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Technical trading patterns: can they truly predict price movements and can they be exploited for excess returns?

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Technical trading patterns:
Can they truly predict price movements
and can they be exploited for excess returns?

by

Martine Therese Ajwa

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1995

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DEDICATION

I would like to dedicate this dissertation to my family--
Husein, Joe, Mom and Papa--whose continuous support behind the
scenes is always appreciated.

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ABSTRACT

Debate exists in financial markets over whether patterns exist in stock prices which can be used to predict future prices and to earn excess returns. Proponents of this idea, technical traders, view stock prices as following trends and exhibiting consistent patterns which can be exploited for gain. Fundamental analysts, however, believe that stock prices change only in response to the arrival of information which occurs randomly and does not generate any predictable patterns in stock prices. To fundamental analysts, consistent profit can only be gained if investors have access to information before everyone else and if they can correctly infer the effect of the news on market prices.

Therefore, the question arises which view of the markets is more accurate. In an attempt to answer this question, this work will be separated into two parts. The first part will ask if predictable patterns in stock prices exist as technical traders surmise, or if these patterns are spurious as fundamental analysts would hypothesize. The second part will ask if profit can be consistently made according to the technical traders' rules for pattern trading, or if these profits are inconsistent.

To evaluate the first part, this work uses a Monte Carlo experiment to compare the number of times three technical

trading patterns are found in four actual stock price series to the number of times these patterns are found in randomly-generated series chosen to mimic the actual stock series. The evidence shows that we cannot reject the hypothesis that these patterns occur as frequently in the random series as they occur in the actual stock series. This finding contradicts the beliefs of technical traders.

To evaluate the second part, this work calculates the returns gained from following technical trading rules regarding the patterns. Total profit is calculated for each stock price series and each pattern assuming an investment of \$1 million and each trading rule exploited. The evidence shows that we cannot reject the hypothesis that average returns from these trading rules are zero.

I. INTRODUCTION

Economists have long sought to develop appropriate models to predict stock prices. Academic models have not always been able to synthesize the diverse prediction methods used on Wall Street. Investors generally use two techniques for forecasting stock prices: fundamental analysis and technical analysis. Under fundamental analysis, the price of a stock reflects the value of the underlying company. Changes in stock prices are the result of conditions which change the value of a company such as the development of a new, profitable product. Therefore, company-specific information is highly useful to determine the fundamental value of a stock. Under technical analysis, the price of a stock depends on supply and demand conditions which, analysts claim, are too complicated to model and often have no relationship to value. Changes in stock prices occur as supply and demand conditions change. These market changes, analysts believe, exhibit predictable patterns which the analyst can use to forecast price movements. Only market data on past prices and volume is of significance to the technical trader.

Although technical traders view stock prices as following trends and exhibiting consistent patterns, fundamental analysts believe that stock prices change only in response to the arrival of relevant information which occurs randomly and

does not generate any predictable patterns in stock prices. To fundamental analysts, any claim to have found consistent patterns in prices could only come from data-snooping.

Technical traders and fundamental analysts also have diverse views of the ability of investors to earn excess profits in financial markets. According to technical traders, since price patterns are consistent, price movements can be predicted to a certain degree and profit opportunities uncovered. According to fundamental analysts, price changes take place solely because information is revealed that there is a change in the underlying fundamentals. If this information is made public, the stock price changes immediately to reflect the news. Therefore, profit can only be gained if investors have access to information before everyone else and if they can correctly infer the effect of the news on market prices.

Therefore, the question arises which view of the markets is more accurate. In an attempt to answer this question, this work will be separated into two parts. The first part will ask if predictable patterns in stock prices exist as technical traders surmise, or if these patterns are spurious as fundamental analysts would hypothesize. The second part will ask if profit can be consistently made according to the technical traders' rules for pattern trading, or if these profits are inconsistent.

To evaluate the first part, this work will use Monte Carlo analysis to compare the number of times three technical trading patterns are found in actual stock price series to the number of times these patterns are found in randomly-generated series chosen to mimic the actual stock series. The evidence shows that we cannot reject the hypothesis that these patterns occur as frequently in the random series as they occur in the actual stock series. This finding contradicts the beliefs of technical traders.

To evaluate the second part, this work will calculate the returns gained from following technical trading rules regarding the patterns. Returns are calculated for each stock price series and each pattern assuming an investment of \$1 million and each trading rule exploited. The evidence shows that we cannot reject the hypothesis that average returns from these trading rules are zero.

The paper is divided into five parts. Part two is a review of the stock price literature and views of how markets operate. Part three describes the methods used and part four presents and discusses the results. Part five concludes with a discussion of extensions of the experiments to other markets and other technical trading rules.

II. LITERATURE REVIEW

The literature review will be divided into three parts. The first part examines several views of the financial markets and specifically the stock market in order to emphasize the debate between fundamental analysts and technical traders. The second part examines some of the empirical studies conducted and other studies made to support these views. The last part provides a brief summary.

A. Diverse Views of Financial Markets

Debate over what drives supply and demand in financial markets has been raging since the inception of the markets. Professional investors generally fall on one or the other side of the debate. They classify themselves as either fundamental analysts or technical analysts although many investors use some ideas from each school in their analysis. These analysts have very different views about how markets operate and how best to make predictions about future stock prices. One academic view of the stock market noted by Keynes in 1936 was more consistent with the technical traders' beliefs. He observed that stock valuation is the outcome of the mass psychology of a large number of ignorant individuals, subject to large fluctuation as the result of changes in opinion due

to factors which do not really make much difference to the prospective yield.

An alternative view of financial markets, the efficient markets hypothesis, became popular among academics in the late 1960s and 1970s. The efficient markets hypothesis is consistent with the fundamental analysts' view of the markets. Initial empirical support for the efficient markets hypothesis was found by Fama (1965) who described stock prices as following a random walk. If stock prices follow a random walk, then stock price changes are random and technical analysis could be of no use in predicting future prices. As a result, technical analysis fell into disrepute.

However, with mounting evidence against the efficient markets hypothesis in the 1980s, economists again began to focus their attention on alternative models of financial markets which again are more consistent with the technical traders' beliefs. These models focus on investors who may follow fads or trade on pseudo-signals (noise) when determining an investment strategy.

The following literature review will briefly discuss these diverse views of financial markets and then discuss some studies of price movements in the stock market and investors' behavior.

1. The Dow theory and technical analysts' view of the markets

Technical analysis is considered by many to be the original form of investment analysis. It has the view that markets are driven by investors who act en masse or according to fads and whims and that prices will therefore exhibit trends. The objective of using technical analysis is to predict future price movements from past price patterns. Technical analysts, also known as chartists, believe they can use these predictions to earn excess returns in the market. Critics believe that technical analysts may have found spurious patterns in stock prices due to their intense scrutiny of stock prices or data-snooping (Merton, 1987).

There are many methods of technical analysis. The oldest is attributed to Charles Dow who, as far back as the late 1800s, emphasized tracking stock market trends. The Dow Theory, as it is called, takes advantage only of price and volume statistics as expressed in certain "averages", deriving nothing from the business statistics on which the fundamentalists depend. The Dow Theory takes advantage of the fact that many stock prices tend to move together and it uses stock market indexes to track the major and minor trends of those prices. The major upward trends are called bull markets and the major downward trends are called bear markets. These are extensive up or down movements which usually last for a

year or more and result in a general appreciation or depreciation in prices of at least 20 percent. Dow also discussed the observed secondary trends which were temporary reversals in position during the major trends. These secondary trends are reported to last from three weeks to three months and to cause a change in direction from the major trend of about one-third to two-thirds of the previous gain or loss.

Other methods used by chartists include 1) detecting certain price patterns which are believed to hold some predictive power about reversals in or continuation of trends, 2) holding only stocks which perform better than a market index and eliminating others, 3) using filter techniques (e.g., buy when price rises 10% above a low), 4) comparing two moving averages where signals to buy and sell occur when a short-term moving average crosses a long-term moving average. All of these techniques embody the ideas that the market moves in discernible trends which continue for significant periods and that the technician can use these tools to correctly detect changes in trend and take advantage of them.

Technical traders provide some explanation why trends arise (Edwards and Magee, 1992). For example, bull markets are explained by the observation that, at the beginning when the market is at a low, there are a few, far-sighted individuals who forecast better future economic conditions and

begin to buy. In general, however, current news is bad and other investors are wary. When increasingly better news about business begins to attract attention, there is a steady advance and increasing activity. Finally, the market booms when the "public" begins to buy as a result of all good financial news, despite the fact that this may be the wrong time to buy.

In other words, according to technical analysts, trends may perpetuate themselves due to the bandwagon effects of crowds wanting to join in the rise of a favorite stock and due to unequal access to fundamental information about a company (Malkiel, 1990). Therefore, according to chartists, investors may be irrational--subject to guesses, mood swings--and may trade as a group, influenced by mass psychology.

Technical traders admit that certain fundamental information as profits and losses will play a role in determining supply and demand for stocks and therefore prices, but as Edwards and Magee (1992) explain in their book:

The market price reflects not only the differing value opinions of many orthodox security appraisers, but also all the hopes and fears and guesses and moods, rational and irrational, of hundreds of potential buyers and sellers, as well as their needs and their resources--in total, factors which defy analysis and for which no statistics are obtainable, but which are nevertheless all synthesized, weighed and finally expressed in the one precise figure at which a buyer and a seller get together and make a deal. (p. 6)

For the chartist, therefore, price is the key piece of information. Forecasts of price changes can be obtained

solely by studying market price and volume data rather than information about a company or its prospects. The avid chartist will even refuse to look at economic and company-related data, finding them distracting (Dreman, 1977).

Typically, the price information used by chartists includes daily or weekly highs, lows, and closing prices. Volume is also tallied as an additional indicator of the relative strength of demand to supply. This information can be plotted in logarithmic charts and evidence of patterns or trends seen by the analyst. In the words of chartists Edwards and Magee (1992):

It has been said that chart interpretation is not a science but an art. It is not an exact science, to be sure, because it has no rules to which there are not exceptions. Its finer points defy expression in rule or precept. It requires judgment in appraisal of many factors, some of which may seem at times to conflict radically with others. (p.139)

Thus, under this form of analysis, one expects to see stock price behavior where investors can be irrational and where trends and fads matter. Stock prices may exhibit mean-reverting behavior and are expected to move in predictable trends which have been seen in the past and are expected to continue in the future.

2. The efficient markets hypothesis

Another view of financial markets, the efficient markets hypothesis, became popular among academics in the late 1960s and 1970s. The efficient markets hypothesis is consistent with the fundamental analysts' view of the markets. It hypothesizes that the markets are driven not by trends and fads, but rather by the arrival of information. The efficient markets hypothesis is the contention that asset prices reflect all available information relevant for judging the future returns of those assets. Thus, the idea of efficiency here refers to the efficiency of information dissemination. Analytically, the efficient markets hypothesis states that asset prices reflect the fundamental value of an asset. In the case of the stock market, the stock price is a rational expectation of future expected dividends on the stock discounted by the opportunity cost, the risk-free rate of return in the case of perfect markets (where investors can borrow and lend at the risk-free rate). These expectations are conditioned on a predetermined information set available to the investors. Since information arrives randomly and is expected to have no effect on price, on average, each time period, asset prices follow a Martingale process under this hypothesis.

In order to discuss the efficient markets hypothesis and

its limitations, it is necessary to discuss the assumptions and implications of the model. Under the hypothesis, market participants are assumed to know the underlying model for pricing assets so they can detect periods of market over- and under-valuation. This may not be true, however. Critics state that it is presumptuous to assume that any participants can truly know the model since it is still a matter of debate. For example, in the foreign exchange market, studies have shown that theoretical models of the exchange rate market fail to predict short-run changes better than the random walk model (Meese and Rogoff, 1983). In the case of the stock market, fundamental value is determined as the present value of the expectation of each future dividend payment. But these expectations are based on forecasts of the future which are difficult to discern. Summers (1986) points out that the same considerations which make deviations from efficient asset prices difficult to isolate statistically for econometricians make it unlikely that they will be arbitrated away or eliminated by speculative trading. Therefore, investors may not be able to determine an underlying model from which to determine fundamental value and speculation may not ensure market prices reflect fundamental values due to these problems of identification. Market efficiency may not exist if no one knows the fundamental value.

A second assumption of this hypothesis is that market

participants are rational in the sense that they are able to determine what effect information has on asset prices and that they correctly exploit this information in their trading practices. This assumption has also been criticized as presumptuous. As Dreman (1977) points out, it is difficult even for professionals to correctly interpret information on a company. For example, often incomplete information is available. Management may describe variables on sales, inventories, pricing, or profitability as "so-so" or "excellent". The question arises how all market participants are able to accurately quantify this information and translate it into a notion of fundamental value. Further, these participants are also assumed to be able to assess sometimes contradictory information on a wide range of businesses. Even brokerage houses have professionals who specialize within an industry and who often disagree if a company is over- or under-valued.

The implications of the efficient markets hypothesis have also been subject to criticism. One implication is that price changes take place solely because information is revealed that there is a change in the underlying fundamentals. For example, investors may receive information about a new product developed by a company which is expected to increase future profits and dividend payments. This information would be expected to generate increased demand for the firm's stock and

an increase in the stock price. If prices were to deviate from fundamental value, under perfect capital markets, arbitrage would occur to bring prices into line. Thus, the implication is that news of changes in the underlying fundamentals is immediately reflected by a change in market prices and that price will not further change until there is other fundamental news.

However, price changes may not always be justified by news. Although studies which examined price changes after news had been received by the markets generally found that prices incorporated news quickly--a point in support of the efficient markets hypothesis--other empirical tests turned the question around by asking how often price changes are justified by news and found contradictory evidence (Cutler et al., 1989).

The second implication of the efficient markets hypothesis follows from the first. If market prices always reflect all available information, it is impossible to earn persistent excess returns on information. Since prices adjust quickly, excess returns may only be possible under the case when an investor has asymmetric information. However, even asymmetric information will not allow an investor to earn persistent excess returns since the very act of trading reveals information that can be used by other traders to benefit. As a result, it may not be profitable for investors

to collect costly information. Thus, this theory implies technical trading schemes and attempts to obtain additional information cannot be used to beat the market consistently. Rather, according to this hypothesis, it would be best to hold a market portfolio to obtain benefits of diversification rather than to attempt to pick winners.

The third implication of the efficient markets hypothesis is that investors will hold the market portfolio and will not bet against each other. If information is rapidly incorporated in prices, little trade will take place between investors. In fact, the only reason trading will occur, once the market has reached an equilibrium, will be if investors wish to alter the leverage of their portfolios. Otherwise, they are removing the systematic risk through diversification. However, the actual volume of trade on exchanges appears much greater than would be justified for only this purpose. Cutler et al. (1990) cite 1988 NYSE statistics that almost 75 percent of the shares trade hands each year and about \$400 billion of foreign currency is traded each day. Therefore, speculation appears to play a larger role than efficient markets would indicate.

3. The contrasting notions of these views

The efficient markets hypothesis and the technical traders' views of the market differ significantly in discussing the behavior of investors, the significance of news in driving the market, the existence of patterns in stock prices, and the ability of investors to gain excess profits consistently.

Under the efficient markets hypothesis, investors are assumed to be motivated by maximizing profit. Their only strategy for obtaining profits is to gather and analyze information relevant to pricing a stock. Competition between investors exists only in obtaining information since it is news which drives market prices.

For chartists, however, investors may have profit as only one of many goals. Investors are able to obtain profit by playing against each other. Therefore, their strategy is to develop rules which exploit the predictable behavior of investors. Understanding the behavior of investors is the key to understanding how the market is driven. To efficient markets' proponents, the market is driven by the arrival of information so understanding the behavior of others is irrelevant.

According to the chartists, human behavior explains why stock prices appear to follow trends and patterns. Efficient

market proponents, however, disagree that these stock price movements are trends but rather that they are random movements due to the random arrival of news. They may refer to the fact that even a random walk series may appear to exhibit trends even though it is driven by random errors.

The argument that chartists put forth is that because stock prices exhibit trends, predictions can be made about stock prices and these predictions can be used to earn profits greater than may be earned through a buy-and-hold strategy as efficient markets proponents would suggest. According to efficient market proponents, however, these "patterns" are just random movements of prices so no excess profits can be gained by using technical rules.

Thus, while the technical analysts view the market as being driven by fads and exhibiting trends and patterns, fundamental analysts view the market as being driven by the arrival of information which generates random changes in price. While technical analysts view the ability of investors to earn excess profits as possible given the "correct" form of analysis, proponents of the efficient markets hypothesis view profits being consistent only with the riskiness of assets held and that a buy-and-hold strategy of a diverse portfolio is the best means to reduce risk and generate normal profit. This study attempts to discern which opinion is more realistic.

B. Stock Market Studies

1. Keynes' observations of the markets

As was mentioned previously, Keynes (1936) observations of the markets were more consistent with technical traders' views. He viewed the market participants as heterogeneous and the pricing game as "the outcome of a mass psychology of a large number of ignorant individuals" with the danger that prices are "liable to change violently as the result of a sudden fluctuation of opinion due to factors which do not really make much difference to the prospective yield since there will be no strong roots of conviction to hold it steady."

In response to the argument that informed traders could profit at the expense of the ignorant traders by forming an opinion about the long-term forecast of the asset yield and waiting, he noted that these professionals were concerned with what the market will value it at in the short term. He likened the professional investment game to a newspaper competition in which the competitors have to pick out the six prettiest faces from one hundred photographs when the prize is awarded to the competitor whose choice most nearly corresponds to the average preferences of the group of competitors. Each competitor will pick the faces which he thinks are the most likely to be chosen by other competitors, rather than choosing

his favorite. But each competitor is faced with the same problem. Therefore, the game becomes an attempt to anticipate "what average opinion expects the average opinion to be" rather than to form one's own educated opinion.

With markets which are focused in this way rather than when each player is attempting to gather pertinent information and develop an informed opinion about over-valued and under-valued assets, Keynes warns this type of strategy contributes to instability in the market, speculation, and "crises of confidence" whereby times of uncertainty encourage more consumption and less new investment.

2. Early evidence in support of efficient markets

The efficient markets hypothesis was developed as an alternative to Keynes' view of the market. It grew out of the assumption that investors act rationally in their own self-interest with limited information. Unlike technical analysis, the efficient markets hypothesis provides an analytic foundation to represent investors' behavior. This representation is discussed in the next section.

a. Analytical representation of the efficient markets hypothesis

A market is said to exhibit informational efficiency if the one-period rate of return that an investor expects to receive on an investment in an asset will be equal to the opportunity cost of using those funds. In much of the early empirical literature, the opportunity cost of investing was set equal to the risk-free rate of interest, r_f . Justification for this assumption was made either by assuming that investors were risk-neutral or by assuming that an asset's risk was diversified away in large portfolios.

Therefore, letting R_t denote the total one-period return on an asset including capital gains as well as dividend payouts, the efficient markets hypothesis asserts that

$$E(R_t | I_t) = (1 + r_f), \quad (1)$$

where E is the expectation taken with respect to a given information set I available at time period t and includes the risk-free rate.

Assuming no dividend payments, the one-period return on the asset is the future price, P_{t+1} , divided by current price

$$R_t \equiv P_{t+1} / P_t. \quad (2)$$

Since P_t is included in the information set, I_t , we can rewrite (1) as

$$E(P_{t+1}|I_t) = (1+r_f) P_t, \quad (3)$$

or equivalently,

$$P_t = \frac{E(P_{t+1}|I_t)}{(1+r_f)}. \quad (4)$$

Fama (1970) described a hierarchy of nested information sets which are used to determine prices. If the information set contains all of the available information which could possibly be relevant to pricing the asset, including privately held information, then strong-form efficiency is said to hold. If only publicly-available information is contained in the information set, semistrong-form efficiency is said to hold. If the information set contains only current and past price history of the asset as well as the risk-free rate, weak-form efficiency is said to hold.

Since these information sets are nested, rejection of any category implies rejection of all stronger forms. Therefore, many of the early tests focused on testing weak-form efficiency.

b. Empirical studies of the random walk hypothesis

The first tests of weak-form efficiency focused on a very specific form of equation (3)--a random walk model. It must be emphasized, however, that a random walk model is just a

specific example of the Martingale process. It was argued that, if only past prices are included in the information set, equation (3) can be written as:

$$E_t(P_{t+1}|P_t, P_{t-1}, \dots) = \alpha_0 + \alpha_1 P_t + \alpha_2 P_{t-1} + \dots + \alpha_n P_{t-n+1}. \quad (5)$$

Under weak-form efficiency, since current price contains all the information relevant to pricing next period's asset, the null hypothesis is that $\alpha_0 = 0$, $\alpha_1 = 1 + r_F$, and $\alpha_2 \dots \alpha_n = 0$. Previous price information should already be incorporated in current price. If, for example, α_2 were found to be significantly different from zero, the null hypothesis would be rejected.

While initial studies could not reject this random walk hypothesis (Fama, 1965), it must be recognized that it is a joint test of both weak-form efficiency and the random walk model. The random walk hypothesis implies weak-form efficiency but the converse is not true. Thus, failure to reject the null hypothesis cannot be used to prove the efficient markets hypothesis and a rejection of the model cannot disprove weak-form efficiency. This weakness was noted and new tests constructed.

c. Studies of return predictability

Not only does the weak-form of efficient markets imply that lagged prices should not play a role in determining next

period's price, but also that changes in prices should be random and therefore serially uncorrelated. Consider the covariance between two adjacent rates of return,

$$\begin{aligned} \text{COV}(R_{t+1}, R_t) &\equiv E([R_{t+1} - E(R_{t+1})][R_t - E(R_t)]) \\ &= E(R_{t+1}[R_t - E(R_t)]) \\ &= E(E(R_{t+1}|R_t)[R_t - E(R_t)]). \end{aligned} \quad (6)$$

Following Ross (1989), under a constant opportunity cost or interest rate which implies that future returns are independent of past returns and that future expected returns should be constant:

$$\begin{aligned} E(R_{t+1}|R_t) &= E[E(R_{t+1}|I_{t+1})|R_t] \\ &= E(1+r_{t+1}|R_t) \\ &= E(1+r_{t+1}). \end{aligned} \quad (7)$$

Putting (6) and (7) together,

$$\text{COV}(R_{t+1}|R_t) = E(1+r_{t+1})E[R_t - E(R_t)] = 0 \quad (8)$$

such that returns are serially uncorrelated.

The early tests often found that short-term returns exhibited positive serial correlation. For example, Fama's 1965 study found first-order positive autocorrelations in daily returns for 23 of 30 Dow Jones Industrial stocks. However, questions were raised about the statistical power of these tests and evidence suggested that the portion of the variance of returns explained by variation in expected returns was less than one percent for individual stocks (Fama, 1991). Therefore, the hypothesis of market efficiency and constant expected returns could not be rejected.

