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The cointegrating relationship between stock prices and trading volume: Evidence regarding the predictability of security returns

Weigand, Robert Alan, Ph.D.

The University of Arizona, 1993
The Cointegrating Relationship Between Stock Prices and Trading Volume: Evidence Regarding the Predictability of Security Returns

by

Robert Alan Weigand

A Dissertation Submitted to the Faculty of the COMMITTEE OF BUSINESS ADMINISTRATION

In Partial Fulfillment of the Requirements For the Degree of

DOCTOR OF PHILOSOPHY

In the Graduate College
THE UNIVERSITY OF ARIZONA

1993
As members of the Final Examination Committee, we certify that we have read the document prepared by Robert Alan Weigand entitled The Cointegrating Relationship Between Stock Prices and Trading Volume: Evidence Regarding the Predictability of Security Returns.

and recommend that it be accepted as fulfilling the requirements for the Degree of Doctor of Philosophy/Business Administration

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Edward A. Dyl 6/28/93
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SIGNED
DEDICATION

This dissertation is dedicated to my family and particularly to my wife, Nancy. Her encouragement, faith and support are an integral part of whatever success I have achieved thus far, as well as any future success the two of us may enjoy. The completion of my doctorate represents another step in the lifetime journey we share so well together.
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ABSTRACT

This study develops and tests the hypothesis that stock prices and trading volume are influenced by the same set of fundamental forces. The implications of this hypothesis for modeling and forecasting stock returns are also explored.

Part 1 identifies several effects likely to contribute to the observed positive correlation between stock prices and trading volume. Among these are the various constraints that prohibit certain classes of investors from short selling; the disposition effect, which is the tendency for investors to hold losing investments too long and sell winners too early; and the prevalence of positive feedback trading strategies in financial markets. Part 1 also presents a simple supply and demand example which demonstrates that both asset prices and trading volume are influenced by the information signals received by traders in efficient markets.

Part 2 presents empirical tests of the hypothesis that stock prices and trading volume are determined by a set of common factors. The presence of a common stochastic trend (cointegration) is shown to be consistent with the above hypothesis. Stock prices and trading volume are found to be cointegrated, which is interpreted as evidence in support of the common factor hypothesis. The theoretically correct method for modeling cointegrated variables, known as an error-correction model (ECM), explains over 4% of the variability in monthly stock returns from 1962-1991.

An index of the total dividends paid to the Standard and Poor's 500 is included as an instrument for the information set hypothesized to be a common factor in stock prices and trading volume. After demonstrating that stock prices, trading volume and the dividend index are part of a trivariate cointegrated system, the dividend index is included into the ECM of stock prices. The explanatory power of the ECM rises to 6.5% due to the inclusion of the dividend index.

Part 3 develops a forecasting model of monthly stock returns based on the ECM presented in Part 2. Out-of-sample forecasts of monthly stock returns are generated from this model, as well as other forecasting models chosen from the literature on the predictability of security returns. Under a variety of conditions, both with and without
transactions costs, trading rules generated by the forecasting model of Conrad and Kaul (1989) consistently outperform a buy and hold strategy. The ECM forecasting model performs no better than a macroeconomic or random walk model, and underperforms a buy and hold strategy in the presence of transactions costs. The overall finding from Part 3 is that the simple time series model of Conrad and Kaul generates forecasts which beat the market conclusively for the thirteen year period spanning January, 1978 to December, 1990.
PART 1:

REVIEW OF THE LITERATURE AND A
THEORY OF STOCK PRICES AND TRADING VOLUME
1.1. Introduction and Overview

Much is thought to be known regarding the theoretical relationship between the market price of an asset and the underlying factors that determine that asset's price. Asset-pricing models usually express the expected return of an asset as a linear combination of factors that are related to the prices of capital assets and whose influence cannot be avoided by diversification. The covariance of the asset's return with changes in the values of these factors is then interpreted as a measure of how much the expected return of the asset is likely to change when the conditions affecting the values of the factors change. While early empirical evidence (Black, Jensen and Scholes (1972), Fama and MacBeth (1973)) provided weak support for the original single-factor model (the Capital Asset Pricing Model of Sharpe (1964), Lintner (1965) and Mossin (1966)), more recent evidence (Fama and French (1992)) casts doubt on the ability of a single-factor model to capture the cross-sectional variation in average stock returns. The empirical evidence indicates that multi-factor models that relate the expected return of a portfolio of securities to the values of various factors thought to capture expected future macroeconomic activity provide a more accurate description of stock returns.¹

