > expma(i-2) & hangmanSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
```

```
  end;
  if z==23 %Rule 23.
      rule(z) = 23;
      for i=3:T-3
          if close(i-2) > expma(i-2) & bearengSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
  end;
  if z==24 %Rule 24.
      rule(z) = 24;
      for i=3:T-3
          if close(i-2) > expma(i-2) & dccSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==25 %Rule 25.
      rule(z) = 25;
      for i=3:T-3
          if close(i-2) > expma(i-2) & bearharSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
if z==26 %Rule 26.
      rule(z) = 26;
      for i=4:T-4
          if close(i-3) > expma(i-3) & thridnSig(i)
              signalArray(i+tlag) = 1;
          end;
      end;
 end;
 if z==27 %Rule 27.
      rule(z) = 27;
      for i=4:T-4
```

```
                if close(i-3) > expma(i-3) & throdnSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;
        if z==28 %Rule 28.
            rule(z) = 28;
            for i=4:T-4
                if close(i-3) > expma(i-3) & twtopSig(i)
                    signalArray(i+tlag) = 1;
                end;
            end;
        end;


            %Reprocess to remove double signals
            for i=HP+1:T-HP+1
                if signalArray(i) == 1 & max(signalArray(i-HP:i-1)) == 1
                    signalArray(i) = 0;
                end;
            end;

            %%%%%%%%%%%%%%%%%%%%%%%%%%%

            %Profit calcs

            %Iterate through buy/sell points calculating profit.

              buys = 0;

            buyCounter = 0;

            buyRetArray = [];

           for i=1:T-HP-1

```

```
                %Calculate buy profit

                if signalArray(i) == 1

                    %Write all returns into array for sigma calc.
                    buyRetArray = [buyRetArray; new_open_returns(i:i+HP-1)];%*
                    buys = buys + 1;

                end;

            end;

            %plot(new_close)
            %hold on
            numBuys(n) = buys;

          if buys==0
                if n==1
                    errorFlag(1,z) = 1;
                    break;
                end;
                convergence(n,:,z,1) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
                counter = counter + 1;
                continue;
            end;


            buySigma = std(buyRetArray);
            buyRet = mean(buyRetArray);


            if n==1     %First time through record profit as original Dow profit.
                origBuyRet = buyRet;
                origBuySigma = buySigma;
            end;

```

```
        %Compare returns to original

        if buyRet > origBuyRet & n~=1
            I_buy = I_buy + 1;
        end;

       if buySigma > origBuySigma & n~=1
            I_buySigma = I_buySigma + 1;
        end;

        %%
        if n~=1
            convergence(n,:,z,l) = [I_buy/(n-1-counter) I_buySigma/(n-1-counter)];
            bootstrapMeans(l*(n-1),:,z) =  [buyRet buySigma];
        end;
        %%

                end;

                if n~=1
        if errorFlag(l,z) == 0
                            probability_buy = I_buy/(N-1-counter);      %N-1 correction since
first time through gets Dow result.
                            probability_buySigma = I_buySigma/(N-1-counter);

            output(l,:,z) = [probability_buy probability_buySigma N-1-counter];

            origMeans(l,:,z) = [origBuyRet origBuySigma];

            %%%%NEW AGGREGATE CODE%%%%

            aggregate(l,:,z) = [I_buy I_buySigma];

            %%%%%%%%%%%%%%%%%%%%%%%%%%

        end;
```

```
                    end;

    end;

end;

for z=1:numRules

   if rule(z) < 10
              fid = fopen(strcat('output\c_egarch_rule',char(rule(z)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    else
          fid = fopen(strcat('output\c_egarch_rule',char(floor(rule(z)/10)+48),char(mod(rule(z),10)+48),'.csv'),'w'); %Changed this line 10 Jan 04
    end;


    fprintf(fid,'%s\n\n','BOOTSTRAP RESULTS:');
    fprintf(fid,'%s\n',',buy,sigma buy,num bootstraps');
          for i=1:size(output,1)
        if errorFlag(i,z) == 0
            fprintf(fid,'%s,%f,%f,%f\n',tickers(i,:),output(i,:,z));
        else
            fprintf(fid,'%s,%s\n',tickers(i,:),'Error: No signal on original series.');
        end;
          end;

     %%%NEW AGGREGATE CODE%%%%
    fprintf(fid,'\n%s\n\n','AGGREGATE RESULTS:');
    fprintf(fid,'\n%s,%f,%f,%f\n\n','Aggregate',sum(aggregate(:,:,z))/sum(output(:,3,z)));
    %%%%%%%%%%%%%%%%%%%%%%%%%

          bsMean = bootstrapMeans(:,:,z);%%
    oMean = origMeans(:,:,z);%%
          averages = [sum(bsMean)/length(bsMean(bsMean~=0)); sum(oMean)/length(oMean(oMean~=0))];%%
```

```
    %averages = [mean(bootstrapMeans(:,:,z)); mean(origMeans(:,:,z))];

    fprintf(fid,'\n%s\n\n','AVERAGES:');
    fprintf(fid,'%s\n',',buy,sigma buy');
    fprintf(fid,'%s,%f,%f\n','mean',averages(1,1),averages(1,2));
    fprintf(fid,'%s,%f,%f\n','dow',averages(2,1),averages(2,2));

    %T-stat count

          tCount = zeros(1,7);
          for i=1:size(tickers,1)
       tCount = tCount +  (abs(Tstats(i,1:end-1)) > Tstats(i,end));
          end
          Tstats(end,1:end-1) = tCount;

          fprintf(fid,'\n%s\n\n','PARAMETER SIGNIFICANCE COUNT:');
          fprintf(fid,'%s\n',',C,MA,AR,K,GARCH,ARCH,LEVERAGE,Tc');
          for i=1:size(Tstats,1)-1
        fprintf(fid,'%s,%f,%f,%f,%f,%f,%f,%f,%f\n',tickers(i,:),Tstats(i,:));
          end;
          fprintf(fid,'%s,%f,%f,%f,%f,%f,%f\n','COUNT',tCount);

    fclose(fid);

end;

%%%%%% CONVERGENCE OUTPUT %%%%%%
fid = fopen('output\c_eg_convergence.csv','w');
fprintf(fid,'Rule,');
for l = 1:size(tickers,1)-1
    fprintf(fid,'Ticker,P_b,P_sigmab, ,');
end;
fprintf(fid,'Ticker,P_b,P_sigma_b\n');
for z = 1:numRules
    for n=1:N
```

```
        fprintf(fid, '%f,', z);
        for l = 1:size(tickers,1)-1
            fprintf(fid, '%s,%f,%f, ,', tickers(l,:), convergence(n,1,z,l), convergence(n,2,z,l));
        end;
        fprintf(fid, '%s,%f,%f\n', tickers(size(tickers,1),:), convergence(n,1,z,size(tickers,1)),
convergence(n,2,z,size(tickers,1)));
    end;
    fprintf(fid, '\n');
end;
fclose(fid);
```