3. Return autocorrelation and mean-reversion studies

More recent studies of the predictability in stock price returns have found conflicting evidence. There have been many studies which have found positive serial correlation of returns at short intervals but negative correlation of returns at longer (greater than one year) intervals (Fama and French, 1988; Lo and MacKinlay, 1988; Poterba and Summers, 1988). These studies suggest that stock prices exhibit mean-reverting behavior. In other words, prices may temporarily deviate from fundamental value and then return to fundamental value.

These mean-reversion studies often use variance-ratio tests to determine if prices are efficient. The idea behind these tests is that stock price volatilities should be the same in the long-run whether prices are mean reverting or efficient if arbitrage takes place. Short-run volatilities, however, would be greater if prices are mean-reverting. As a result, the ratio of long-run volatility to short-run volatility should be smaller if prices are mean-reverting. As Poterba and Summers (1988) explain, using the variance of stock returns as the measure of volatility, the variance of k-year returns (r_k) should be k times the variance of 1-year returns (r_1) under efficient markets:

$$\text{Var}(r_k) = k \cdot \text{Var}(r_1) \quad (9)$$

or,

$$\frac{\text{Var}(r_k)}{k \cdot \text{Var}(r_1)} = 1. \quad (10)$$

However, if prices are mean reverting and excessively volatile in the short-run, this ratio should be less than one to reflect the higher relative short-run variance.

Poterba and Summers (1988) calculated variance ratios for investment horizons of 1-month to 8 years for monthly NYSE stock returns less U.S. T-bill returns as well as monthly NYSE real stock returns measured using the CPI. Their tests suggest that returns are positively serially correlated for periods less than 1 year and negatively serially correlated at horizons longer than 2 years with ratios falling well below unity the further the time horizon. Similar results were found for most of the 16 other countries they examined. Thus, these variance-ratio tests were supportive of mean-reverting behavior for both U.S. stock indexes and the majority of foreign stock indexes. Cutler et al. (1990) confirmed the Poterba and Summers results by finding significant monthly autocorrelations in U.S. stock market excess returns over the short-term T-bill rate. However, these studies have been criticized on many grounds ranging from the question about the power of their tests to the question of using a random walk as the null hypothesis. In fact, random walk behavior may not be consistent only in the case of efficient markets, but it may also be consistent with a series of share prices which deviate

from fundamentals in a persistent manner (Summers, 1986).

In related work, Fama and French (1988) used regression tests to examine the existence of mean reversion. With mean-reverting behavior, a regression of stock returns on a constant and past returns, the coefficient on past returns should be negative. In earlier studies, the time horizon was weekly or monthly returns. However, Fama and French used much longer time horizons. They regressed multiyear returns on past multiyear returns for investment horizons of one to ten years. They found that the coefficients on past returns became negative for two-year returns, reached even lower values for three- to five-year returns, and then approached zero as the investment horizon increased to eight years. More specifically, they found that approximately 25 to 45 percent of the variation in 3 to 5 year stock returns is predictable from past returns which they stated was consistent with markets in which prices take long, temporary swings away from fundamental value. They attributed these temporary components to fads.

It must be noted that criticism of these mean-reversion studies exists. Engle and Morris (1991) summarize these studies and note that some critics argue the evidence for mean reversion is weak, either because the data samples are too small or because the evidence depends entirely on the behavior of stock prices before World War II. They also note that

other critics argue that mean reverting behavior can exist in an efficient market when real interest rates vary over time. However, the models finding mean-reversion of stock prices assumed a constant real interest rate and therefore constant real returns under efficient markets.

Despite these criticisms, the early studies which found support for efficient markets were questioned and attention was refocused on the possible existence of bubbles, fads, and trends. Economists began to search for alternative hypotheses to efficient markets. One theory of why stock prices may exhibit this mean-reverting behavior has been put forth by Cutler et al. (1990). They hypothesize that many traders pay attention to recent trends in returns. These "feedback traders" believe that if a stock's returns have been high in the recent past, they are likely to be high in the future and, conversely, if returns have been low in the recent past, they are likely to be low in the future. When feedback traders act upon these beliefs, they cause price to deviate from fundamental value. For example, if a stock has had recent high returns, feedback traders will buy that stock and push prices higher still. Risk-averse traders may only take limited positions if they detect valuation errors in the short-run (Summers, 1986). In the long-run, however, arbitragers are believed to bring prices back in line with fundamental value.

Therefore, mean-reverting prices support the technical traders' view that patterns can occur in stock prices and that these patterns may be manipulated to earn excess profits. It must be noted that several technical trading rules take advantage of the feedback trading idea to buy when high and sell when low.

If prices are mean-reverting, there are several implications. First, expected returns may vary through time rather than being constant as implied by efficient markets. For example, if prices suddenly jump above fundamental value and then slowly return, greater than average returns will be realized at the onset followed by lower than average returns as prices return. Second, mean-reversion implies that prices are excessively volatile in the short-run. In the case where fundamental value and prices rise due to new information, prices will have a tendency to rise more than fundamental value dictates and then slowly revert to the new, higher level.

These findings of mean-reverting behavior of prices and implication of excessive volatility in the markets was supported by another branch of studies which focused on price volatility.

4. Excess volatility of prices

Pre-dating the mean-reversion studies, some research on the stock market provided evidence that stock prices may not always reflect fundamental value. A seminal study by Shiller in 1981 found that the volatility in stock returns is not entirely explained by changes in dividends. Since an efficient stock market price can be expressed as the value of all discounted future expected dividend payments, then changes in expected future dividends would be expected to change current price. He hypothesized that if stock market prices reflected fundamental value as the efficient markets hypothesis indicates, the variance of expected future dividends should be much greater than the variance of actual stock prices. Intuitively, he described market price as a moving average. A change in one expected future dividend payment would not change price dramatically. As a proxy for expected future dividends, he used actual dividends and found that the variance of dividends was much smaller than the variance of actual prices. Indeed, his volatility tests show that stock price changes over the past century are five to thirteen times higher than would be justified by new information about future real dividends so he concludes, "the failure of the efficient markets model is thus so dramatic that it would seem impossible to attribute the failure to such

things as data errors, price index problems, or changes in tax laws." Later work by Shiller (1984) attributed this excess volatility in prices to a mass psychology behavior by investors.

Numerous studies on the excess variability of stock prices relative to dividends followed, including those by West (1988) and Campbell and Shiller (1988). The drawback of the majority of these later studies is that they also use simple constant expected return models, the major critique of Shiller's 1981 study. As Fama (1991) notes, with much evidence that expected stock and bond returns vary with expected inflation rates, interest rates, and other term-structure variables, efficiency tests on models with constant expected returns are not informative. Unfortunately, volatility tests which attempt to model varying expected returns also run into the problem of a joint hypothesis of the model specification and market efficiency. A rejection of the hypothesis could indicate rejection of the model rather than of market efficiency just as occurred in the constant expected returns models before.

Other studies of stock price returns examined the effect of information on stock price volatility. In an attempt to study market volatility as a result of news, French and Roll (1986) compared U.S. stock prices during periods when the exchange was closed on Wednesdays and when it was open on

Wednesdays. Under efficient markets, it was hypothesized that prices should be less volatile when the market is open on Wednesdays since any news can be directly incorporated into prices. However, they found that the market was less volatile when the market was closed Wednesdays.

According to the efficient markets hypothesis, price changes should occur only when there is news of changes in fundamentals. While studies which examined price changes after news had been received by the markets generally found that prices incorporated news quickly, Cutler et al. (1989) turned the question around and found contradictory evidence. They asked the question how often changes in stock returns were the result of news. They found that a substantial portion (less than 1/2 in most cases) of changes in stock returns were not explained by macroeconomic or political news. Indeed, these researchers concluded that there is a possibility that many investors do not formulate their own estimates of fundamental value but rather that investors look at current market prices as the gauges of value which are then used to formulate perceptions of fundamental value.

As before, the implications of excessive volatility of prices are that investors may be able to detect patterns in prices and gain excess profits from the exploitation of these patterns. Unfortunately, there is not conclusive evidence that excessive volatility really exists.

5. Speculative bubbles studies

Another branch of stock market studies related to the excess volatility literature concerns testing for speculative bubbles in stock prices. The idea of a speculative bubble is that market participants may rationally cause prices to deviate from fundamental value when prices depend positively on their own expected rate of change. Under such a condition, the arbitrary, self-fulfilling expectation of a price change may drive actual price changes (Flood and Garber, 1980). It is believed that eventually, expectations of positive price changes are revised such that the bubble bursts and price returns to fundamental value.

Examples of such speculative bubbles are plentiful. They include Tulipmania of the 1630s, John Law's Mississippi bubble of 1716-1721, the bubble involving the South Sea Company of 1711, the Florida land boom of the 1920s, the stock market boom of the 1920s and subsequent crash in 1929, and most recently, the stock market boom of the 1980s and subsequent crash in 1987.

Speculative bubbles, by some accounts, begin with an event which is extraneous to the market and generates much irrational speculative activity. As Dreman (1977) describes some of the bubbles in stock prices, the excessive price rises "could not have occurred without the development of a mania

which created its own social reality far removed from past standards of value." However, Garber (1990) goes to great lengths to describe the events surrounding Tulipmania, the Mississippi and South Seas bubbles and attribute rational, market-fundamental explanations to each. In these cases, he points to events which could rationally describe why speculators would perceive an increased probability of large returns. For example, in the case of Tulipmania, he pointed to the idea that the bulbs whose prices increased were those affected by a mosaic virus which produced a new pattern in the flower. This bulb could only be reproduced by budding of the mother bulb. Therefore, he explains that a few of the most beautiful, but rare varieties became cherished and as their reputation grew, so did their price. In addition, he points to a shift in fashion toward the appreciation of tulips in a short time period which generated rising prices for all the rare bulbs.

Although attempts have been successful to attribute some of these rises and crashes to fundamentals, White (1990) believes that not all the bubbles can be justified as existing in efficient markets. He examined the 1929 stock market crash and suggests that it may have been fundamentals which initiated the boom beginning in the mid-1920s but that fundamentals could not sustain it. He notes that changes in dividends did not keep pace with stock prices and that

management in several corporations warned the public that they believed that future earnings would not justify the high prices. He also notes that the typical explanation that easy credit made the boom sustainable may not be a suitable answer since interest rates on brokers' loans increased sharply after 1927 suggesting that it was the rising tide of speculation which increased funds demanded and not any independent creation of credit. With major changes in industry at the time, fundamentals became difficult to assess which, according to White, made the environment ripe for a bubble to occur. Concerning the crash of 1929, he suggests the most likely explanation is that the downturn in the business cycle, made more severe by tight credit, prompted a revision in expectations.

In a detailed discussion of the crash of 1987, Arbel and Kaff (1989) point to signs that the stock market was considered overvalued in 1987 long before the crash occurred. Prices and volume were continuously increasing over the period 1982-87 but P/E ratios in the U.S. were about 23 before the crash, the highest since World War II, and prices were also running about three times book value. Although they do not focus on causes of the initial build of stock prices, they do provide some ideas as to why expectations changed in the fall of 1987. Climbing interest rates, a fear of inflation, a rise in the twin deficits, the value of the dollar declining

against most currencies, the collapse of the bond market, concerns over corporate performances and national leadership all contributed to the 476 point gradual decline in the Dow Jones Industrial Average in the 52 volatile days preceding Black Monday and a 508 point plunge on Black Monday.

The debate over whether these historical events are speculative bubbles or not cannot be easily solved by simple empirical tests. As with all other tests of market efficiency, determining an accurate measurement of fundamental value is a major problem. The only way to detect if a bubble has occurred is to know that prices have systematically deviated from fundamental value. While some economists have postulated that the failure of variance bound tests like that of Shiller (1981) can be due to speculative bubbles, Flood and Hodrick (1986) show in a model which includes bubbles that they can derive a similar variance bound condition. Therefore, variance bound tests may not be adequate for detecting bubbles.

As Summers (1986) discusses, most tests of market efficiency have little power to reject market efficiency. Questions about market efficiency remain unanswered.

6. Other studies questioning efficient markets

There are other anomalies in the stock market which suggest that prices do not reflect fundamental value. One example is the January effect. The January effect refers to the fact that small stocks have outperformed stock price indexes by a substantial amount each January over the past 50 years or so. Ritter (1988) attributed this effect to the fact that individual investors tend to sell these stocks in December to realize capital losses for tax purposes, but then buy back the stocks in January. Arbitrage does not eliminate the price effects of this temporary trading as the efficient markets hypothesis suggests should occur.

Although it is logical to believe that these predictable patterns will be located by investors and arbitrated away such that prices reflect fundamental value, Summers (1986) points out that the same considerations which make deviations from fundamental value difficult to isolate statistically for econometricians make it unlikely that they will be arbitrated away or eliminated by speculative trading.

Therefore, with findings that stock prices do not always reflect fundamental value and also that autocorrelation exists in stock returns, some have suggested that there is reason to believe that returns can, to some extent, be predicted. If this is true, then it may be possible for technical analysts

to detect predictable patterns in prices to earn excess returns.

This is the conclusion reached in a recent paper by Brock et al. (1992). The paper discusses the use of a few technical trading rules to predict future price changes. Using bootstrapping techniques, they generate returns from an artificial Dow series and apply the trading rules to these series. These artificial series are simulated from four typical stock price models: a random walk with drift, an AR(1), a GARCH-M, and an EGARCH. Comparisons are then made between returns in these simulated series and the actual Dow Jones series. Their findings lead them to conclude that technical analysis helps to predict stock price changes since the profits under the technical trading rules are not consistent with returns generated by any of the four types of simulated series. However, they admit that they have not accounted for transaction costs.

7. Studies about investor behavior

Any answer to the question about whether changes in stock prices can be predicted for gain must also address the actual behavior of players in the stock market. The behavior of traders is key to understanding why it may not be the case that excess profits may be arbitrated away.

a. Market players and their investment strategies

The first question may ask who are the major players in the stock market and how do they behave? These major players are usually professionals, often called "smart money." They can manage pension plans, profit reinvestment plans, and work at large institutional brokerages. It is often assumed that these are the rational players who are well-versed in all aspects of business to determine whether stocks are over- or under-valued. However, Dreman (1977) provides many instances where these players, perhaps due to pressures from superiors to gain profit in the short-run, have performed more poorly using their strategies than had they held a market portfolio. For example, he says that corporate pension and profit-sharing plans would have been worth \$13 billion more during the period 1966-1975 had they done as well as the S&P 500. He states that this finding and others contradict the basic premise of efficient markets that the operations of these professionals keep prices at fundamental value.

Then one may ask what types of trading strategies are used by major traders in the market. It is true some experts do incorporate technical analysis in the formation of at least short-run expectations of returns. A survey of chief foreign exchange dealers in the London market was conducted by Allen and Taylor (1990). They found that at short forecasting

horizons (interday to one week), approximately 90% of respondents used some chartist input in forming expectations of exchange rates. At longer forecast horizons (one to three months or six months to one year), the weight given to fundamentals increased and with forecast horizons of one year or longer, 30% of respondents relied on pure fundamentals while 85% judged fundamentals to be more important than charts. Therefore, fundamental analysis may not be of the utmost importance in at least short-term forecasts in the currency markets. Technical analysis is also used in other markets. In a book by Jack Schwager titled *The New Market Wizards* (1992), he interviews several professional traders who have records of beating the markets consistently. One trader, Linda Bradford Raschke explains:

One of my favorite patterns is the tendency for the markets to move from relative lows to relative highs and vice versa every two to four days. This pattern is a function of human behavior. It takes several days of a market rallying before it looks really good. That's when everyone wants to buy it, and that's the time when the professionals, like myself, are selling. Conversely, when the market has been down for a few days, and everyone is bearish, that's the time I like to be buying. (p. 300)

In other words, she has been able to determine short-term patterns in asset prices and has capitalized on these movements using no fundamental analysis.

Rather than citing certain professional traders who claim to use technical analysis, it may be more instructive to ask if there is evidence in the markets that many traders do use a

buy-and-hold strategy as efficient markets would indicate. If most investors, or at least the major investors, were to use a buy-and-hold strategy, one may not expect to see a large volume of trading in the markets. However, there is evidence to the contrary. Cutler et al. (1990) cite 1988 NYSE statistics that almost 75 percent of the shares trade hands each year. In the foreign exchange market, about \$400 billion of foreign currency is traded each day. These figures indicate that there is much speculation in asset markets.

b. Block buying and selling

With much speculation occurring in asset markets, investors must be playing against each other rather than against states of nature. For a trade to occur, each investor must have different beliefs about the information he possesses. But, as Black (1986) notes, differences in beliefs must derive ultimately from differences in information. In reality, investors try to obtain much, costly information about the assets which they believe will give them an "upper hand" in the markets. They consult brokers, buy books, read newspapers and newsletters written by financial advisors. They consult with financial gurus who claim to have had success beating the market. If many investors listen to these few voices, block buying and selling can occur.

This tendency for investors to listen to others when deciding their investment strategy has been called a mass psychology of the market. Some economists other than Keynes believe that mass psychology plays a large role in stock price changes. Shiller (1984) documents some studies of investor behavior leading him to believe that mass psychology is prevalent in the stock market. Indeed, Shleifer and Summers (1990) conclude from their survey of the evidence that news alone does not move stock prices; uninformed changes in demand change them as well.

Block buying and selling behavior was modeled by Denton (1985) to discuss the effect of professional advice on a speculative market. One case he mentions occurred when people listened to a single investment professional, Joseph Granville, which spurred a 23-point plunge in the Dow Jones average on January 7, 1981. Granville's advice was to sell everything delivered by Telex and telephone worldwide on the preceding Tuesday. What followed the next day in New York was a selling fury which brought the Dow below 1,000 in the biggest single day's trading of the exchange's first 188 years. In this case, the advice given by Granville became a self-fulfilling prophecy. Ex-post it was rational to follow his advice even if it were not based on fundamental analysis.

Denton (1985) proposes a model of markets dominated by random fluctuations where all participants are equally

rational and well-informed. Some agents are advisors or "wise owls" and others are investors. When investors are allowed to choose their advisors based on an observed track record which has arisen solely because of luck (but investors do not know skill plays no role), and if they are allowed to change advisors toward those with better track records, then the number of "wise owls" from whom investors take advice decreases over time. The result is block buying and selling as time progresses, making the market more unstable.

Other disciplines have also documented group behavior under uncertainty. Social psychologists have shown experimentally that the greater the uncertainty, and the fewer the objective criteria, the more we measure reality against the opinions of others.¹ As Dreman (1977) documents, a Professor of Psychology at Yale, Irving Janis, has discussed the phenomenon called Groupthink and stated that the most frequent behavior of individuals in groups shows "instances of mindless conformity and collective misjudgment of serious risks which are collectively laughed off in a clubby atmosphere of relaxed conviviality." Therefore, fads or group actions may influence traders if those actions are unfounded in sound judgment.

Dreman (1977) suggests that not only naive traders, but

¹See for example Muzafer Sherif, "An Experimental Approach to the Study of Attitudes," *Sociometry*, vol. 1 (1937), pp. 90-98.

also professional traders are subject to these Groupthink pressures. He discusses many examples of institutional investors being subject to social pressures and says that Groupthink may account for a significant portion of all professional investment errors and may also explain why professionals have not outperformed the markets.

c. Noise trading

An alternate theory to the efficient markets hypothesis has been put forth by economists to incorporate some of the evidence of the speculation in markets, the mean-reversion of prices, autocorrelated returns, and speculative bubbles. This more recent theory has been developed based on the views of Keynes and discusses the existence of uninformed or noise traders in financial markets.

A single definition of noise is difficult to find. The term noise can be used in several contexts. In general, noise refers to the confusion added to prices by the accumulation of a large number of small events or by the aggregation of small actions of a large number of people. Black (1986) defines noise in financial markets as contrasting with information. Therefore, noise traders are uninformed traders--those that trade on noise as if it were information.

Trading on noise is not to be confused with

irrationality. Noise arises because traders are uncertain about future outcomes and have incomplete information sets. Uncertainty arises from several sources: uncertainty about fundamental value, uncertainty about future risk and return, and uncertainty about how much information is reflected in current prices. Given uncertainty and limited information, these traders make the best decisions they are able to. When trading is based on errors of information, noise is added to prices. Thus, the market signal inherent in price is distorted by uncertainty and that distortion is noise.

As Keynes postulated, noise traders' demand for assets is affected by beliefs or sentiments that are not fully consistent with long-run economic fundamentals. Instead of using models that reflect fundamentals, they use "models" that seem to be more successful in predicting the short-run direction of asset prices. Some noise traders are chartists. Others are non-chartist traders who try to profit by predicting the market's reaction to any news or rumors without necessarily using any particular kind of model. One type of noise trader mentioned previously was a "feedback trader" whose trading actions accentuated trends (Cutler et al., 1990).

In this scenario, changes in price may be a response to pseudo-signals that investors believe convey information about future returns but that would not convey such information in a

fully rational model (Black, 1986). Such pseudo-signals can include the advice of brokers.

Many models of noise trading assume that the noise traders are in the majority. Indeed, Keynes (1936) noted that those who attempt to make a serious estimate of the fundamental values "are often so much in the minority that their behavior does not govern the market." A minority of traders, called arbitrageurs or smart money, is assumed to know or have a good idea about the fundamental values of assets. As Shleifer and Summers (1990) explain, when noise traders act as a group, perhaps listening to the advice of a Wall Street guru, their trading actions may not offset each other and could cause price to deviate from fundamental value.

To describe the noise trading theory more succinctly, its two basic assumptions should be noted. From these assumptions arises an explanation why stock prices can exhibit correlated returns and mean reversion. The first assumption is that noise trading activities are not random and do not necessarily cancel one another out. If noise trading activities are correlated, they can lead to aggregate shifts in demand for assets. Second, the noise trading hypothesis assumes that arbitrage is limited because arbitrageurs are risk-averse and are subject to noise trader or price resale risk. Noise trader risk occurs when arbitrageurs are uncertain if prices will deviate further away from fundamental value in the

presence of noise traders. If arbitrageurs have a finite time horizon during which they must liquidate a position, then they run the risk that assets may be mispriced in the future. Thus, arbitrage cannot fully counter unjustified movements in asset prices prompted by noise trading.

C. Summary of the Literature

The literature and empirical studies of asset markets have come full circle. Keynes' observations of the markets as being driven by uninformed traders who cause excessive volatility in prices was replaced by the efficient markets hypothesis. Empirical studies of the markets brought into question the implications of efficient markets. Correlated returns, excessive volatility of prices, and mean reversion were found in some studies. An alternative hypothesis of noise traders has been developed to try to explain these anomalies but tests of this hypothesis based on complicated models are still underway.

Therefore, the debate rages on. Whether fundamental analysts' views of the markets are correct or if technical traders' views of the markets are correct remains unanswered.

III. METHODS

A. Description of the Experiment

As was mentioned in the introduction, this study attempts to answer two questions. First, is it possible to find predictable patterns in stock prices as technical traders surmise or are these patterns spurious as efficient markets advocates would state? The null hypothesis will be that these patterns occur just as frequently in stock market data as they do in random series generated to mimic several stock price series. To test this hypothesis, we conduct a Monte Carlo experiment to generate a distribution for the number of times a pattern can be found in 10,000 random series. Univariate Box-Jenkins analyses are performed on three individual stock price series and the Dow Jones Industrial Average to obtain an appropriate model for each series. Models are estimated then bootstrapping techniques are used to randomly generate errors for the models and therefore to generate series which mimic the actual price series. These 10,000 series are each passed through a filter designed to detect the relevant pattern. The experiment is repeated for three different patterns across each of four price series.

The second question this study attempts to answer is if profit can be made consistently by following the technical traders' rules for pattern trading, ignoring transaction

costs. To answer this question, the study runs each data series through a filter designed to detect one pattern and determine the profit from following the recommended buying or selling strategy given an investment of \$1 million in funds each trade.

B. Description of the Data Series Used

Daily closing prices and volume data were collected for the Dow Jones Industrial Average, Aluminum Company of America, General Motors, and Procter and Gamble. The Dow Jones Industrial Average data run from 1/4/60 through 9/30/94 (Pierce, 1991; Standard and Poor's Corp, various dates). Data from the other companies extends from 1/2/62 when daily price data became readily available to 9/30/94 (Standard and Poor's Corp, various dates). Stock prices were adjusted to account for stock splits.

The individual company stock prices were chosen because they were all represented in the Dow Jones Industrial Average during the entire time period and were chosen to be in the most non-related businesses of all eighteen Dow Jones Industrial Average candidates. Aluminum Company of America (Alcoa) manufactures primary and fabricated aluminum, alumina and alumina chemicals. General Motors (GM) assembles automobiles, trucks, tractors, and military motor vehicles; it

manufactures parts and accessories, and acts as a finance company. Procter and Gamble (PG) manufactures many household items including soaps, detergents, cleaners, personal hygiene products, pharmaceuticals, paper products, shortenings, and cosmetics. Although it may be argued that Alcoa and GM have related businesses since Alcoa is the potential supplier of primary products to GM, other candidates which were primary goods manufacturers such as Bethlehem Steel or Exxon were not better choices.

While technical traders usually use price information including highs, lows, and closing prices as well as volume when detecting patterns and trading signals, this study chose to ignore the highs and lows for the following reasons: 1) closing price is a data point typically chosen as representative of trading prices achieved during a single day, and 2) Box-Jenkins time-series analysis and subsequent estimation procedures used to generate random series focus on a single data point for each time period.

C. Univariate Analysis to Generate Random Series

Over the years, many different models of stock prices have been proposed. Many of these models include explanatory variables such as dividends or earnings in an attempt to determine a measure of fundamental value of a stock. This

study, however, was concerned with generating series which mimic the movement of actual stock prices over time rather than constructing a measure of fundamental value.

Box and Jenkins (1976) have proposed a class of ARIMA models which they suggest are suited for modeling time-series data and generating forecasts. Since stock prices, like many economic series, may be considered to be the outcome or realization of a stochastic process and since the ARIMA models are constructed to represent this stochastic process, the ARIMA models are a candidate as at least a starting point to identify the stock price series.

Graphs of the price series (Figure 3.1) reveal that they appear to exhibit trends (except GM), perhaps some seasonal behavior, and a strong irregular component. The ARIMA models are particularly suited to incorporate this behavior.

There are limitations, however, to the Box-Jenkins models. One such limitation is that their methods must be used to model stationary data. However, it is obvious from the graphs that these price data do not have constant means and autocovariances across time as stationarity requires.

Although structural changes can make a series appear to be non-stationary, there was no reason to assume that any events occurred in each stock price series to permanently change the series. Events like the crash of 1987 and the oil price hikes of 1973 and 1979 were assumed to cause temporary

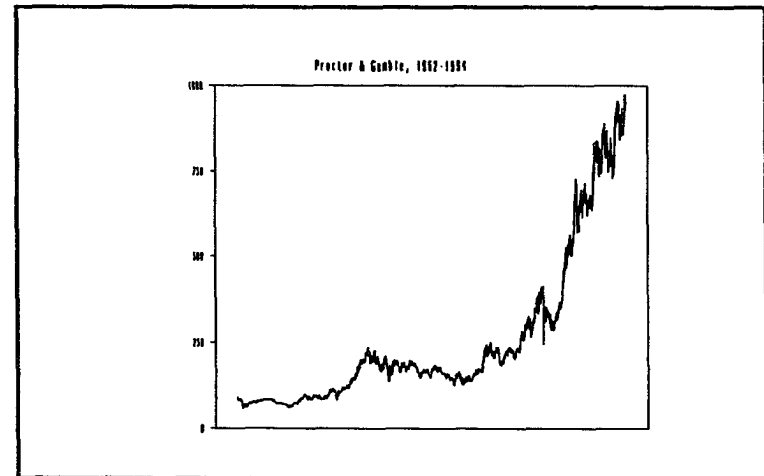
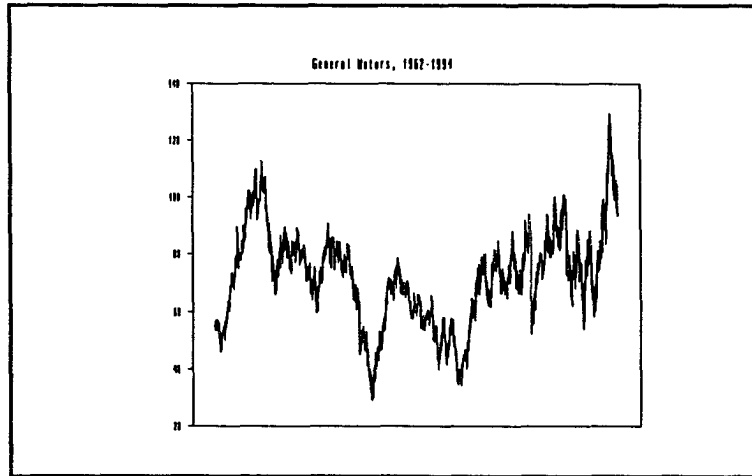
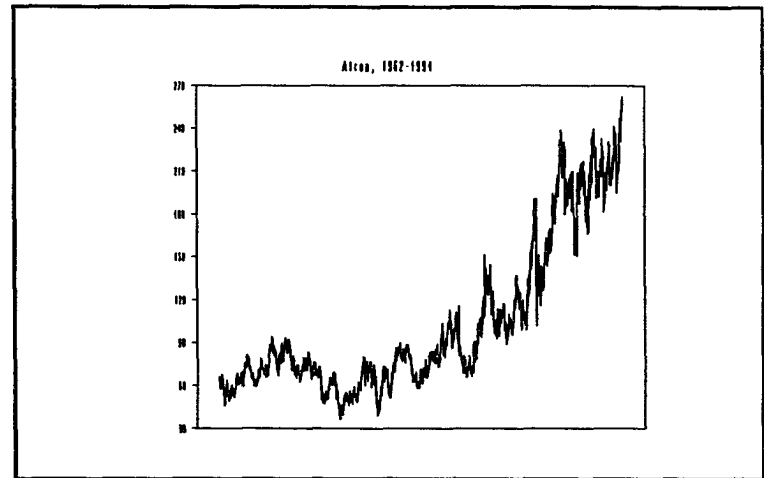
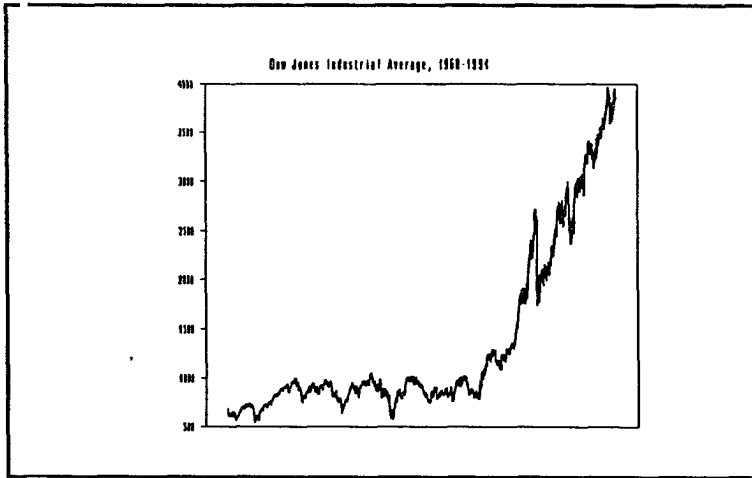


Figure 3.1. Graphs of the stock price series.

aberrations in stock prices so no formal tests for structural change were performed.

Typically, Box-Jenkins identification procedures dictate differencing a series to render it stationary. First differencing, however, imposes a unit root on the model. Although correlograms of first differences of each series appear to be stationary, there are formal tests to see if first differencing is appropriate. These tests were devised by Dickey and Fuller (1979, 1981) and Phillips and Perron (1988).

1. Unit root tests

Since the four price series examined appear from graphs and correlograms to be non-stationary, there must be a test performed to determine if first differencing is appropriate to render the series stationary.

To test for a single unit root, augmented Dickey-Fuller (1981) and Phillips-Perron (1988) tests were performed. Estimation requires an hypothesized model with autoregressive terms. Even if the true model is a mixed process, it can be approximated by a finite-order autoregressive process (Said and Dickey, 1984). Therefore, lag length tests were performed on each series. These tests involved regressing price returns (the first difference of prices) on lagged values and reducing

the model step by step. The initial model included twenty autoregressive terms which were systematically excluded using F-tests.² After the appropriate mix of autoregressive terms was determined, a final model to be tested for each series was formed by including both a constant and trend term. Although there was no indication of autocorrelated errors in the final models, the Phillips-Perron test was also used since it allows the errors to be weakly dependent and heterogeneously distributed while the Dickey-Fuller test places more stringent requirements on the error terms.

The method of testing for a unit root actually tests for a unit root under different models, starting with the largest and then pairing down each model. Results of the tests are presented in Tables 3.1 through 3.4. With the constant and trend term included in each model, unit roots could not be rejected across all series at the 5 percent level except Alcoa. At the 2.5 percent level, however, the unit root could not be rejected for the Alcoa series. In asset prices, there is no reason to believe the trend component should be important as the next step confirmed. In the presence of a unit root, the trend term was found to be insignificant across all series and so was eliminated from the next model tested.

²Twenty lags were chosen because, according to Said and Dickey (1984), an unknown ARIMA(p,1,q) process can be approximated by an ARIMA(n,1,0) process of order $T^{1/3}$ where T in this study is at most 8745.

Table 3.1. Unit root tests for Dow Jones Industrials.

Model	Estimates	Test	Conclusion
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_{t-1} + \alpha_3 \Delta y_{t-1} + \alpha_4 \Delta y_{t-2} + \alpha_5 \Delta y_{t-4} + \alpha_6 \Delta y_{t-5}$	$\alpha_0 = 0.0034 (1.42)$ $\alpha_1 = 0.0000 (1.88)$ $\alpha_2 = -0.0005 (-1.44)$ $\alpha_3 = 0.0577 (5.40)$ $\alpha_4 = -0.0302 (-2.82)$ $\alpha_5 = -0.0202 (-1.89)$ $\alpha_6 = 0.0185 (1.73)$	D.F.: -1.41 P.P.: -1.45 *: -3.41	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-4} + \alpha_5 \Delta y_{t-5}$	$\alpha_0 = -0.0000 (-0.13)$ $\alpha_1 = 0.0000 (1.26)$ $\alpha_2 = 0.0574 (5.37)$ $\alpha_3 = -0.0305 (-2.86)$ $\alpha_4 = -0.0206 (-1.92)$ $\alpha_5 = 0.0182 (1.70)$		Eliminate trend
$\Delta y_t = \alpha_0 + \alpha_1 y_t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-4} + \alpha_5 \Delta y_{t-5}$	$\alpha_0 = -0.0003 (-0.20)$ $\alpha_1 = 0.0001 (0.35)$ $\alpha_2 = 0.0575 (5.38)$ $\alpha_3 = -0.0304 (-2.85)$ $\alpha_4 = -0.0205 (-1.91)$ $\alpha_5 = 0.0183 (1.71)$	D.F.: 0.40 P.P.: 0.37 *: -2.86	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-4} + \alpha_4 \Delta y_{t-5}$	$\alpha_0 = 0.0002 (1.93)$ $\alpha_1 = 0.0576 (5.39)$ $\alpha_2 = -0.0304 (-2.84)$ $\alpha_3 = -0.0204 (-1.90)$ $\alpha_4 = 0.0184 (1.72)$		Eliminate constant
$\Delta y_t = \alpha_1 y_t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-4} + \alpha_5 \Delta y_{t-5}$	$\alpha_1 = 0.0000 (1.95)$ $\alpha_2 = 0.0576 (5.38)$ $\alpha_3 = -0.0304 (-2.84)$ $\alpha_4 = -0.0204 (-1.91)$ $\alpha_5 = 0.0184 (1.72)$	D.F.: 1.95 *: -1.95	Fail to reject unit root

Δy_t is the first difference of the log of stock price at time t.

(.) indicates t-value.

D.F. indicates Dickey-Fuller statistic.

P.P. indicates Phillips-Perron statistic.

* represents critical value at the 5% level for over 500 observations.

Table 3.2. Unit root tests for Aluminum Company of America.

Model	Estimates	Test	Conclusion
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_{t-1} + \alpha_3 \Delta y_{t-1} + \alpha_4 \Delta y_{t-9}$	$\alpha_0 = 0.0108 (3.37)$ $\alpha_1 = 0.0000 (3.19)$ $\alpha_2 = -.0028 (-3.41)$ $\alpha_3 = 0.0585 (5.32)$ $\alpha_4 = -.0343 (-3.12)$	D.F.: -3.56 P.P.: -3.49 *: -3.41	Reject unit root for this improbable model.
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-9}$	$\alpha_0 = -.0000 (-0.09)$ $\alpha_1 = 0.0000 (0.59)$ $\alpha_2 = 0.0571 (5.19)$ $\alpha_3 = -.0357 (-3.24)$		Eliminate trend
$\Delta y_t = \alpha_0 + \alpha_1 y_t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-9}$	$\alpha_0 = 0.0028 (1.41)$ $\alpha_1 = -.0006 (-1.33)$ $\alpha_2 = 0.0575 (5.23)$ $\alpha_3 = -.0352 (-3.20)$	D.F.: -1.35 P.P.: -1.32 *: -2.86	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-9}$	$\alpha_0 = 0.0002 (0.84)$ $\alpha_1 = 0.0571 (5.19)$ $\alpha_2 = -.0356 (-3.24)$		Eliminate constant
$\Delta y_t = \alpha_1 y_t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-9}$	$\alpha_1 = 0.0000 (0.71)$ $\alpha_2 = 0.0571 (5.19)$ $\alpha_3 = -.0356 (-3.24)$	D.F.: 0.71 *: -1.95	Fail to reject unit root

Δy_t is the first difference of the log of stock price at time t.

(.) indicates t-value.

D.F. indicates Dickey-Fuller statistic.

P.P. indicates Phillips-Perron statistic.

* represents critical value at the 5% level for over 500 observations.

Table 3.3. Unit root tests for General Motors.

Model	Estimates	Test	Conclusion
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-3} + \alpha_5 \Delta y_{t-4}$	$\alpha_0 = 0.0079 (2.63)$ $\alpha_1 = 0.0000 (0.22)$ $\alpha_2 = -.0019 (-2.63)$ $\alpha_3 = -.0397 (-3.61)$ $\alpha_4 = -.0233 (-2.12)$ $\alpha_5 = -.0268 (-2.43)$	D.F.: -2.73 P.P.: -2.81 *: -3.41	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-3} + \alpha_4 \Delta y_{t-4}$	$\alpha_0 = 0.0000 (0.16)$ $\alpha_1 = 0.0000 (0.06)$ $\alpha_2 = -.0407 (-3.70)$ $\alpha_3 = -.0242 (-2.20)$ $\alpha_4 = -.0276 (-2.51)$		Eliminate trend
$\Delta y_t = \alpha_0 + \alpha_1 y_t + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-3} + \alpha_4 \Delta y_{t-4}$	$\alpha_0 = 0.0079 (2.64)$ $\alpha_1 = -.0019 (-2.62)$ $\alpha_2 = -.0397 (-3.61)$ $\alpha_3 = -.0233 (-2.12)$ $\alpha_4 = -.0268 (-2.43)$	D.F.: -2.72 P.P.: -2.79 *: -2.86	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-2} + \alpha_2 \Delta y_{t-3} + \alpha_3 \Delta y_{t-4}$	$\alpha_0 = 0.0001 (0.42)$ $\alpha_1 = -.0407 (-3.70)$ $\alpha_2 = -.0242 (-2.20)$ $\alpha_3 = -.0276 (-2.51)$		Eliminate constant
$\Delta y_t = \alpha_1 y_t + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-3} + \alpha_4 \Delta y_{t-4}$	$\alpha_1 = 0.0000 (0.27)$ $\alpha_2 = -.0407 (-3.70)$ $\alpha_3 = -.0242 (-2.20)$ $\alpha_4 = -.0276 (-2.51)$	D.F.: 0.27 *: -1.95	Fail to reject unit root

Δy_t is the first difference of the log of stock price at time t.

(.) indicates t-value.

D.F. indicates Dickey-Fuller statistic.

P.P. indicates Phillips-Perron statistic.

* represents critical value at the 5% level for over 500 observations.

Table 3.4. Unit root tests for Procter and Gamble.

Model	Estimates	Test	Conclusion
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 y_{t-1} + \alpha_3 \Delta y_{t-1} + \alpha_4 \Delta y_{t-2} + \alpha_5 \Delta y_{t-4}$	$\alpha_0 = 0.0047 (2.08)$ $\alpha_1 = 0.0000 (2.39)$ $\alpha_2 = -.0012 (-2.10)$ $\alpha_3 = 0.0270 (2.45)$ $\alpha_4 = -.0328 (-2.98)$ $\alpha_5 = -.0433 (-3.93)$	D.F.: -2.20 P.P.: -2.29 *: -3.41	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-4}$	$\alpha_0 = 0.0000 (0.01)$ $\alpha_1 = 0.0000 (1.21)$ $\alpha_2 = 0.0264 (2.40)$ $\alpha_3 = -.0334 (-3.04)$ $\alpha_4 = -.0438 (-3.98)$		Eliminate trend
$\Delta y_t = \alpha_0 + \alpha_1 y_t + \alpha_2 \Delta y_{t-1} + \alpha_3 \Delta y_{t-2} + \alpha_4 \Delta y_{t-4}$	$\alpha_0 = -.0001 (-0.07)$ $\alpha_1 = 0.0001 (0.36)$ $\alpha_2 = 0.0265 (2.40)$ $\alpha_3 = -.0333 (-3.03)$ $\alpha_4 = -.0437 (-3.97)$	D.F.: 0.33 P.P.: 0.32 *: -2.86	Fail to reject unit root
$\Delta y_t = \alpha_0 + \alpha_1 \Delta y_{t-1} + \alpha_2 \Delta y_{t-2} + \alpha_3 \Delta y_{t-4}$	$\alpha_0 = 0.0003 (2.11)$ $\alpha_1 = 0.0266 (2.41)$ $\alpha_2 = -.0333 (-3.02)$ $\alpha_3 = -.0437 (-3.97)$		Reject model which does not include constant

Δy_t is the first difference of the log of stock price at time t.

(.) indicates t-value.

D.F. indicates Dickey-Fuller statistic.

P.P. indicates Phillips-Perron statistic.

* represents critical value at the 5% level for over 500 observations.

The second model which included a constant term was rejected in the presence of a unit root for all series except Procter and Gamble. For the other three series, the constant term was found to be insignificant in the presence of a unit root at the 5% level and so was eliminated from the model. Also at the 5% level, the unit root could not be rejected across the remaining series.

Therefore, unit roots could not be rejected for any of the series. First differencing of the log of the price series may be considered as appropriate to render the series stationary and to perform the Box-Jenkins identification. Correlograms presented in the next section also suggest that first differencing produces stationary series.

2. Box-Jenkins model identification

Box-Jenkins procedures to identify ARIMA models using correlograms was followed. Logarithms of the price series were taken before first differencing. The resulting correlograms are presented in Figure 3.2. They appear to represent stationary series since the sample autocorrelation function (acf) and partial autocorrelation function (pacf) converge rapidly to zero.

The Box-Jenkins identification procedure, however, is very subjective. Upon examining correlograms, researchers may

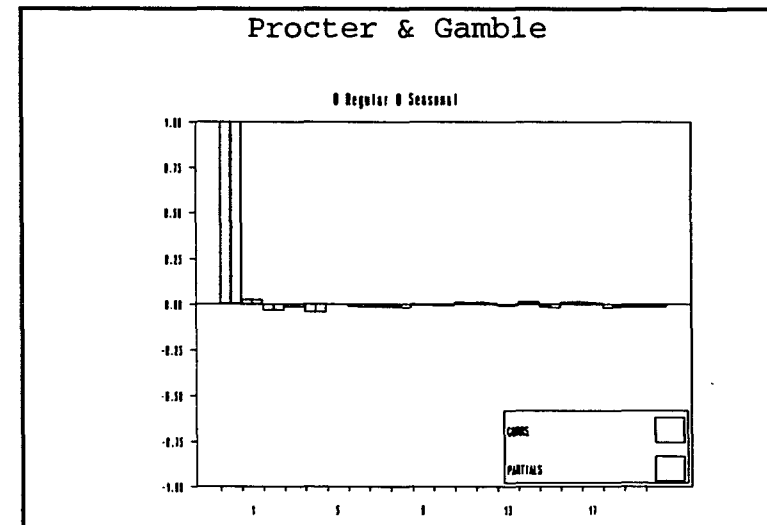
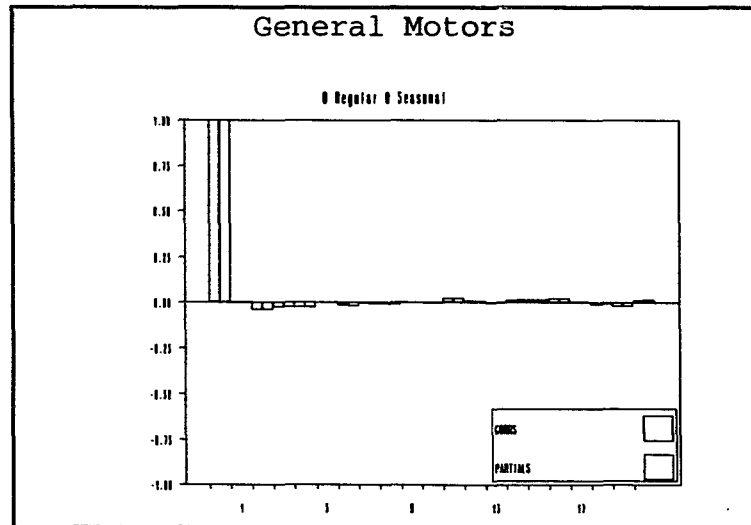
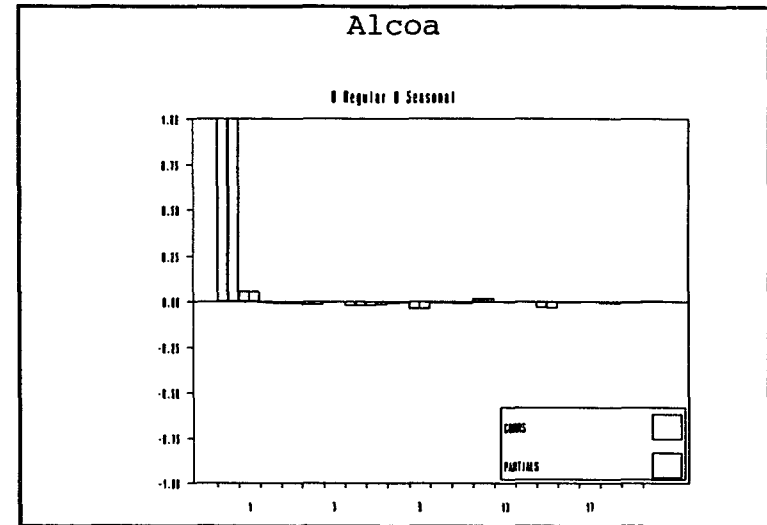
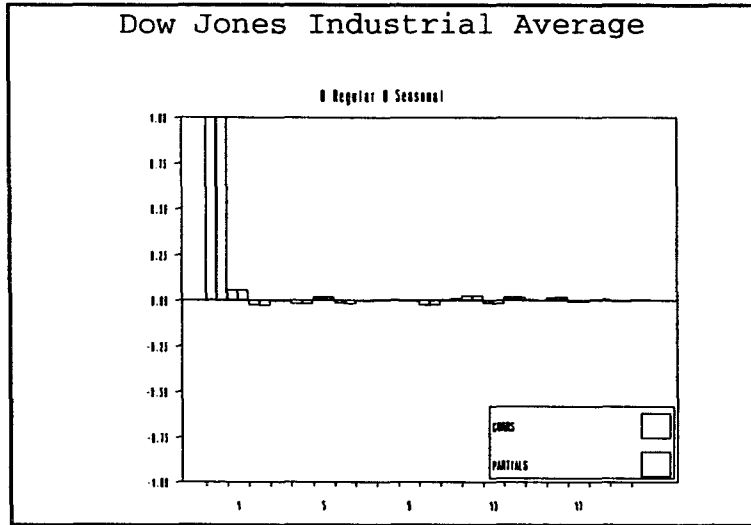


Figure 3.2. Correlograms of the first difference of the log price series.

conclude that a correlogram represents different models. Therefore, other objective tests must be used to focus on the most appropriate model. Often, the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criteria (SBC) statistics are used for this purpose (Enders, 1995):

$$\begin{aligned} \text{AIC} &= T \ln (\text{residual sum of squares}) + 2n \\ \text{SBC} &= T \ln (\text{residual sum of squares}) + n \ln(T) \end{aligned}$$

where T = number of observations
 n = number of parameters estimated.

The smaller these statistics, the better the fit of the model. By construction, the SBC will select the most parsimonious model.

The Dow Jones Industrial Average correlogram revealed a small-order autoregressive or moving-average component. Models with a constant and either one or two moving-average terms were compared. The SBC was lower on the more parsimonious MA(1) model. The AIC and SBC were comparable on an AR(2) model but the MA(1) model was the most parsimonious and so was the favored model. Under the MA(1) model, while the residuals themselves appear as white noise, the residuals squared do not. Therefore, the residuals squared were included in the estimation procedure as will be discussed in the next section.

The correlogram for Alcoa reveals a small-order

autoregressive or moving-average. Models with moving-average terms of order one and which included and excluded a constant term were compared. The constant term was found to be insignificant. This model was compared to an AR(1) and the AIC and SBC were comparable. The AIC and SBC for an ARMA(1,1) were worse so it was eliminated from consideration. Since other stock prices in this study seem to have the moving-average component, the MA(1) was chosen. Again, the residuals squared were not white noise so they will be included in an estimation procedure.

General Motor's correlogram reveals some small spikes at lags 2, 3, and 4. A model with moving-average lags at 2, 3, and 4 was compared to an autoregressive model with the same lags. The AIC and SBC were comparable. Later estimation procedures revealed that a smaller-order model with moving-average term at lag 2 was the best model since models with more lags would not converge. A model including the residuals squared was also estimated since they were not white noise.

The correlogram for Procter and Gamble also revealed a small-order autoregressive or moving-average component. Two of the more parsimonious models, a MA(2) and an AR(2) were found to have similar AIC and SBC statistics. Again, the residuals squared in both models were not white noise and later estimation procedures revealed that including a second lag meant the models would not converge.

As was noted before, this Box-Jenkins analysis was used to get a preliminary idea of the model. As was evident across the series, ARCH processes were present and had to be included in the estimation procedure.

3. Model estimation

With ARCH processes present across the preliminary models chosen, regressions were run on the squared residuals to determine the appropriate lag length under each of the preliminary models. Since asset prices theoretically include ARCH or ARCH-M processes (Engle, 1982; Engle, Lillen, and Robbins, 1987), both types of models were estimated in each case, and the best fitting model was chosen.

For the Dow Jones Industrial Average, under a MA(1) model with constant term, a regression including ten lags (a two-week time period) of residuals squared was run. F-tests were conducted to determine if lags could be excluded. Although the F-value of eliminating lags 6 through 10 was 2.93, when lags 9 through 10 were eliminated, the F-value dropped to 2.28 (significant at 10.1% level). Keeping in mind the idea of parsimony, an ARCH(1) process was chosen as the best candidate for estimation. Using non-linear maximum likelihood, four possible models were estimated (Appendix A). The model which achieved the highest maximum function value and significant

coefficients was the ARCH-M model and so was chosen as the model to generate random series.

For Alcoa, the MA(1) model with no constant term had been chosen as a candidate. Lag length tests performed on the residuals squared series indicated the presence of an ARCH(5) process. Therefore, the candidate for estimation was a MA(1) with ARCH(5) residuals. A problem arose, however, in the estimation procedure since models which included so many lags of the ARCH process would not converge in 100 iterations, despite attempts to generate better initial values. The acf value of the first lag in the residuals squared was 0.39 but dropped to 0.02 and under for the subsequent lags. Therefore, the first lag was the most significant and chosen to be included in model estimation. Three separate models were estimated (Appendix A). The model which included all significant variables was the MA(1) without a constant and ARCH(1) errors.

For General Motors, the moving-average model with lags 2, 3, and 4 and no constant term was the initial candidate. Lag length tests for the residuals squared series indicated the presence of an ARCH(5) process. The candidate for estimation was therefore an MA{2,3,4} with ARCH(5) errors. Estimation of this model again posed a problem since, despite many attempts to determine the best initial values, the model would not converge in 100 iterations. In some cases the ARCH process

was reduced to one lag since it was the most significant of the five terms, and in other cases the moving-average component was reduced to include only the MA{2} term since it, too, was the most significant of the three moving-average lags and since there was no theoretical reason to believe lags 3 or 4 would affect stock returns. Estimation results of the convergent models are presented in Appendix A. Of the seven models tested, only the MA{2} with ARCH(5) errors contained coefficients which were all significant and had the highest likelihood value so this was the model chosen to generate future random series.

For Procter and Gamble, the MA(2) model with a constant was chosen as the initial candidate for estimation. Lag length tests indicated that the residuals followed an ARCH(3) process. Convergence of models with ARCH(3) processes again was not achieved despite attempts to alter starting values. Since the first lag of the ARCH process had the most significant coefficient, models with ARCH(1) processes were estimated. Of the five models estimated (Appendix A), the one with significant coefficients and the highest likelihood value was the ARCH-M model so this was the model chosen to generate future random series.

Therefore, a variety of univariate models were found for these four stock price series. All of them, however, exhibited ARCH or ARCH-M errors as may be expected for asset

prices. Before discussing the generation of random series using these models and the Monte Carlo method, the filtering techniques used to detect technical trading patterns will be clarified in the next two sections.

D. Description of the Technical Trading Patterns

The three technical trading patterns in this study were chosen to be representative of different classes of patterns. Perhaps the best known of these, the Head and Shoulders Top, is seen in stock price series which are reversing their trend from upward to downward, according to technical analysts. The Symmetrical Triangle may represent either a reversal or consolidation pattern where prices do not change direction but continue the same trend. The Rectangle, like the Symmetrical Triangle, can represent either a reversal or consolidation pattern. These patterns have been named according to their shape. A description of the shapes and technical trading explanations for the existence of each pattern are discussed below. Much of this discussion is paraphrased from Edwards and Magee (1992) who provide the most detailed description of all patterns.

1. Head and Shoulders Top

The Head and Shoulders Top received its name because it consists of three humps or local maxima where the middle maximum (the "head") is higher than the other two (the "shoulders"). Prices must decline on either side of the "head" to a point which is lower than each shoulder, but there is no requirement that one shoulder be higher or lower than the other. Technical analysts also draw in a "neckline" on their charts as the pattern progresses. This "neckline" is a line which connects the two local minima on either side of the head and is used to help determine when to buy or sell. This idea will be discussed in the next section.

Volume on the Head and Shoulders Top can also be an indicator of the progression of the pattern. Volume usually rises on advances, but less so in the right shoulder. However, there is no clear rule as to volume requirements in this pattern.

A reversal of trend is often indicated by this pattern. According to analysts, this reversal of trend occurs because "supply overcomes demand" (p. 63, Edwards and Magee, 1992). More specifically, they describe the left shoulder as occurring because a well-informed group expects price to rise perhaps due to good anticipated company earnings and then begins to quietly buy shares. Other potential buyers find few

offerings and they must increase their bids to make the purchase. An advance begins. The good news is made public which further pushes prices up and others are attracted by the rising price.

Now the well-informed group wants to begin selling, but does it slowly such that profits are not lost by a sudden dumping of their shares. A lull in demand occurs perhaps because prospective buyers sense the increase in supply. The group now begins to stop selling and may even buy back some shares to stop the decline. This completes the "left shoulder".

The "head" begins when an advance resumes and a new wave of demand occurs as price reaches above the previous high of the "left shoulder". The group again continues to slowly sell its shares, before the second wave of demand is exhausted. At that point, prices begin to decline which completes the "head".

A second, "right shoulder" occurs when, at the low, traders who were waiting for the prices to go back below the head begin to buy while those who were anxious to sell on the decline are finally able to get out. This action causes a minor reaction or temporary boost of prices followed by a steady decline.

For technical traders, the signal to sell after a Head and Shoulders Top has developed comes when price closes below

the neckline by approximately 3% of the market price. This constitutes a "breakout" or signal.

Although there are many variations of the Head and Shoulders Top (such as the case where there are two left and two right shoulders), this study focused only on the simple case described above.

2. Symmetrical Triangle

A Symmetrical Triangle is formed when prices fluctuate up and down but where these fluctuations become smaller as they progress. Before constructing a triangle, there must be four reversals of minor trend since the Symmetrical Triangle appears with two "boundary lines" which meet at an apex. Each boundary line can only be constructed after two local maxima or two local minima have been found. The apex is always to the right so the triangle appears to lie on its side.

The Symmetrical Triangle may indicate a temporary aberration from trend (consolidation) or a reversal of trend. There is seldom any clue given on the chart to tell in which direction prices will break out of the triangle until the action finally occurs (Edwards and Magee, 1992).

Triangles occur, supposedly, because the market participants are unsure which way trend will go. As Edwards and Magee (1992) describe, a triangle is formed when prices

begin to rise, say from 20 to 40. No reason is provided for this initial advance by the authors. As some investors see such a price, they begin to sell and price falls say to 25. Other would-be investors who watched price rise to 40 but were unwilling to buy then now enter the trading which brings price up again, say to 35. At that point, the investors who saw price rise to 40 but failed to grab any profits may have decided to be less greedy and sell at 35, sending price downward again. As this example demonstrates, the Triangle exemplifies "doubt, vacillation, stalling, until finally a decision is reached" and prices break from the pattern (p. 110, Edwards and Magee, 1992).

For technical traders, the signal to buy or sell after a Symmetrical Triangle has formed occurs when prices close by about a 3 percent margin beyond the boundary line. Although this signal can occur if prices rise above or below the boundary lines, if prices rise above the boundary line, then the signal occurs only if volume rises as well.

3. Rectangle

The Rectangle formation resembles that of the Symmetrical Triangle. It consists of a series of side-wise price fluctuations bounded on the top and bottom by horizontal or near-horizontal lines.

Also like the Symmetrical Triangle, the Rectangle may indicate either a temporary aberration from trend (consolidation) or a reversal of trend. No advance notice about which way prices will break through the pattern is apparent.

While it appears that the only difference between Symmetrical Triangles and Rectangles is the slope of the boundary lines, Edwards and Magee (1992) characterize the Rectangle as resulting from a conflict between two groups of traders rather than resulting from doubt. These two groups are owners of stock who wish to dispose of their shares at a certain price and others who wish to accumulate the stock at a certain, lower figure. The holders of stock may be an investment trust or perhaps a large individual shareholder, each of which has a good reason for wanting to sell at the top price. The potential buyers could also be an investment trust or group of insiders who wish to buy at the bottom. In any case, these two opposing groups "bat the ball back and forth (up and down, that is) between them until ultimately, and usually quite suddenly, one team is exhausted (or changes its mind) and the other then proceeds to knock the ball out of the lot" (p. 142, Edwards and Magee, 1992).

Therefore, prices may break out of the pattern in either direction. For technical traders, the signal to buy or sell occurs when prices close by about a 3 percent margin beyond

the boundary line. Higher volume must also occur when prices break out above the boundary line.

E. Programming to Detect Patterns

In the last section, the three patterns were described. While for technical traders, detecting these patterns is a subjective "art", this study has attempted to make the detection of patterns more objective by constructing programs to detect them. All programs were written using RATS (Regression Analysis of Time Series), version 4.0.

1. Head and Shoulders Top program

A program to detect the Head and Shoulders Top must find three consecutive local maxima where the second is higher than the other two. The Head and Shoulders pattern is generally one which occurs over relatively long time periods, from several weeks to several months. In order to make sure that the program was detecting local maxima which occurred over longer time periods, two elements were added to this program. First, the series was smoothed by taking a ten-day moving average (two trading weeks). A one-week smooth was not as effective in minimizing the minor ups and downs which should be irrelevant in detecting such a long-term pattern. Second,

local maxima were chosen as a two-week high. That way, there was at least a two-week period between local maxima. The maximum chosen over a one-week period was not as adept at finding what appeared to be the pattern.

The program was therefore designed to perform the following tasks: 1) smooth the series, 2) detect three consecutive local maxima, 3) determine if the second of the three maxima was the greatest, 4) continue the filtering process until all patterns were found, and 5) record a "hit" for each pattern found and sum up the hits across the series.

Figure 3.3 depicts a Head and Shoulders Top found by this program in the Dow Jones Industrial Average. The actual and smoothed series are shown. Also depicted is a neckline which was used in later programs to detect sell signals.

2. Symmetrical Triangle program

A program which detects Symmetrical Triangles must find two alternating local maxima and local minima where the second maximum is lower than the first and the second minimum is higher than the first. These extrema are then used to construct boundary lines which are necessary to detect a signal to buy or sell. The boundary lines meet at an apex so the pattern resembles a triangle on its side.

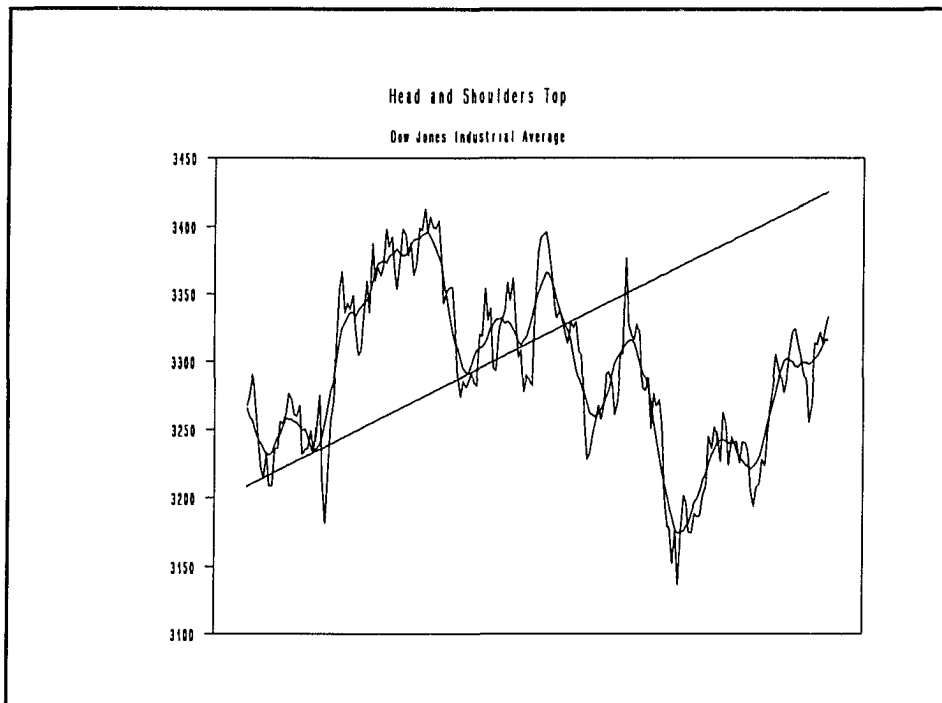


Figure 3.3. Example of Head and Shoulders Top found in the Dow Jones Industrial Average.

While it was advantageous to use smoothing in the previous program, the Symmetrical Triangle program did not smooth the series since the pattern represents sharp vacillations in price. In addition, according to Edwards and Magee (1992), about three-quarters of Triangles turn out to be consolidation patterns rather than reversal patterns which take longer to develop. Therefore, local extrema were determined as a weekly (five-day) maximum or minimum.

The Symmetrical Triangle program progresses by 1) finding four alternating minima and maxima, 2) determining if the

second maximum is less than the first and if the second minimum is greater than the first, 3) continuing the filtering process at the point after the first extremum is found, and 4) recording a "hit" if a triangle is found and summing these numbers across each series.

An example of the Symmetrical Triangle found in the Procter and Gamble series is depicted in Figure 3.4. This is an example of a reversal where prices change direction (at least temporarily).

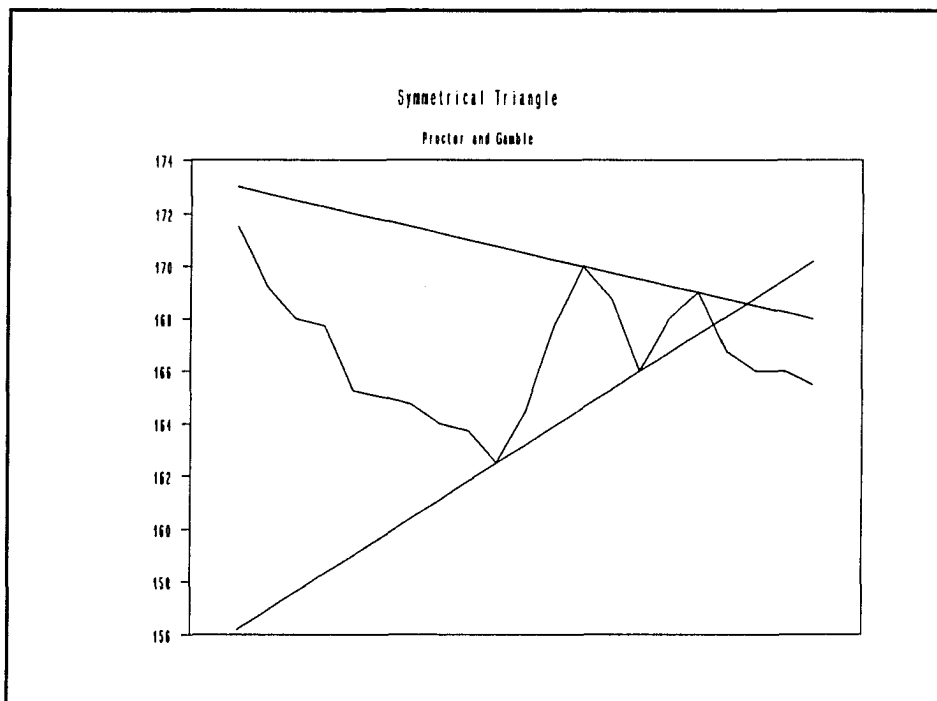


Figure 3.4. Example of the Symmetrical Triangle in the Procter and Gamble series.

3. Rectangle program

Like the Symmetrical Triangle program, a program which detects Rectangles must find two alternating local maxima and local minima. However, in this case, the maxima must be equal (or nearly so) and the minima must be equal (or nearly so) to construct two horizontal (or nearly-horizontal) boundary lines through each set.

Since this study also looked at the Symmetrical Triangle pattern which is similar in nature except for the slope of the boundary lines, it was necessary to strike a balance between making the requirement of horizontal boundary lines for the Rectangle fairly strict to differentiate it from the Triangle and allowing some leeway in the slope requirement to ensure that patterns which technical traders would call Rectangles are detected by the program. Keeping this balance in mind, the program allowed the boundary line slope to be up to 0.05 in absolute value with not more than a 0.05 difference in absolute value between the two slopes. This figure was determined by running the filter through the actual price series with alternate slopes of 0.1, 0.05, and 0.01 in absolute value. The lowest value was too restrictive to detect many patterns while the highest value detected patterns which appeared more like convergent or divergent Triangles.

A second step taken in the program which differed from

the Symmetrical Triangle program was that the series was smoothed using a five-day (one week) moving average. Smoothing was used in this case because the two extreme boundary prices are key to the vacillating movement within the Rectangles and not the small movements within the Rectangle.

Therefore, the program 1) smoothed the series, 2) detected four alternating extrema, 3) constructed boundary lines through the extrema, 4) determined whether the slopes of the boundary lines met the slope criteria discussed above, 5) recorded a "hit" if the criteria were met and computed the total hits per series, and 6) continued the filtering process.

An example of a Rectangle with boundary lines found in the Alcoa series is in Figure 3.5. This example depicts the boundary lines, the actual series, and the smoothed series through which the boundary lines are determined.

F. Monte Carlo Analysis

Having described the models that were estimated for each of the four stock price series and the pattern detection programs, a description of the Monte Carlo simulation methods may be addressed. This analysis is used to answer the question if patterns occur more frequently in actual stock price series than they do in random series.

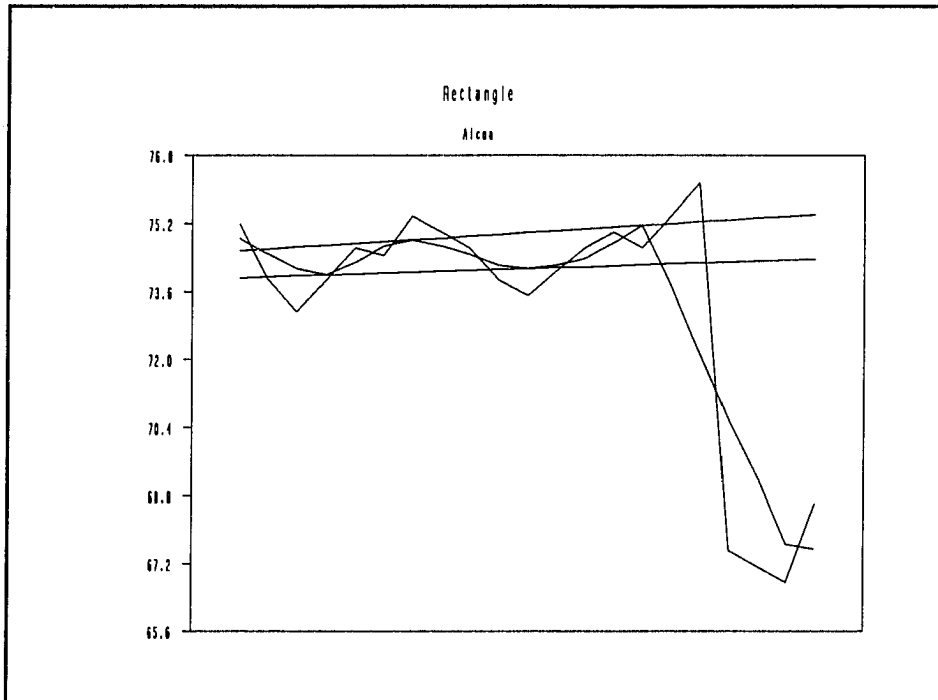


Figure 3.5. Example of a Rectangle in the Aluminum Company of America series.

1. A description of Monte Carlo methods

Monte Carlo experiments are often used in econometric studies, as well as in this study, to help determine the finite-sample properties of estimators and test statistics. In most Monte Carlo work, quantities of interest are approximated by generating many random realizations of some stochastic process and then averaging them in some way (Davidson and MacKinnon, 1993). Just one example of Monte Carlo work used in an econometric study was completed by Dickey and Fuller (1979) on unit root processes. Under a null

hypothesis of nonstationarity, OLS testing of a unit root process is inappropriate. Dickey and Fuller proposed a method to devise appropriate critical values for this test. They generated thousands of time series using three models: a simple random walk, a random walk with drift, and a random walk with drift and linear time trend. For each generated series, they then estimated the value of the coefficient and standard error when a simple OLS regression was run. With these estimates, Dickey and Fuller could construct a distribution to detect how far these estimates were away from unity. For the simple random walk, for example, they found that 95% of the estimated values were within 1.95 standard errors from unity.

In this study, the object of the experiment is similar to that of Dickey and Fuller. It was to determine appropriate critical values for a distribution of the number of times each pattern is found in each stock price series. With these critical values, a test of the null hypothesis could be conducted.

Each Monte Carlo experiment must specify three factors. First, there must be a model and its estimators or test statistics. In this experiment, the "models" are the patterns and the "test statistic" is the number of times a pattern is found in a particular stock price series. Second, each Monte Carlo experiment must specify a data-generating process (DGP).

In this study, the DGP is the ARCH or ARCH-M model estimated for each stock price series and error terms which have been bootstrapped. The DGP and bootstrapping method will be described in detail in the next section. Third, each Monte Carlo experiment must specify the number of replications to be performed. Typical numbers used are large: 1000, 2000, 5000, or 10,000.

This experiment proceeds by generating a single series from the DGP and calculating the test statistic (the number of times a pattern is found). It is repeated ten thousand times so there are ten thousand replications of this test statistic which constitutes a sample distribution of the number of times a pattern is found within the randomly generated series. The number of replications used was large to minimize experimental error. The sample distribution is then used to determine critical values for the number of times a pattern is found within a given series. The statistic estimated from the actual price series is then compared with these critical values to test the null hypothesis.

2. Bootstrapping and the data-generating process

The idea of bootstrapping is to use an available data set in a Monte Carlo experiment to approximate the distribution of error terms in the relevant data-generating process. In an

experiment involving stock prices, it may be particularly appropriate to use this bootstrapping method. As was apparent from the literature review, there is no well-accepted, easily identified model of stock prices. Indeed, when stock price models are estimated, the error terms often exhibit a high degree of kurtosis. With this in mind, it would be a mistake to use error terms generated from some normal or uniform distribution to simulate the random series. Therefore, in this experiment, bootstrapping is an ideal method to use in the DGP.

The bootstrapping portion of the experiment proceeded as follows. First, the residuals were calculated from the estimated stock price models and then stored. Second, the residuals were bootstrapped to generate ten thousand series for each stock price model and each pattern. This means that the series of residuals used to generate each simulated stock price series was determined by randomly resampling the actual residual series with replacement. Thus, each bootstrap sample of residuals contained some of the original observations more than once and others of them not at all. Third, the appropriate pattern detection program was run through each of the series and the number of times each pattern was detected was recorded.

G. Programming to Detect Signals to Buy and Sell

While the Monte Carlo analysis is used to answer one question posed in this study, a second question remains: can technical trading rules earn investors excess returns, ignoring transactions costs? To answer this question, programs were developed for each pattern examined to extend the pattern detection process such that it also found appropriate technical trading signals to buy and sell.

These new programs were run on each stock price series for each pattern to calculate the returns for a \$1 million trade upon each signal. Statistics on average returns for each strategy and each stock series were tabulated as well as on the total present value of all signal returns.

1. Head and Shoulders Top

The Head and Shoulders Top, according to technical traders, occurs when there is a reversal of trend from up to down. Therefore, this pattern produces a signal in some instances to sell stock.

The signal itself is generated when the market price closes by approximately 3 percent below the "neckline" after the "right shoulder" has been completed (Edwards and Magee, 1992). Thus, a program necessary to detect the signal was

designed to 1) find the Head and Shoulders Top pattern, 2) compute a neckline, 3) detect the signal, if relevant, and 4) compute profits from any signal for short-selling and then purchasing shares after various short-sell periods.

The pattern detection program as described in section E1 above was therefore expanded to find the signal and compute profits. The neckline is drawn on charts as tangent to the two local minima from the smoothed series on either side of the "head". To compute the neckline, the program found these local minima and then made a neckline through them. Then, the point of intersection between the actual stock price series and the neckline occurring after the right shoulder maximum was detected and the market price recorded, if applicable.³ If, for a 50-day period after the development of the right shoulder, the stock price series fell by at least 3 percent of the recorded neckline market price, a signal was detected to sell. Since there were no guidelines for an appropriate duration to short-sell, three different periods were examined. Returns were calculated for two- five- or ten-day periods from the signal date by multiplying the \$1 million investment times the rate of return: $((p(t) - p(t+i)) / p(t))$, where i is the short-sell period. This RATS program is in Appendix B.

³With smoothing using the centered 10-day moving average, it is conceivable that actual stock prices could have fallen sharply such that this program may have detected a right shoulder before technical traders could without the advance knowledge of prices.

2. Symmetrical Triangle

While the Head and Shoulders Top produces a sell signal, the Symmetrical Triangle formation may indicate a signal to buy if the price rises above the upper boundary line or a signal to sell if the price declines below the lower boundary line.

A signal is generated when market prices close by approximately 3 percent beyond the boundary line before the apex is reached (Edwards and Magee, 1992). Thus, the program to detect this signal was designed to 1) find the Symmetrical Triangle, 2) compute upper and lower boundary lines, 3) detect the apex as the intersection of the boundary lines, 4) detect the signal to buy or sell, if relevant, and 5) compute returns from the signal for various holding periods.

The Symmetrical Triangle detection program described in section E2 above was expanded to find the appropriate signal and to compute returns. To construct the upper boundary line, the program extended a line through the two local maxima found to detect the formation. The lower boundary line was constructed by connecting the two local minima. Then, the point of intersection between the two lines (the apex of the Triangle) was recorded. The next step was to detect the point where prices intersected either boundary line after the Symmetrical Triangle formation had occurred. This "breakout

point" could come only after all four local extremum were in place and before the apex was reached. Therefore, the program had to define two separate cases to know the appropriate starting point for a breakout detection. If the triangle began with a local maximum, then the pattern could only be completed and a starting point recorded for a breakout signal after the second local minimum was detected. If, however, the Symmetrical Triangle began with a local minimum, the starting point for a breakout signal could occur only after the second local maximum.

Given the period between this starting value and the apex, a breakout signal could occur through either the upper or lower boundary line. If the stock price series exceeded the upper boundary line by 3 percent before the apex was reached, a signal was recorded for an "up breakout". If the series fell below the lower boundary by 3 percent before the apex was reached, a signal was recorded for a "down breakout".

As Edwards and Magee (1992) describe, an "up breakout" must be confirmed by a marked increase in trading volume. However, a "down breakout" as in the case of a Head and Shoulders Top does not require confirmation by a pickup in activity. Therefore, for "up breakouts", average volume over the ten-day period prior to the signal was computed and the signal for an "up breakout" was confirmed only if volume on the signal date exceeded that average.

Returns for either breakout were then computed. An "up breakout" is a signal to buy. Returns were computed for purchasing stock at the signal price and then selling after various holding periods. For each signal, this number was calculated by taking \$1 million times the rate of return generated for this i -day holding period: $((p(t+i) - p(t)) / p(t))$. Again, since there were no specific guidelines for an appropriate holding period, three were examined: two-, five- and ten-day periods. A "down breakout" is a signal to sell. Returns in this case were computed just as under the Head and Shoulders Top. The RATS program is in Appendix C.

3. Rectangle

Like the Symmetrical Triangle, the Rectangle can produce a signal to buy if closing prices rise 3 percent above the upper boundary line and if volume confirms this movement or a signal to sell if closing prices fall 3 percent below the lower boundary line (Edwards and Magee, 1992).

Therefore, a program to detect a signal was designed to 1) find the Rectangle formation, 2) compute the boundary lines, 3) detect the signal to buy or sell, if relevant, and 4) compute returns from the signal for various holding periods.

The Rectangle detection program described in E3 above was

expanded to find the relevant signals and to compute returns. Boundary lines had already been constructed in the detection program as joining the two local maxima in the smoothed series (the upper boundary line) and the two local minima in the smoothed series (the lower boundary line). As was mentioned before, the Rectangle was only detected if the slopes of the boundary lines met criteria for being near-horizontal.

As with the Symmetrical Triangle signal program, a breakout could only occur after all extrema were in place and the Rectangle formation was therefore defined. If the actual stock price series exceeded the upper boundary line by 3 percent at any point up to a 50-day period from the time the Rectangle was defined, a signal was recorded for an "up breakout". If the price series fell below the lower boundary by 3 percent at any point up to a 50-day period from the time the Rectangle was defined, a signal was recorded for a "down breakout". The "up breakout" was confirmed only if volume on the signal date exceeded a prior ten-day average.

Returns for either breakout were recorded in the same manner as for the Symmetrical Triangle. The RATS program is in Appendix D.

IV. RESULTS AND DISCUSSION

Monte Carlo experiments were conducted to test the null hypothesis that technical trading patterns occur just as frequently in actual stock price series as they do in random series generated to mimic stock prices. From these experiments, critical values were determined. In general, the null hypothesis could not be rejected at a 10% significance level for the two-tailed test. The results of these experiments are discussed in the next section.

Programs were also designed to detect three different technical trading patterns and to compute returns generated by exploiting signals to buy or sell given \$1 million was traded upon each signal. These programs are in Appendix B through D. T-tests were conducted on average profits generated by following these technical trading signals ignoring transaction costs. The results indicate that none of the patterns in the four stock series generate consistent and significantly positive returns. Indeed, in most cases, average returns were negative. This finding indicates that, in general, these patterns cannot be exploited to consistently generate excess profits as technical traders believe. A discussion of these results is in the second section below.

A. Monte Carlo Results

This section will be divided into three parts. The first part will discuss the results of the Monte Carlo experiments to determine critical values for the number of times a Head and Shoulders Top occurs in random stock price series generated to mimic four different price series. The second part examines results for the Symmetrical Triangle for each of these series and the last part examines the Rectangle formation. These results are summarized in Table 4.1.

1. Head and Shoulders Top

Construction of the Head and Shoulders Top filter was discussed in the Methods section. The pattern itself appears like three humps with the middle hump being the highest. In the Monte Carlo experiments, this filter was run through ten thousand randomly-generated series chosen to mimic each of the four stock price series and the number of times the pattern was found was recorded. The generation of the random series for each of the stocks and the results of the Monte Carlo experiments for each stock are discussed in the following sections.

Table 4.1. Results of the Monte Carlo experiments.

Pattern	Series	# hits actual series	# hits below actual	# hits above actual	5% lower boundary	95% upper boundary	Reject H_0
Head and Shoulders Top	DJIA	40	3643	5336	34 (5.48%)	48 (5.4%)	No
	AA	43	8044	1362	33 (6.59%)	46 (5.29%)	No
	GM	33	1513	7732	30 (6.0%)	42 (7.95%)	No
	PG	32	1226	8118	30 (7.28%)	42 (7.19%)	No
Symmetrical Triangle	DJIA	134	1803	7986	124 (5.08%)	166 (5.65%)	No
	AA	150	9046	834	114 (5.39%)	154 (5.35%)	No
	GM	148	9154	743	112 (5.75%)	151 (5.37%)	No
	PG	161	10000	0	95 (5.8%)	131 (5.62%)	Yes
Rectangle	DJIA	1	7568	613	0 (75.68%)	2 (6.13%)	No
	AA	9	4731	5004	0 (5.05%)	191 (5.04%)	No
	GM	22	2171	7725	8 (5.76%)	428 (5.0%)	No
	PG	15	8943	940	0 (5.65%)	22 (5.24%)	No
Parentheses indicate percentage of series contained within boundary.							

a. Dow Jones Industrial Average

As discussed in the Methods section, the univariate model chosen to estimate the Dow Jones Industrial Average was an ARCH-M:

$$\begin{aligned} \log p_t &= \log p_{t-1} + 0.001251 + 0.15\epsilon_{t-1} - 0.109\sqrt{h_t} + \epsilon_t \\ h_t &= 0.00005938 + 0.295\epsilon_{t-1}^2. \end{aligned} \quad (11)$$

In order to generate the random series for Monte Carlo experiments, the fitted residuals, which drive price in the equation above, had to be collected. An initial value of $\epsilon_0 = 0$ was assigned. Using this initial value, the h_t series is determined using the second equation above. Since the p_t series is known, the residuals could then be found using the first equation.

For the Monte Carlo experiments, the idea became to generate a p_t series given the bootstrapped residuals. Each series was generated by using an initial value, p_0 , equal to the actual starting Dow price of 685.47 and bootstrapped error terms, ϵ_t , using the following formula to transform the series to levels:

$$\begin{aligned} p_t &= \exp[\log p_{t-1} + 0.001251 + 0.15\epsilon_{t-1} \\ &\quad - 0.109\sqrt{0.00005938 + 0.295\epsilon_{t-1}^2} + \epsilon_t]. \end{aligned} \quad (12)$$

This p_t series was then smoothed by a 10-day moving average and the number of times the Head and Shoulders Top pattern was

found in the series was recorded. This experiment was repeated ten thousand times.

A distribution for the number of "hits" found in each of these random series is in Figure 4.1. Approximately five percent or 548 series generated 34 or fewer hits and 540 series generated 48 or more hits. Therefore, approximate 5 percent critical values for each of the tails were 34 and 48. Since the Dow Jones Industrial Average recorded 40 Head and Shoulders Tops, the null hypothesis could not be rejected. It could not be concluded that the Head and Shoulders Top occurred more frequently in the Dow Jones Industrial Average than in random series.

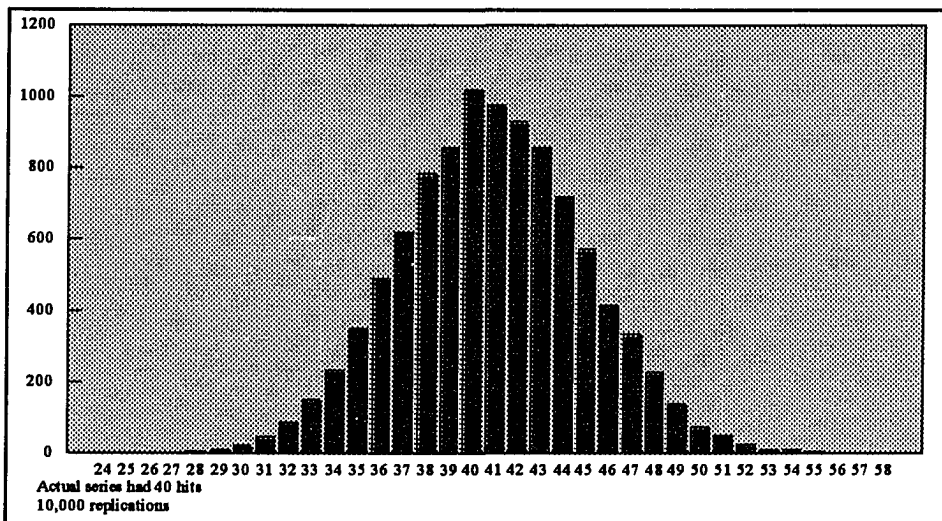


Figure 4.1. Head and Shoulders hits for simulations of the Dow Jones Industrial Average.

b. Aluminum Company of America

For Aluminum Company of America, the univariate model chosen to estimate the series was an ARCH, as discussed in the Methods section:

$$\begin{aligned} \log p_t &= \log p_{t-1} + 0.1276615841\epsilon_{t-1} + \epsilon_t \\ \epsilon_t &= v_t \sqrt{0.002630749 + 0.174290871\epsilon_{t-1}^2}. \end{aligned} \quad (13)$$

In this case, the v_t sequence is driving the price sequence. To determine the actual v_t series, an initial value for $\epsilon_0 = 0$ was assigned. Given this value and the price sequence, the first equation above can be used to determine the errors and then the second equation is used to determine the v_t sequence:

$$\begin{aligned} \epsilon_t &= \log p_t - \log p_{t-1} - 0.1276615841\epsilon_{t-1} \\ v_{t+1} &= \epsilon_{t+1} (0.002630749 + 0.174290871\epsilon_t^2)^{-1/2}. \end{aligned} \quad (14)$$

This v_t sequence was stored for bootstrapping in the Monte Carlo experiments.

In the Monte Carlo experiments, each series was generated by using an initial value, p_0 , equal to the actual Alcoa starting price of 64, an initial value of ϵ_0 equal to zero, and using the bootstrapped variance series, v_t . The following formulas were used to generate the error series, ϵ_t , and to generate the price series, transformed to levels:

$$\begin{aligned} \epsilon_t &= v_t \sqrt{0.0002630749 + 0.174290871 \epsilon_{t-1}^2} \\ p_t &= \exp[\log p_{t-1} + 0.1276615841 \epsilon_{t-1} + \epsilon_t]. \end{aligned} \quad (15)$$

This p_t series was then smoothed using a 10-day moving average. The number of times the Head and Shoulders Top formation was found in this series was recorded. This process continued for the ten thousand replications. A distribution for the number of "hits" found in each of these random series is in Figure 4.2. Approximately 5 percent of the 10,000 series (659) generated 33 or fewer hits and 529 series generated 46 or more hits. Since the actual Alcoa series exhibited 43 hits, this value fell within the critical values of 33 and 46 so the null hypothesis could not be rejected.

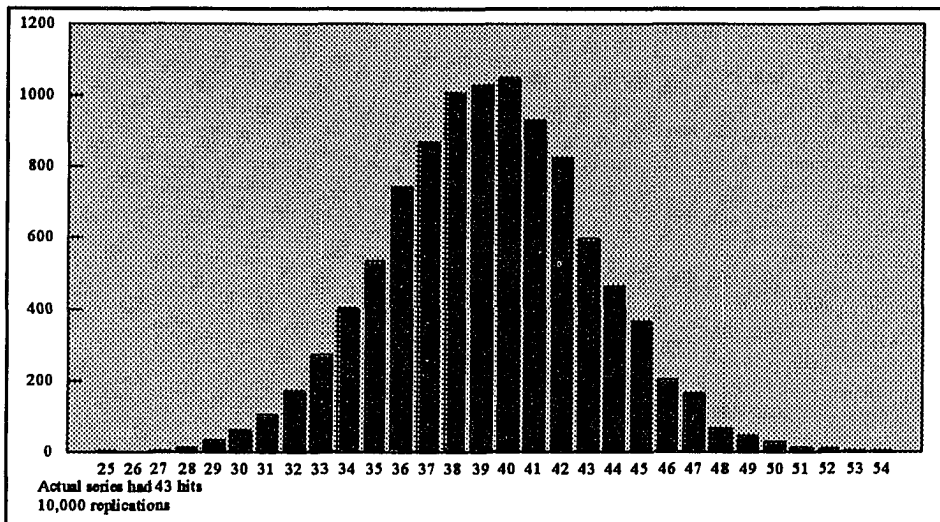


Figure 4.2. Head and Shoulders Top hits for simulated Alcoa price series.

c. General Motors

For General Motors, the univariate model chosen to estimate this series in the Methods section was an ARCH:

$$\begin{aligned} \log p_t &= \log p_{t-1} - 0.03659\epsilon_{t-2} + \epsilon_t \\ \epsilon_t &= v_t [0.000122 + 0.156\epsilon_{t-1}^2 + 0.126\epsilon_{t-2}^2 \\ &+ 0.08352\epsilon_{t-3}^2 + 0.0851\epsilon_{t-4}^2 + 0.06052\epsilon_{t-5}^2]^{1/2} \end{aligned} \quad (16)$$

As with the Alcoa series, the actual variance series, v_t , had to be determined for bootstrapping in the Monte Carlo experiments. From the first equation above, the residuals can be determined by assigning five initial errors as zero and using the known price sequence. The variance sequence could then be determined using the second equation.

In the Monte Carlo experiments, each random series was generated using an initial value, p_0 , equal to the actual General Motors starting price of 55.25, and initial five errors, ϵ_t , equal to zero, and using the bootstrapped variance series, v_t . The following formulas were therefore used to generate the error series, ϵ_t , and the price series transformed to levels:

$$\begin{aligned} \epsilon_t &= v_t [0.000122 + 0.156\epsilon_{t-1}^2 + 0.126\epsilon_{t-2}^2 \\ &+ 0.08352\epsilon_{t-3}^2 + 0.0851\epsilon_{t-4}^2 + 0.06052\epsilon_{t-5}^2]^{1/2} \\ p_t &= \exp[\log p_{t-1} - 0.03659\epsilon_{t-2} + \epsilon_t] \end{aligned} \quad (17)$$

This p_t series was smoothed and the number of "hits" was recorded for each of the ten thousand replications. A

distribution for the number of hits found in these random series is in Figure 4.3. Approximately 5 percent of the 10,000 series (600) generated 30 or fewer hits and 795 series generated 42 or more hits. Since the actual General Motors series generated 33 hits, this value fell between the critical values so the null hypothesis that the Head and Shoulders Top occurs just as frequently in the actual price series as it does in random series could not be rejected.

d. Procter and Gamble

For Procter and Gamble, the estimated model was an ARCH-M:

$$\begin{aligned} \log p_t &= \log p_{t-1} + 2.5272014019h_t + \epsilon_t \\ h_t &= 0.0001245635 + 0.2407205633\epsilon_{t-1}^2 \end{aligned} \quad (18)$$

Since the residual series is driving prices here, the ϵ_t series was determined for bootstrapping purposes in Monte Carlo experiments. Just as with the Dow Jones Industrial Average series, given the initial value, $\epsilon_0 = 0$, the h_t series is determined from the second equation and given prices, the residual series is determined from the first equation above.

In the Monte Carlo experiments, each series was generated using the actual starting value of the Procter and Gamble series, $p_0 = 88.375$, and bootstrapping the error terms found above, ϵ_t , using the following formula which transforms the

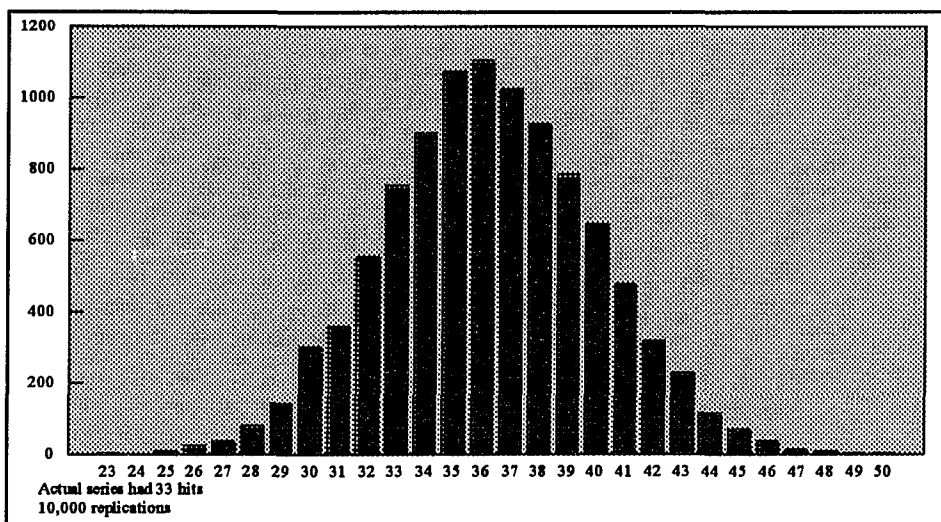


Figure 4.3. Head and Shoulders Top hits for simulations of General Motors.

series to levels:

$$\begin{aligned}
 p_t &= \exp[\log p_{t-1} + 2.57272014019h_t + \epsilon_t] \\
 h_t &= 0.0001245635 + 0.2407205633\epsilon_{t-1}^2.
 \end{aligned}
 \tag{19}$$

The p_t series was smoothed and the Head and Shoulders Top detection program run through it to determine the number of "hits".

Ten thousand replications of this process produced the distribution of hits in Figure 4.4. Approximately 5 percent of the 10,000 random series (728) had 30 or fewer hits and 719 series had 42 or more hits. Since the actual Procter and Gamble series produced 32 hits, the null hypothesis could not be rejected.

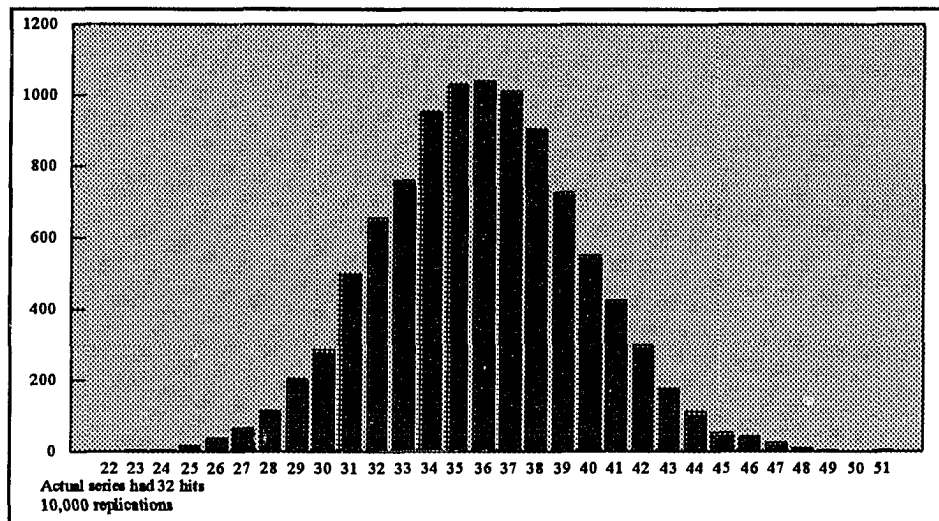


Figure 4.4. Head and Shoulders Top for simulations of Procter and Gamble.

e. General conclusions about the Head and Shoulders Top

A Monte Carlo study has revealed that, for the four stock price series used, it is not possible to reject the null hypothesis that this pattern occurs more frequently in the actual stock price series than in random series which mimic stock price movements. This piece of evidence contradicts technical traders' claims that this pattern is not the result of random movements in stock prices.

Although it may be argued that it is these estimated models which allow the generated series to behave much like stock price series and that the generated series would therefore reflect these patterns, the errors which generate the series are randomly chosen from the true distribution.

Therefore, any "trends" or "reversal movements" which occur in the generated series are completely random. These findings indicate that the Head and Shoulders Top pattern is just as consistent with a random model as a "mass psychology" model.

2. Symmetrical Triangle

Construction of the Symmetrical Triangle filter was discussed in the Methods section. The Symmetrical Triangle is a pattern which looks like a triangle on its side, with the apex on the right. The following sections describe the results of the Monte Carlo experiments which detect how many times the Symmetrical Triangle is found in each of the ten thousand generated series across each stock price series.

a. Dow Jones Industrial Average

For the Dow Jones Industrial Average, the generation of random series for Monte Carlo experiments occurred in the same manner for the Symmetrical Triangle as for the Head and Shoulders Top. Although the generated series had been smoothed to detect the Head and Shoulders pattern, no smoothing was used to detect the Symmetrical Triangle formation.

The Symmetrical Triangle detection program was run on

each of the ten thousand random series generated and the number of times the pattern was found in each series was recorded. A distribution for the number of these "hits" found in the random series is reflected in Figure 4.5.

Approximately 5 percent (508) of the 10,000 series generated 124 or fewer hits and 565 series generated 166 or greater hits. Since the Dow Jones Industrial Average exhibited 134 Symmetrical Triangles over the 34-year period, and since the critical values were 124 and 166 hits, we cannot reject the null hypothesis that Symmetrical Triangles occur just as frequently in random series as they do in the Dow Jones Industrial Average.

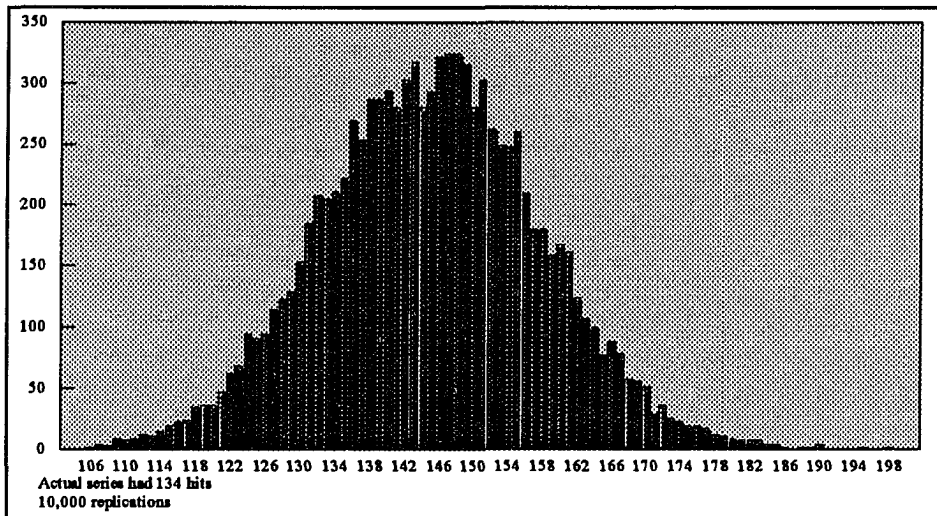


Figure 4.5. Symmetrical Triangle for the simulated Dow Jones Industrial Average.

b. Aluminum Company of America

The generation of random series for Monte Carlo experiments occurred in the same manner for Alcoa when detecting the Symmetrical Triangle as when detecting the Head and Shoulders Top. For ten thousand replications, the number of times the Symmetrical Triangle was found in these random series was computed. The distribution of these "hits" is in Figure 4.6. The approximate 5 percent critical values were 114 and 154 since 539 of 10,000 series had 114 or fewer hits and 535 series had 154 or more hits. The Alcoa series itself exhibited 150 Symmetrical Triangles so the null hypothesis could not be rejected.

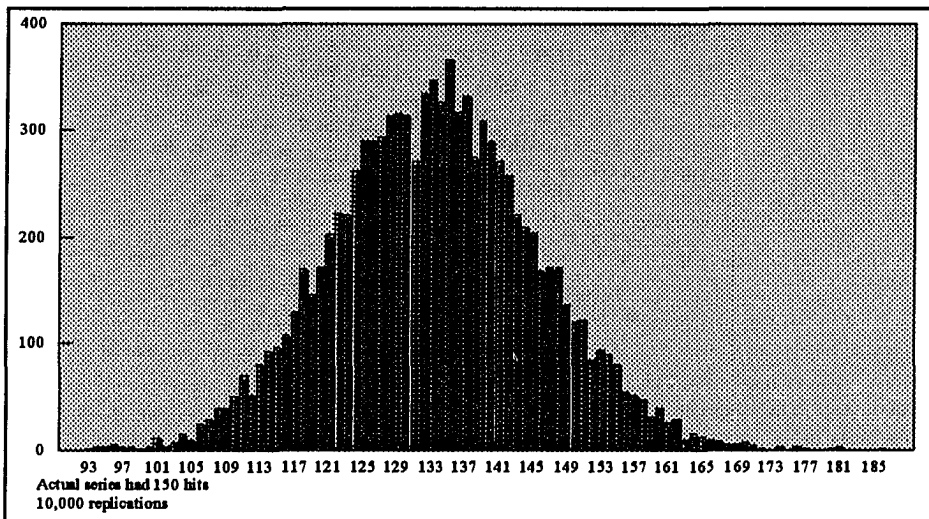


Figure 4.6. Symmetrical Triangle for simulations of Alcoa.

c. General Motors

Random series which mimic the General Motors stock price series were generated for the Monte Carlo experiment as described in the Head and Shoulders Top section. The number of Symmetrical Triangles that was found in each of the ten thousand replications is shown in Figure 4.7. One hundred twelve or fewer hits occurred in 575 of these 10,000 series (about 5 percent) while 151 or more hits occurred in 537 series. One hundred forty-eight Symmetrical Triangles were found in the General Motors series over the same time period so the null hypothesis could not be rejected.

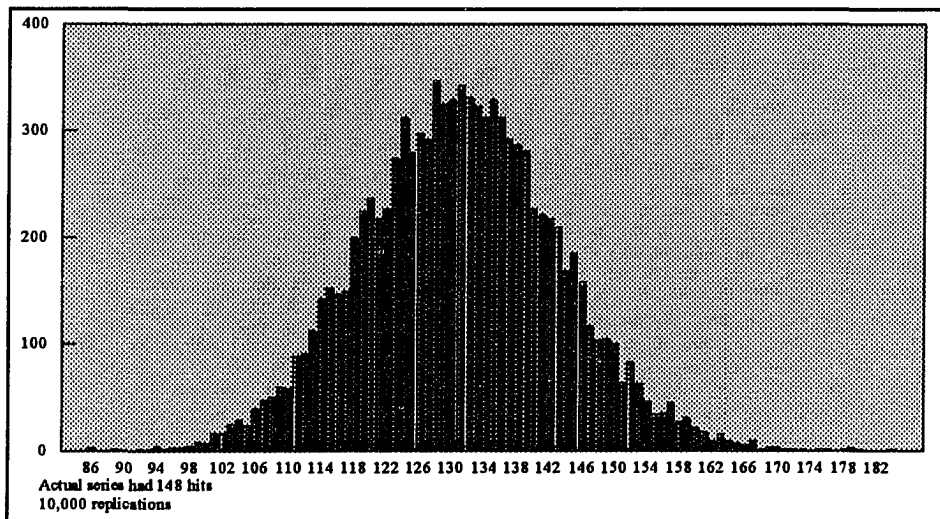


Figure 4.7. Symmetrical Triangle for simulations of General Motors.

d. Procter and Gamble

Ten thousand random series were generated in the same manner for the Symmetrical Triangle Monte Carlo experiment as they were for the Head and Shoulders Top formation. A distribution of the number of Symmetrical Triangles found in each series is in Figure 4.8. The approximate 5 percent critical values were 95 and 131 hits but the Procter and Gamble series exhibited 161 hits. In fact, none of the simulated series had more than 158 hits. Therefore, unlike all the other cases in this study, the null hypothesis that this pattern occurs just as frequently in randomly generated series as it does in the actual stock price series can be rejected at even the one percent critical level.

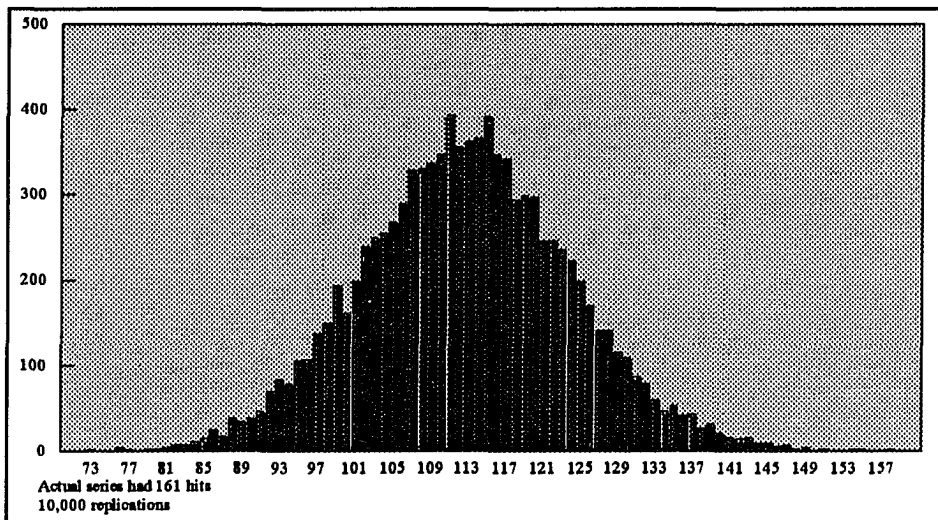


Figure 4.8. Symmetrical Triangle for simulations of Procter and Gamble.

Perhaps more importantly, technical traders may argue that the Symmetrical Triangle formation which occurred more frequently in this series could have been used to generate excess profits. This argument is examined in the second part of this chapter and will be shown to be false. In fact, average returns for this pattern and the Procter and Gamble stock price series are negative across all cases studied. Therefore, even if the frequency with which the Symmetrical Triangle was found in the Procter and Gamble series is important to predict stock price movements, as technical traders believe, the ability of chartists to earn excess profits from finding this pattern is called into question.

3. Rectangle

The construction of the Rectangle filter was discussed in the Methods section. This pattern is composed of four alternating extrema where the two maxima are approximately of the same height and two minima which are also of approximately the same height. It should be noted that in the Monte Carlo experiments, the distributions which occur from the ten thousand replications across each price series appear dramatically different from the previous studies. Specifically, these distributions are skewed to the right. The reason for this anomaly lies in the construction of the

Rectangle filter and will be discussed more below.

a. Dow Jones Industrial Average

The simulation of ten thousand series for the Monte Carlo experiments occurred for the Dow Jones Industrial Average just as in the two previous experiments. The Rectangle detection program was run on each of these generated series after smoothing by a five-day moving average. The distribution for the number of hits found in each series is in Figure 4.9.

This distribution is skewed to the right. The reason for this lies in the construction of the Rectangle filter program. Few Rectangles were found because of the stringent condition that its boundary lines be nearly horizontal to ensure that it could not be mistaken for a Triangle. Even so, 7568 of the 10,000 series recorded less than one hit, the number found for the Dow Jones Industrial Average, and 613 series exhibited more than one hit. Therefore, the null hypothesis that the Rectangle pattern occurs just as frequently in random series could not be rejected.

b. Aluminum Company of America

The Rectangle detection program was run on 10,000 simulations of the Aluminum Company of America stock price

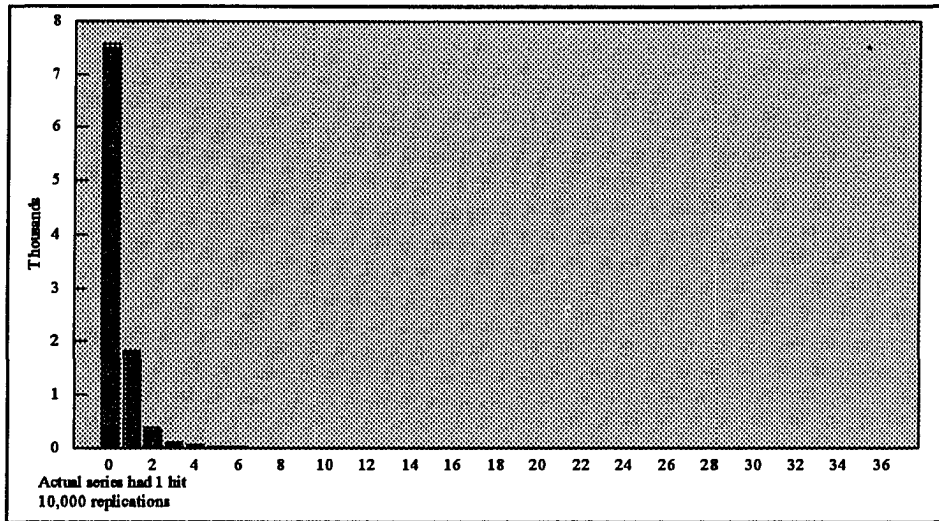


Figure 4.9. Rectangle for simulations of the Dow Jones Industrial Average.

series as described before. The resulting distribution is in Figure 4.10. This distribution is a bit different than the one for the Dow Jones Industrial Average even though it is also skewed to the right. While there were many series where very few hits were detected because of the stringent conditions for detecting a Rectangle, there were also series where hundreds of Rectangles were found. In this case, the problem may also lie in the construction of the Rectangle detection program. While technical traders have noted that prices may theoretically bounce up and down between two boundary prices for an extended time period, this behavior was not detected in actual price series. Therefore, in constructing the detection program, the updating procedure

used to go from one detected Rectangle to another may be faulty. This program could be counting a single Rectangle formation several times since it only seeks four consecutive extrema. If a fifth extrema were to occur within the same boundaries, a second Rectangle would be recorded.

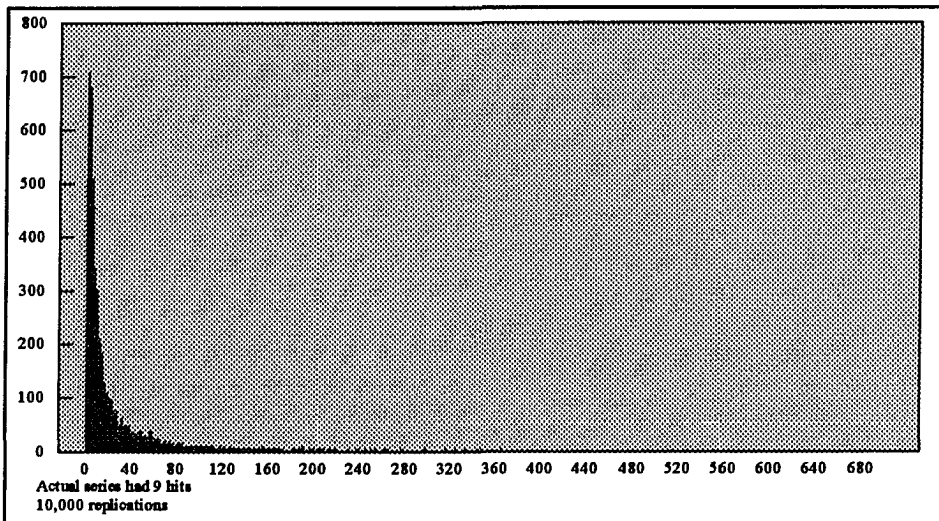


Figure 4.10. Rectangle for simulations of Alcoa.

In any case, the Alcoa series recorded 9 Rectangles. The Monte Carlo experiment recorded 4731 series of 10,000 which had fewer than nine hits and 5004 series had more. Approximate five percent critical values were 0 and 191. Therefore, the null hypothesis could not be rejected.

c. General Motors

The Rectangle detection program was run on ten thousand simulations of the General Motors stock price series as described before. Figure 4.11 depicts the resulting distribution of Rectangles found. This distribution exhibits the same skewness as the previous two and results from the limitations of the Rectangle detection program. Approximate 5 percent critical values in this distribution are 8 and 428 since 576 of 10,000 series recorded 8 or fewer hits and 500 series recorded 428 or more hits. The General Motors series exhibited 22 hits so the null hypothesis could not be rejected.

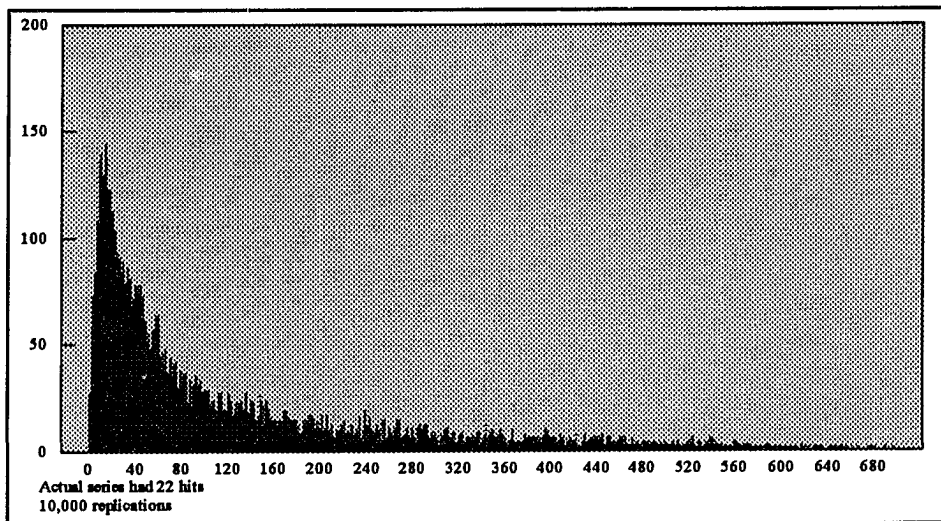


Figure 4.11. Rectangle for simulations of General Motors.

d. Procter and Gamble

For ten thousand simulations of the Procter and Gamble series, the Rectangle detection program generated the distribution of hits found in Figure 4.12. Five hundred sixty-five of the 10,000 series generated zero hits; 524 series generated 22 or more hits. With the Procter and Gamble series recording 15 hits, and critical values of zero and 22, the null hypothesis could not be rejected.

e. General conclusions about the Rectangle formation

As with the Head and Shoulder Top formation, there was no indication that the Rectangle formation could be detected in actual stock price series more frequently than in random series generated to mimic stock price movements.

It should be noted that the distribution of hits looked much different for this formation than the previous two. In many cases, there were zero to very few hits recorded. In few cases there were very many Rectangles recorded such that the distributions were skewed to the right. One such reason for this oddity resulted from the Rectangle detection program.

While this oddity may not be important for the Alcoa and General Motors series since they each had 5004 and 7725 of 10,000 series recording greater hits, respectively, it could

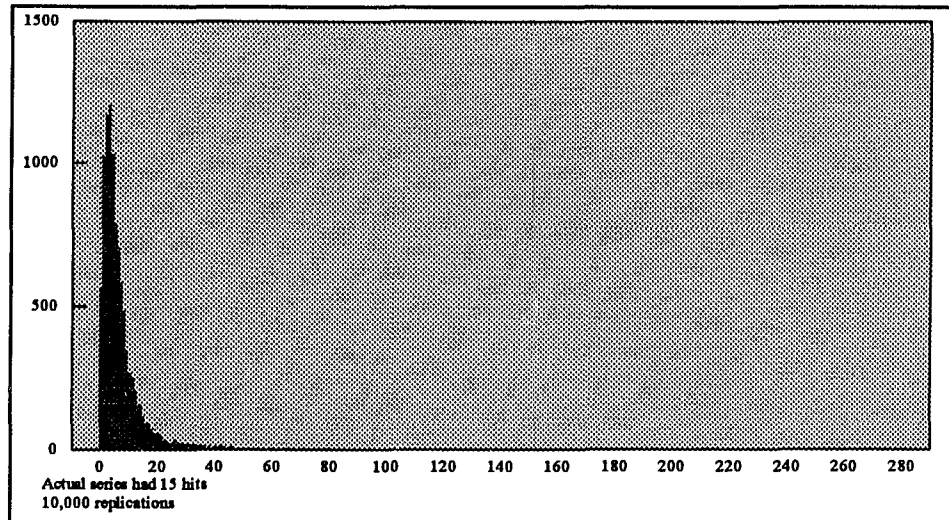


Figure 4.12. Rectangle for simulations of Procter and Gamble.

be more problematic for the other two series. Simulations of the Dow Jones Industrial Average resulted in 613 of 10,000 series which recorded greater hits and Procter and Gamble recorded 940 of 10,000. If this program were altered to make sure that only one Rectangle could be detected over possibly longer time periods, then the numbers of hits found for simulations of the Dow Jones Industrial Average and the Procter and Gamble series that were greater than the number found for the actual stock price series could conceivably be lower and could conceivably result in a rejection of the null hypothesis.

B. Returns from Pattern Signals on Stock Prices

In the last section, results indicated that we cannot conclude in most cases that the technical trading patterns occur more often in stock price series than they do in random series. This result contradicts technical traders' beliefs about the existence of patterns explained by a "mass psychology" of the stock market.

But there remains another related question. According to technical traders, these patterns help investors predict price movements so they can exploit this knowledge for gain. The technical trading signals explored in this study really just exemplify trend chasing. For example, the signal in each case occurs after prices change by 3 percent and the signal generated is that prices are expected to continue in the same direction. Thus, the question is if the signals to buy or sell generated by these patterns are profitable.

It should be noted that by ignoring transaction costs, the technical trading schemes should be favored. These strategies involve several rounds of buying and selling so transaction costs should be higher. Despite this consideration, in all but one of the many cases studied, returns under the technical trading schemes could not generate average returns which were significantly different from zero.

1. Calculating average returns

In order to compare average returns generated by the three trading patterns, it was assumed that an investor traded \$1 million upon each signal to buy or sell. Computation of this average return across trading signals is explained below. Since there were no guidelines for any of the patterns about how long an investor should wait to complete the trade, three different holding periods were considered: a short-term (2-day) period, a medium-term (5-day) period, and a longer-term (10-day) period. If no signal occurred, no action was taken.

For a buy signal generated from the Symmetrical Triangle or Rectangle patterns, the profit from each trade was computed as

$$\$1,000,000 \left\{ \frac{P_{t+i} - P_t}{P_t} \right\}, \quad (20)$$

where i is the holding period. For a sell signal generated from any of the patterns, the profit from each trade was computed as

$$\$1,000,000 \left\{ \frac{P_t - P_{t+i}}{P_t} \right\}. \quad (21)$$

For each of these patterns, stock series, and holding or short-sell periods, the average return and t-values were calculated. The average return was calculated as a simple

average of the profits for each stock series, each pattern and each holding period. T-values were calculated under the null hypothesis of zero returns so a two-tailed test is appropriate. The results are presented in Table 4.2.

2. Average returns from the Head and Shoulders Top

Detection of the Head and Shoulders Top may, under certain conditions, produce a signal to sell. As was mentioned in the Methods chapter, this signal comes when prices fall by 3 percent below the "neckline" after the right shoulder has been established. Since there were no guidelines for how long a period the short sell should last, three different short-sell periods were examined.

As Table 4.2 indicates, average returns generated from the Head and Shoulders Top pattern could be positive or negative, depending on the short-sell period and the stock series examined. For the Dow Jones Industrial Average and Alcoa, the results were mixed since both positive average returns and negative average returns were generated depending on the short-sell period. However, for the Dow Jones Industrial Average and 5- or 10-day holding periods, the Head and Shoulders Top provided the highest average returns across all trading strategies. For General Motors, the returns were consistently positive and higher than for all other patterns

Table 4.2. Average returns from each trading strategy across holding or short-sell periods.

Pattern	Stock series	Holding or short-sell period		
		2-day	5-day	10-day
Head and Shoulders Top	DJIA	-2410.24 (-0.75)	15634.18 (0.71)	14316.91 (0.70)
	AA	4405.86 (0.71)	2109.10 (0.22)	-154.04 (-0.01)
	GM	3837.35 (0.53)	9587.07 (1.00)	16428.83 (1.52)
	PG	-1923.86 (-0.27)	-5958.30 (-0.51)	-10839.87 (-0.84)
Symmetrical Triangle	DJIA	-828.62 (-0.21)	1246.64 (0.21)	3992.87 (0.63)
	AA	7588.00** (2.31)	5533.67 (1.00)	8560.05 (1.38)
	GM	-472.20 (-0.11)	-4795.10 (-0.60)	-2667.65 (-0.25)
	PG	-1309.60 (-0.36)	-3340.42 (-0.76)	-8643.60 (-1.47)
Rectangle	DJIA	-4443.48	-14489.60	-28802.11
	AA	-2308.88 (-0.29)	700.31 (0.07)	-26144.02 (-0.94)
	GM	-7776.59 (-1.47)	-9672.96 (-1.49)	-3661.10 (-0.32)
	PG	-2592.36 (-0.75)	-6783.03 (-1.55)	6947.73 (1.05)

DJIA is the Dow Jones Industrial Average

AA is Aluminum Company of America

GM is General Motors

PG is Procter and Gamble

() indicates t-value

* indicates significant at the 10% level

** indicates significant at the 5% level

*** indicates significant at the 1% level

examined. But for Procter and Gamble, they were consistently negative. The result for Procter and Gamble may have occurred since the stock price series has a very strong positive trend but the Head and Shoulders Top signal calls for a short-sell.

There were also no consistently positive average returns across a single short-sell period. Both positive and negative average returns were recorded for a given holding period across all four stock series, however, three of four stock series had positive average returns for the five-day short-sell period.

In any case, results are mixed. The only conclusion from this pattern is that it cannot generate average returns which are significantly different from zero. This finding refutes technical traders' beliefs that the Head and Shoulders Top can not only be used to generate excess returns, but also that it is one of the more "reliable" patterns to use.

3. Average returns from the Symmetrical Triangle pattern

The Symmetrical Triangle formation can produce a signal to buy if prices exceed the upper boundary by 3 percent or a signal to sell if prices fall below the lower boundary by 3 percent. As with the Head and Shoulders Top formation, this study assumed that \$1 million would be used to purchase or short-sell upon every signal generated by this pattern. In

addition, the holding or short-sell period was again varied since there were no guidelines for the appropriate period to use.

As Table 4.2 indicates, in only one of the twelve cases studied were returns significantly different from zero. For the Alcoa series, the Symmetrical Triangle formation signal provided the highest average returns of all patterns studied and across all stock price series. Indeed, average returns were all positive for the Alcoa series but this was the only stock series for which this conclusion was true. For the Dow Jones Industrial Average, average returns were both positive and negative depending on the holding period and for the other two series, they were negative across all holding periods.

As with the Head and Shoulders Top formation, there was no single holding period for which average returns were positive across all stock price series. While the two-day holding period generated average returns which were significantly different from zero for the Alcoa series, the other three series recorded negative average returns for this holding period.

4. Average returns for the Rectangle formation

As with the Symmetrical Triangle, the Rectangle formation can produce a signal to buy or to sell when stock prices fall

outside the boundary lines by 3 percent. The program used to detect buy or sell signals computed the return to \$1 million for each signal produced under various holding or short-sell periods.

In Table 4.2, there are no t-values reported for the Dow Jones Industrial Average under the Rectangle pattern. The reason for this is that there was only one signal generated by the formation so no distribution of average returns could be derived.

As Table 4.2 indicates, there was no case where average returns were significantly different from zero. In fact, in only two of the twelve cases were average returns positive, excluding transaction costs. Therefore, like the previous two patterns, there is no indication for these stock series that the Rectangle can generate excess returns.

As with the other two patterns, there was no single holding period which generated superior average returns across the stock series.

Higher returns were found for only the Procter and Gamble series under the 10-day holding period for the Rectangle formation. For all other stock price series and holding periods, the other two formations generated higher average returns than the Rectangle. Part of the reason for this result may again come from the stringent restriction placed upon the detection of Rectangles since in most series, very

few Rectangles were found.

5. General conclusions about average returns

In response to the question if technical traders can earn consistent returns from exploiting signals generated by the three patterns studied here, the answer here is strongly negative. Even though the Head and Shoulders pattern is considered to be the most "reliable" by technicians in terms of predicting price movements and even though transaction costs are excluded, the Head and Shoulders Top as well as other patterns did not generate average returns which were consistently different from zero. In fact, for only one stock series and one holding period were returns significantly different from zero. Technical traders claim that they do earn consistent positive returns but all evidence here contradicts their claim.

Chartists may argue that it is the detection of several different patterns within a single series which generates the excess returns. This argument was not specifically examined in this study, but it may be argued that it would take at least one pattern generating significantly positive returns for an investor to generate consistent excess returns. None of the patterns produced significantly positive returns across all holding periods in the long-run.

Chartists could also argue that they would not always use a specific holding period, but that the decision to change position is subjective. However, from the beginning, this study has attempted to take this subjective analysis and make it more objective. No guidelines for an appropriate holding period were proposed by chartists. Therefore, this study is attempting to be consistent by using a single holding period across each signal examined but looking at different possible holding periods.

Another possible critique by chartists could be that actual decisions to buy or sell must be confirmed not only by the signals used in this study, but also by the simultaneous detection of similar patterns in other stock price series. While this study does not examine the simultaneity of signal detection, an extension of this work could focus on that question.

6. Results on present value of returns

The results for average returns calculated above do not take into account the timing of returns. In order to examine that question, another series of tests were conducted to calculate the present value of returns generated by the signals across patterns and short-sell or holding periods.

For each signal, the present value of the returns was

calculated by "discounting" the value of each profit or loss forward. The daily interest rate used in this calculation for each stock price series was determined as the intercept term of a regression on the first log difference of each price series. Results of this test are presented in Table 4.3.

Although the numbers are generally larger in magnitude than those for average profit returns, the conclusions remain the same. With the exception of General Motors, the Head and Shoulders Top does not generate consistent positive returns across short-sell periods. With the exception of Alcoa, the Symmetrical Triangle signal does not generate consistent positive returns across holding and short-sell periods. And for the Rectangle formation, in only one of the twelve cases studied is the present value of returns positive.

Table 4.3. Present value of profit returns from each trading strategy across holding periods.

Strategy	Stock series	Holding or short-sell period		
		2-day	5-day	10-day
Head and Shoulders Top	DJIA	-77604.89	272859.47	248776.79
	AA	146276.25	-49979.39	-322812.44
	GM	77572.25	176684.86	297737.02
	PG	-34338.59	-64403.23	-228565.91
Symmetrical Triangle	DJIA	-35246.07	14222.43	55112.99
	AA	499380.30	382275.67	697373.71
	GM	-32625.42	-123389.66	-89063.71
	PG	2661.80	-42195.50	-408704.41
Rectangle	DJIA	-6539.70	-21316.47	-42343.84
	AA	-16045.97	-4496.45	-342903.38
	GM	-163864.42	-218294.30	-83789.40
	PG	-74028.56	-205412.56	249514.17

DJIA is the Dow Jones Industrial Average
AA is Aluminum Company of America
GM is General Motors
PG is Procter and Gamble

V. CONCLUSIONS

A. Results of the Monte Carlo Analysis

In eleven of the twelve cases studied, the Monte Carlo experiments showed that the null hypothesis that patterns occur just as frequently in series generated to mimic stock price movements as they do in actual stock price series could not be rejected. These results refute technical traders' beliefs that stock price trends are perpetuated by a "mass psychology" of investors and that these trends exhibit predictable patterns. The results also constitute another piece of evidence in support of efficient markets since these stock price movements may indeed be random.

There are limitations, however, to this part of the study. First, this study only examined three technical trading patterns and four stock price series. Since these patterns and series only constitute a sample, it is possible that the results could differ for other patterns or other stock price series. Second, pattern detection occurred using objective criteria, not subjective criteria as technical analysts use. One idea behind this study was to quantify pattern detection by writing computer programs which detect the three patterns. Some Wall Street firms have done the same. However, it is possible that some of the patterns detected by the program would be glossed over by chartists

while chartists may have found additional patterns that were not detected by the program. Even so, in constructing the detection program, graphical checks were made on the actual stock price series to make sure that patterns were found as accurately as possible and smoothing techniques were used on two patterns to simulate what the "eyeball" may see in price series. Third, the univariate models chosen to generate the realizations of random price series may not be the true models of each stock price series. However, the purpose of this study was to generate realizations which mimic stock price movements. By using these models and bootstrapping techniques, the realizations did exhibit comparable movements in prices.

B. Returns from Technical Trading Signals

A finding which is perhaps more important than the Monte Carlo analysis for technical traders is that average returns from their strategies were not consistently and significantly different from zero. In only one case of the thirty-six studied were average returns significantly different from zero. Even in that case, the results were not consistent across short-sell or holding periods. Technical traders believe that detection of the patterns studied will help them to predict future price movements and to earn excess profits

from these predictions. However, this study refutes their claim. These findings support the implication of the efficient markets hypothesis that it is impossible to earn consistent excess returns from technical trading schemes.

There are limitations to this part of the study as well. First, as was mentioned before, only a sample of stock prices and patterns was used. Conclusions are therefore drawn only about these stock prices and patterns. Second, returns for the technical trading patterns were calculated for one of several possible holding periods. There were no technical trading guidelines about how long an investor should take a position for any of the patterns examined. Technical traders could disagree with applying a single holding period to calculate returns, but the idea of the study was to apply an objective measure to calculate returns. Third, a critique to which technical traders acknowledge their analysis is subject, "trends" are often exploited only after most profit can be earned. In this case, a signal to buy or sell occurred only after prices had changed by 3 percent. But these were the guidelines to which chartists adhere.

C. Possible Extensions

There are many directions in which this work can be extended. First, other stock price series can be used. It

may be interesting to extend the Monte Carlo experiments across international stock price indices. While this and other studies have found evidence in support of efficient U.S. markets, there have been fewer studies conducted on the efficiency of foreign stock markets.

Second, other technical trading patterns can be used. There are numerous technical trading rules. While this study has focused on the more popular patterns in stock prices, others such as Brock et al. (1992) have concentrated on different technical trading rules. Their study examined the returns from such rules as the moving-average. These rules could be applied to the stock price series used here and more results presented.

Third, while the stock market was the focus of this study, technical traders have different rules across other markets like currency and other futures markets. While the patterns examined here pertain to the stock market, different trading rules can be examined in other markets to determine if excess returns exist there.

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APPENDIX A. MODEL ESTIMATION FOR THE STOCK PRICE SERIES

Model estimation for the Dow Jones Industrial Average.

Model	Coefficients	Function Value	Conclusion
$\Delta y_t = b_0 + b_1 \epsilon_{t-1} + \epsilon_t$ $\epsilon_t = v_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2}$	$b_0 = .00034 (3.8)$ $b_1 = .151 (26.8)$ $\alpha_0 = .00006 (100.6)$ $\alpha_1 = .2947 (51.1)$	37096	Try ARCH-M
$\Delta y_t = b_0 + b_1 \epsilon_{t-1} + b_2 \sqrt{h_t} + \epsilon$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = .0013 (3.7)$ $b_1 = .15 (20.7)$ $b_2 = -.109 (- 3.0)$ $\alpha_0 = .00006 (99.8)$ $\alpha_1 = .295 (49.9)$	37120	Try alternate ARCH-M. This is the best model.
$\Delta y_t = b_0 + b_1 \epsilon_{t-1} + b_2 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = .00049 (3.4)$ $b_1 = .14867 (23.2)$ $b_2 = -2.05 (- 1.6)$ $\alpha_0 = .00006 (99.8)$ $\alpha_1 = .29392 (48.9)$	37099	Try without MA process.
$\Delta y_t = b_0 + b_1 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = .00037 (4.2)$ $b_1 = -.206 (- 0.5)$ $\alpha_0 = .00006 (111.5)$ $\alpha_1 = .279 (52.0)$	37054	MA term should be included.

Δy_t is the first difference of the log of stock price at time t.

ϵ_t is the residual at time t.

v_t is a white noise process.

h_t is the variance of residuals at time t.

(.) indicates t-value.

Model estimation for Aluminum Company of America.

Model	Coefficients	Function Value	Conclusion
$\Delta y_t = b_1 \epsilon_{t-1} + \epsilon_t$ $\epsilon_t = v_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2}$	$b_1 = .1277 (12.6)$ $\alpha_0 = .00026 (171.1)$ $\alpha_1 = .17429 (22.7)$	29235	Try an ARCH-M model. This is the best model.
$\Delta y_t = b_1 \epsilon_{t-1} + b_2 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_1 = .1276 (12.6)$ $b_2 = .0067 (0.6)$ $\alpha_0 = .00026 (165.4)$ $\alpha_1 = .1739 (22.3)$	29235	ARCH may be better model. Check other ARCH-M to verify.
$\Delta y_t = b_0 + b_1 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = .00089 (1.8)$ $b_1 = -2.48 (-1.8)$ $\alpha_0 = .00026 (151.9)$ $\alpha_1 = .190 (24.1)$	29175	ARCH is better.

Δy_t is the first difference of the log of stock price at time t.
 ϵ_t is the residual at time t.
 v_t is a white noise process.
 h_t is the variance of residuals at time t.
 (.) indicates t-value.

Model estimation for General Motors.

Model	Coefficients	Function Value	Conclusion
$\Delta y_t = b_1 \epsilon_{t-2} + \epsilon_t$ $\epsilon_t = v_t \sqrt{\text{ARCH}(5) \text{ PROCESS}}$	$b_1 = -.037 \quad (-3.28)$ $\alpha_0 = .00012 \quad (56.4)$ $\alpha_1 = .156 \quad (22.7)$ $\alpha_2 = .126 \quad (13.5)$ $\alpha_3 = .0835 \quad (9.27)$ $\alpha_4 = .0851 \quad (7.66)$ $\alpha_5 = .0605 \quad (7.43)$	30635	Try alternate ARCH model. This is the best model.
$\Delta y_t = b_1 \epsilon_{t-2} + b_2 \epsilon_{t-3} + b_3 \epsilon_{t-4} + \epsilon_t$ $\epsilon_t = v_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2}$	$b_1 = -.042 \quad (-4.87)$ $b_2 = -.019 \quad (-2.39)$ $b_3 = -.029 \quad (-3.40)$ $\alpha_0 = .0002 \quad (90.4)$ $\alpha_1 = .207 \quad (25.9)$	30474	Model with more ARCH lags would not converge. Try ARCH-M.
$\Delta y_t = b_1 \epsilon_{t-2} + b_2 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \alpha_3 \epsilon_{t-3}^2 + \alpha_4 \epsilon_{t-4}^2 + \alpha_5 \epsilon_{t-5}^2$	$b_1 = -.011 \quad (-0.31)$ $b_2 = .0511 \quad (1.64)$ $\alpha_0 = .00007 \quad (13.3)$ $\alpha_1 = .178 \quad (6.19)$ $\alpha_2 = .0928 \quad (2.99)$ $\alpha_3 = .0503 \quad (1.71)$ $\alpha_4 = .0516 \quad (2.10)$ $\alpha_5 = .0421 \quad (1.77)$	4432	Try without MA(2) term.
$\Delta y_t = b_1 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \alpha_3 \epsilon_{t-3}^2 + \alpha_4 \epsilon_{t-4}^2 + \alpha_5 \epsilon_{t-5}^2$	$b_1 = .0002 \quad (0.02)$ $\alpha_0 = .0001 \quad (57.1)$ $\alpha_1 = .1551 \quad (22.3)$ $\alpha_2 = .1279 \quad (13.4)$ $\alpha_3 = .0843 \quad (9.35)$ $\alpha_4 = .0854 \quad (7.66)$ $\alpha_5 = .0594 \quad (7.38)$	30631	Try fewer lags for residual variance.
$\Delta y_t = b_1 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_1 = -.006 \quad (-0.6)$ $\alpha_0 = .0002 \quad (90.6)$ $\alpha_1 = .207 \quad (26.1)$	30445	Try alternate ARCH-M model.

Model estimation for General Motors (cont.)

Model	Coefficients	Function Value	Conclusion
$\Delta y_t = b_1 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \alpha_3 \epsilon_{t-3}^2 + \alpha_4 \epsilon_{t-4}^2 + \alpha_5 \epsilon_{t-5}^2$	$b_1 = .4085 \quad (0.65)$ $\alpha_0 = .0001 \quad (57.1)$ $\alpha_1 = .1547 \quad (22.4)$ $\alpha_2 = .1278 \quad (13.4)$ $\alpha_3 = .0848 \quad (9.40)$ $\alpha_4 = .0857 \quad (7.69)$ $\alpha_5 = .0594 \quad (7.41)$	30631	ARCH-M coeff. is still insignif. Try ARCH.
$\Delta y_t = b_0 + \epsilon_t$ $\epsilon_t = v_t \sqrt{\text{ARCH}(5) \text{ PROCESS}}$	$b_0 = -.000 \quad (-0.23)$ $\alpha_0 = .0001 \quad (56.9)$ $\alpha_1 = .156 \quad (22.5)$ $\alpha_2 = .128 \quad (13.5)$ $\alpha_3 = .0843 \quad (9.36)$ $\alpha_4 = .0851 \quad (7.65)$ $\alpha_5 = .0593 \quad (7.36)$	30631	First model is best.

Δy_t is the first difference of the log of stock price at time t.

ϵ_t is the residual at time t.

v_t is a white noise process.

h_t is the variance of residuals at time t.

(.) indicates t-value.

Model estimation for Procter and Gamble.

Model	Coefficients	Function Value	Conclusion
$\Delta y_t = b_0 + \epsilon_t$ $\epsilon_t = v_t \sqrt{\alpha_0 + \alpha_1 \epsilon_{t-1}^2}$	$b_0 = .0004 \quad (2.65)$ $\alpha_0 = .0001 \quad (80.7)$ $\alpha_1 = .2404 \quad (44.1)$	32045	This was simplest model which converged.
$\Delta y_t = b_0 + b_1 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = -.001 \quad (-1.57)$ $b_1 = .138 \quad (2.01)$ $\alpha_0 = .0001 \quad (80.1)$ $\alpha_1 = .240 \quad (39.0)$	32047	Get rid of constant.
$\Delta y_t = b_1 \sqrt{h_t} + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_1 = .0308 \quad (2.83)$ $\alpha_0 = .0001 \quad (80.9)$ $\alpha_1 = .2406 \quad (43.6)$	32046	Try alternate ARCH-M.
$\Delta y_t = b_0 + b_1 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_0 = -.000 \quad (-0.46)$ $b_1 = 3.315 \quad (1.74)$ $\alpha_0 = .0001 \quad (80.4)$ $\alpha_1 = .2401 \quad (41.4)$	32047	Get rid of constant.
$\Delta y_t = b_1 h_t + \epsilon_t$ $h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2$	$b_1 = 2.527 \quad (3.10)$ $\alpha_0 = .0001 \quad (81.2)$ $\alpha_1 = .2407 \quad (43.1)$	32046	Best model

Δy_t is the first difference of the log of stock price at time t.

ϵ_t is the residual at time t.

v_t is a white noise process.

h_t is the variance of residuals at time t.

(.) indicates t-value.

APPENDIX B. HEAD AND SHOULDERS TOP SIGNAL PROGRAM

*This program will detect signal for short sell in head and shoulders top.

```

cal(daily) 60 1 2
all 0 93:7:9
open data c:\martine\dow.prn
data(format=free,org=obs) / dow
set y / = dow
set x = (y(t-4)+y(t-3)+y(t-2)+y(t-1)+y(t)+y(t+1)+y(t+2)+$
        y(t+3)+y(t+4)+y(t+5))/10
do i=1,2
  compute n = 5
  compute hits = nlow = nmed = nhigh = max = 0
  compute intersects = signals = 0
  compute totalpv = 0.0
  branch loop2
:loop1
*   if n == 8237
    if n == 8740
      branch loop5
    if max == 0
      compute n = n + 1
    if max == 0
      branch loop2
    if max == 1
      branch loop3
*
:loop2
  compute max = 0
  if (x(n) >= x(n+1)).and.(x(n) >= x(n-1)).and.$
    (x(n+1) >= x(n+2)).and.(x(n-1) >= x(n-2)).and.$
    (x(n+2) >= x(n+3)).and.(x(n-2) >= x(n-3)).and.$
    (x(n+3) >= x(n+4)).and.(x(n-3) >= x(n-4)).and.$
    (x(n+4) >= x(n+5)).and.(x(n-4) >= x(n-5))
    compute max = 1
  branch loop1
*
:loop3
  compute flag = 0
  if nlow == 0
    compute flag = 1
  if flag == 1
    compute nlow = n
  if flag == 1
    compute n = n + 1
  if flag == 1
    branch loop2
  if nmed == 0
    compute flag = 1
  if flag == 1
    compute nmed = n
  if flag == 1
    compute n = n + 1
  if flag == 1
    branch loop2
  if nhigh == 0
    compute flag = 1

```

```

if flag == 1
  compute nhigh = n
if x(nmed) <= x(nlow) .or. x(nmed) <= x(nhigh)
  compute n = nlow + 1
if x(nmed) > x(nlow) .and. x(nmed) > x(nhigh)
  branch loop4
compute nlow = nmed = nhigh = 0
branch loop2
*
:loop4
compute hits = hits + 1
*
display 'peaks at' nlow nmed nhigh
compute min = flag = s = 0
compute min1 = min2 = 0
compute n = nlow
do n=nlow,nmed
  if x(n-2) >= x(n-1) .and. x(n-1) >= x(n) .and. $
    x(n) <= x(n+1) .and. x(n+1) <= x(n+2)
    compute min = 1
    if (min == 1) .and. (min1 == 0)
      compute min1 = n
    if (min == 1) .and. (min2 == 0)
      compute min2 = n
    if (min1 > 0) .and. (min2 > 0)
      compute flag = 1
    if flag == 1 .and. x(min1) > x(min2)
      compute min1 = min2, min2 = 0
    if (flag == 1) .and. (x(min1) <= x(min2))
      compute min2 = 0
    compute min = flag = 0
end do n
if min1 == 0
do n=nlow,nmed
  if x(n-1) >= x(n) .and. x(n) <= x(n+1)
    compute min = 1
    if (min == 1) .and. (min1 == 0)
      compute min1 = n
    if (min == 1) .and. (min2 == 0)
      compute min2 = n
    if (min1 > 0) .and. (min2 > 0)
      compute flag = 1
    if flag == 1 .and. x(min1) > x(min2)
      compute min1 = min2, min2 = 0
    if (flag == 1) .and. (x(min1) <= x(min2))
      compute min2 = 0
    compute min = flag = 0
end do n
compute min = flag = mina = minb = 0
compute n = nmed
do n=nmed,nhigh
  if x(n-2) >= x(n-1) .and. x(n-1) >= x(n) .and. $
    x(n) <= x(n+1) .and. x(n+1) <= x(n+2)
    compute min = 1
    if (min == 1) .and. (mina == 0)
      compute mina = n
    if (min == 1) .and. (minb == 0)
      compute minb = n
    if (mina > 0) .and. (minb > 0)
      compute flag = 1
    if flag == 1 .and. x(mina) > x(minb)

```

```

    compute mina = minb, minb = 0
    if (flag == 1).and.(x(mina)<=x(minb))
        compute minb = 0
    compute min = flag = 0
end do n
if mina == 0
do n=nmed,nhigh
    if x(n-1)>=x(n).and.x(n)<=x(n+1)
        compute min = 1
    if (min == 1).and.(mina == 0)
        compute mina = n
    if (min == 1).and.(minb == 0)
        compute minb = n
    if (mina > 0).and.(minb > 0)
        compute flag = 1
    if flag == 1.and.x(mina)>x(minb)
        compute mina = minb, minb = 0
    if (flag == 1).and.(x(mina)<=x(minb))
        compute minb = 0
    compute min = flag = 0
end do n
* display 'troughs at' min1 mina
compute slope = (x(mina) - x(min1))/(mina - min1)
set m = t - mina
set neckline = slope*m + x(mina)
do n=nhigh,(nhigh+50)
    if y(n)<=neckline(n)
        compute s = n
    if s > 0
        break
    compute n = n + 1
end do n
* if s == 0
* display 'no intersection'
if (s > 0)
    compute intersects = intersects + 1
if s > 0
do n=s,(nhigh+50)
* if n >= 8237
    if n >= 8740
        break
* if (y(n) <= .97*y(s))
* display 'signal at' n y(n)
    if (y(n) <= .97*y(s))
        compute signals = signals + 1
    if (y(n) <= .97*y(s))
        compute profit = 1000000*((y(n) - y(n+2))/y(n))
    if (y(n) <= .97*y(s))
        compute pvalue = profit*(1 + (.0002844709*(8242 - n - 2)))
    if (y(n) <= .97*y(s))
        display n profit pvalue
    if (y(n) <= .97*y(s))
        compute totalpv = totalpv + pvalue
    if (y(n) <= .97*y(s))
        break
    compute n = n + 1
end do n
compute n = nmed + 1
compute nlow = nmed = nhigh = 0
branch loop2

```

```
*  
:loop5  
    display 'hits =' hits  
    display 'intersections=' intersects  
    display 'signals=' signals  
    display 'totalpv=' value  
*  
end do i
```

APPENDIX C. SYMMETRICAL TRIANGLE SIGNAL PROGRAM

```
*This program will detect pattern and signal for Symmetrical
*Triangle pattern
```

```
cal(daily) 62 1 2
all 0 93:8:4
open data c:\martine\pg.prn
data(format=free,org=obs) / pg vol
```

```
set x / = pg
do i=1,2
  compute min1 = min2 = max1 = max2 = 0
  compute signals = hits = 0
  compute totalpv = 0.0
  compute n = 5
  branch loop1
```

```
*checking for max or min
```

```
:loop1
  compute max = min = 0
  if (x(n) >= x(n+1)).and.(x(n) >= x(n-1)).and.$
    (x(n+1) >= x(n+2)).and.(x(n-1) >= x(n-2))
    compute max = 1
  if (x(n) <= x(n+1)).and.(x(n) <= x(n-1)).and.$
    (x(n+1) <= x(n+2)).and.(x(n-1) <= x(n-2))
    compute min = 1
  if max == 1
    branch loop2
  if min == 1
    branch loop3
  compute n = n + 1
  if n == 8239
*   if n == 8740
    branch loop7
  branch loop1
```

```
*finding consecutive maxima
```

```
:loop2
  compute flag = 0
  if max1 == 0
    compute flag = 1
  if flag == 1
    compute max1 = n
  if flag == 1
    compute n = n + 1
  if flag == 1
    branch loop1
  if max2 == 0
    compute flag = 1
  if flag == 1
    compute max2 = n
  if (max2 > 0).and.(min2 > 0)
    branch loop4
  compute n = n + 1
  branch loop1
```

```
*finding consecutive minima
```

```
:loop3
```

```

compute flag = 0
if min1 == 0
  compute flag = 1
if flag == 1
  compute min1 = n
if flag == 1
  compute n = n + 1
if flag == 1
  branch loop1
if min2 == 0
  compute flag = 1
if flag == 1
  compute min2 = n
if (min2 > 0).and.(max2 > 0)
  branch loop4
compute n = n + 1
branch loop1

:loop4
*cases where triangles found
if (max1<min1).and.(min1<max2).and.(max2<min2).and.$
(x(max1)>x(max2)).and.(x(min1)<x(min2))
  branch loop5
if (min1<max1).and.(max1<min2).and.(min2<max2).and.$
(x(max1)>x(max2)).and.(x(min1)<x(min2))
  branch loop5
*updating n when no triangle found
if max1<min1
  compute n = max1 + 1
if max1>min1
  compute n = min1 + 1
compute min1 = min2 = max1 = max2 = 0
branch loop1

:loop5
  compute hits = hits + 1
* display 'triangle' max1 max2 min1 min2
*detecting signal for buy/sell with triangle
compute u = d = 0
compute upslope = (x(max2) - x(max1)) / (max2 - max1)
set m = t - max1
set upline = upslope*m + x(max1)
compute loslope = (x(min2) - x(min1))/(min2 - min1)
set p = t - min1
set loline = loslope*p + x(min1)
*Case where triangle begins with max
if max1<min1
  do n = min2,min2+100
    if loline(n) >= upline(n)
      compute s = n
*     if loline(n) >= upline(n)
*     display 'apex at' s
    if loline(n) >= upline(n)
      break
    compute n = n + 1
  end do n
if max1<min1
  compute n = min2 + 1
if max1<min1
  while n <= s {

```

```

        if 0.97*x(n)>=upline(n)
            compute u = n
        if 1.03*x(n)<=loline(n)
            compute d = n
    *       if (u > 0).or.(d > 0)
    *       display 'up signal at' u 'down signal at' d
        if (u > 0).or.(d > 0)
            branch loop6
        compute n = n + 1
    }
*Case where triangle begins with min
    if max1>min1
        do n = max2,max2+100
            if loline(n) >= upline(n)
                compute s = n
    *       if loline(n) >= upline(n)
    *       display 'apex at' s
            if loline(n) >= upline(n)
                break
            compute n = n + 1
        end do n
    if max1>min1
        compute n = max2 + 1
    if max1>min1
        while n <= s {
            if 0.97*x(n)>=upline(n)
                compute u = n
            if 1.03*x(n)<=loline(n)
                compute d = n
    *       if (u > 0).or.(d > 0)
    *       display 'up signal at' u 'down signal at' d
            if (u > 0).or.(d > 0)
                branch loop6
            compute n = n + 1
        }
    *   display 'no signal'
    if max1<min1
        compute n = max1 + 1
    if max1>min1
        compute n = min1 + 1
    compute min1 = min2 = max1 = max2 = 0
    branch loop1

:loop6
*check increasing volume on up breakout. Down breakout has no volume
*criterion
    if u > 0
        compute avevol = (vol(u-10)+vol(u-9)+vol(u-8)+vol(u-7)+$
            vol(u-6)+vol(u-5)+vol(u-4)+vol(u-3)+vol(u-2)+vol(u-1))/10
    *   if (u > 0).and.(vol(u)<avevol)
    *   display 'u=' u 'volume did not confirm'
        if (u > 0).and.(vol(u)<avevol)
            compute u = 0
*find signal and profit if up breakout
    if u > 0
        compute signals = signals + 1
    if u > 0
        compute profit = 1000000*((x(n+10) - x(n))/x(n))
    if u > 0
        compute pvalue = profit*(1 + (.0002844709*(8242 - n - 10)))

```

```
if u > 0
    display n profit pvalue
if u > 0
    compute totalpv = totalpv + pvalue
*find signal and profit if down breakout
if d > 0
    compute signals = signals + 1
if d > 0
    compute profit = 1000000*((x(n) - x(n+10))/x(n))
if d > 0
    compute pvalue = profit*(1 + (.0002844709*(8242 - n - 10)))
if d > 0
    display n profit pvalue
if d > 0
    compute totalpv = totalpv + pvalue
if max1<min1
    compute n = max1 + 1
if max1>min1
    compute n = min1 + 1
compute min1 = min2 = max1 = max2 = 0
branch loop1

:loop7
display 'hits =' hits
display 'signals =' signals
display 'totalpv =' totalpv

end do i
```


APPENDIX D. RECTANGLE SIGNAL PROGRAM

```
*This program will detect pattern and signal for rectangle
*pattern
```

```
cal(daily) 62 1 2
all 0 93:8:3
open data c:\martine\gm.prn
data(format=free,org=obs) / gm vol

set y / = gm
*set x 60:1:4 93:7:7 = (y(t-2)+y(t-1)+y(t)+y(t+1)+y(t+2))/5
set x 62:1:4 93:8:1 = (y(t-2)+y(t-1)+y(t)+y(t+1)+y(t+2))/5
do i=1,2
  compute min1 = min2 = max1 = max2 = 0
  compute signals = hits = 0
  compute totalpv = 0.0
  compute n = 5
  branch loop1

*checking for max or min
:loop1
  compute max = min = 0
  if (x(n) >= x(n+1)).and.(x(n) >= x(n-1)).and.$
    (x(n+1) >= x(n+2)).and.(x(n-1) >= x(n-2))
    compute max = 1
  if (x(n) <= x(n+1)).and.(x(n) <= x(n-1)).and.$
    (x(n+1) <= x(n+2)).and.(x(n-1) <= x(n-2))
    compute min = 1
  if max == 1
    branch loop2
  if min == 1
    branch loop3
  compute n = n + 1
  if n == 8225
*   if n == 8730
    branch loop8
  branch loop1

*finding consecutive maxima
:loop2
  compute flag = 0
  if max1 == 0
    compute flag = 1
  if flag == 1
    compute max1 = n
  if flag == 1
    compute n = n + 1
  if flag == 1
    branch loop1
  if max2 == 0
    compute flag = 1
  if flag == 1
    compute max2 = n
  if (max2 > 0).and.(min2 > 0)
    branch loop4
  compute n = n + 1
  branch loop1
```

```

*finding consecutive minima
:loop3
  compute flag = 0
  if min1 == 0
    compute flag = 1
  if flag == 1
    compute min1 = n
  if flag == 1
    compute n = n + 1
  if flag == 1
    branch loop1
  if min2 == 0
    compute flag = 1
  if flag == 1
    compute min2 = n
  if (min2 > 0).and.(max2 > 0)
    branch loop4
  compute n = n + 1
  branch loop1

:loop4
*checking if maxima and minima alternate
  if (min1<max1).and.(max1<min2).and.(min2<max2).and.$
    (x(min1)<x(max1))
    branch loop5
  if (max1<min1).and.(min1<max2).and.(max2<min2).and.$
    (x(min1)<x(max1))
    branch loop5
*updating n
  if max1<min1
    compute n = max1 + 1
  if max1>min1
    compute n = min1 + 1
  compute min1 = min2 = max1 = max2 = 0
  branch loop1

:loop5
*construct lines and verify they have parallel, near-zero slope
  compute upslope = (x(max2) - x(max1))/(max2 - max1)
  compute loslope = (x(min2) - x(min1))/(min2 - min1)
  if (abs(upslope-loslope)<=0.05).and.(abs(loslope)<=0.05).and.$
    (abs(upslope)<=0.05)
    branch loop6
*updating n
  if max1<min1
    compute n = max1 + 1
  if max1>min1
    compute n = min1 + 1
  compute min1 = min2 = max1 = max2 = 0
  branch loop1

:loop6
  compute hits = hits + 1
  * display 'rectangle found'
  * display min1 max1 min2 max2 'upslope' upslope 'loslope' loslope
  compute u = d = b = 0
*constructing lines to detect signal
  set m = t - max1
  set upline = upslope*m + x(max1)
  set p = t - min1

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set loline = loslope*p + x(min1)
*Finding break and signal in case where rectangle begins with max
if max1<min1
  do n = min2,min2+50
    if y(n) > upline(n)
      compute b = n
    if y(n) < loline(n)
      compute b = n
*     if b > 0
*       display 'break at' b
    if b > 0
      break
    compute n = n + 1
  end do n
  if (max1<min1).and.(b == 0)
    compute n = min2 + 1
*   if (max1<min1).and.(b == 0)
*     display 'no break'
  if (max1<min1).and.(b == 0)
    compute min1 = min2 = max1 = max2 = 0
  if (max1<min1).and.(b == 0)
    branch loop1
  if max1<min1
    do n = min2,min2+50
      if 0.97*y(n)>=upline(n)
        compute u = n
      if 1.03*y(n)<=loline(n)
        compute d = n
*     if (u > 0).or.(d > 0)
*       display 'up signal at' u 'down signal at' d
      if (u > 0).or.(d > 0)
        branch loop7
      compute n = n + 1
    end do n
*Finding break and signal in case where rectangle begins with min
  if max1>min1
    do n = max2,max2+50
      if y(n) > upline(n)
        compute b = n
      if y(n) < loline(n)
        compute b = n
*     if b > 0
*       display 'break at' b
      if b > 0
        break
      compute n = n + 1
    end do n
    if (max1>min1).and.(b == 0)
      compute n = max2 + 1
*   if (max1>min1).and.(b == 0)
*     display 'no break'
  if (max1>min1).and.(b == 0)
    compute min1 = min2 = max1 = max2 = 0
  if (max1>min1).and.(b == 0)
    branch loop1
  if max1>min1
    do n = max2,max2+50
      if 0.97*y(n)>=upline(n)
        compute u = n
      if 1.03*y(n)<=loline(n)

```

```

        compute d = n
*       if (u > 0).or.(d > 0)
*       display 'up signal at' u 'down signal at' d
        if (u > 0).or.(d > 0)
            branch loop7
        compute n = n + 1
    end do n
*   display 'no signal'
    compute n = b
    compute min1 = min2 = max1 = max2 = 0
    branch loop1

:loop7
*check increasing volume on up breakout.  Down breakout has no volume
*criterion
    if u > 0
        compute avevol = (vol(u-10)+vol(u-9)+vol(u-8)+vol(u-7)+$
            vol(u-6)+vol(u-5)+vol(u-4)+vol(u-3)+vol(u-2)+vol(u-1))/10
*       if (u > 0).and.(vol(u)<avevol)
*       display 'u=' u 'volume did not confirm'
        if (u > 0).and.(vol(u)<avevol)
            compute u = 0
*find signal and returns if up breakout
    if (u > 0).or.(d > 0)
        compute signals = signals + 1
        if u > 0
            compute profit = 1000000*((y(n+10) - y(n))/y(n))
            if u > 0
                compute pvalue = profit*(1 + (.000061724*(8241 - n - 10)))
            if u > 0
                display n profit pvalue
            if u > 0
                compute totalpv = totalpv + pvalue
*find returns if down breakout
    if d > 0
        compute profit = 1000000*((y(n) - y(n+10))/y(n))
        if d > 0
            compute pvalue = profit*(1 + (.000061724*(8241 - n - 10)))
        if d > 0
            display n profit pvalue
        if d > 0
            compute totalpv = totalpv + pvalue
* update n
    compute n = b
    compute min1 = min2 = max1 = max2 = 0
    branch loop1

:loop8
    display 'hits =' hits
    display 'signals =' signals
    display 'totalpv =' totalpv

end do i

```