The modern view of what constitutes relevant information, and how such information affects the prices and expected returns of financial securities, has been shaped in large part by the asset-pricing literature. The U.S. market for common stocks, for example, is widely regarded as efficient, at least in the "weak-form" sense of Fama (1970). This definition of market efficiency maintains that the prices of common stocks reflect all relevant historical information, and that only new, unanticipated information can affect the

demand to hold shares of stock. When investors receive new information that affects either their desire to hold or willingness to supply shares of a certain security, they will adjust their inventories by trading amongst each other until all outstanding shares of that security are once again held by someone. The new equilibrium price of the security that equates the supply of shares with the demand to hold shares reflects the aggregated interpretations of the news by all investors who are potential buyers or sellers of that security. Implicit in this view of market efficiency is that market participants, in the aggregate, can distinguish relevant news from irrelevant news. An example of relevant news would be any unanticipated change in a macroeconomic factor that is believed to affect everyone's portfolio of stocks in a systematic manner, i.e., a factor that cannot be avoided by diversification. Irrelevant news, therefore, would be information regarding some type of risk that could be diversified away, or also information that was already reflected in the current level of stock prices.

The efficient-markets view of securities prices rapidly adjusting to reflect new information requires one of two things: either investors interpret the new information heterogeneously, or different classes of investors hold different opinions as to what constitutes relevant information, or both. If either of these conditions are not met, then investors' desires to alter their holdings of securities will go unsatisfied. A positive level of trading volume requires a difference of opinion among investors regarding either the implications or definition of relevant information.

This requirement serves to highlight a fundamental inconsistency between the asset-pricing literature and the modern view of efficient capital markets. One pervasive assumption of all the asset-pricing models, whether of the equilibrium or arbitrage variety, is that investors possess homogenous expectations, which means that investors receive and interpret all information in an identical manner. Note also that the assumption of
Homogenous expectations precludes investors from having different definitions of relevant information. Homogenous expectations implies that all investors agree on the expected end-of-period value of the asset in question. Thus, while the asset-pricing literature offers potential explanations for the relationship between information and securities prices, the assumption that all investors are in perfect agreement regarding the implications of new information does not allow for the mechanism by which that information is generally thought to become impounded into prices: trade between investors.  

The absence of a comprehensive theory that allows for a plausible definition of relevant information, as well as the manner in which this information affects the prices of financial securities, led Stephen Ross (1987) to write:

"...There is no serious research as yet on volume data. This is in large part because we have no serious theories that purport to explain the volume of trade ... It seems clear that the only way to explain the volume of trade is with a model that is at one and the same time appealingly rational and yet permits divergent and changing opinions in a fashion that is other than ad hoc. If I had to point to a single priority order of business for intertemporal pricing theory, it would be the construction of such a theory ..."

Subsequent to Ross' observation, several new theories of volume have emerged. These will be reviewed and discussed in Section 1.2. None of these enjoys the widespread acceptance afforded to the various approaches to asset pricing and efficient markets referred to earlier, however.

---


3 Among these are Karpoff (1986), Admati and Pfleiderer (1988), and Holthausen and Verrecchia (1990).
The absence of a comprehensive theory of trading volume does not mean that the academic literature has failed to recognize the importance of volume, however. It has long been thought that unusual increases in trading volume are associated with the arrival of new information.\(^4\) Recently, some empirical studies have incorporated an analysis of trading volume in an attempt to assess the information content of investor behavior and corporate announcements.\(^5\) Additionally, a positive correlation between price variability and trading volume, as well as between volume and the direction of price changes, has been well documented in the literature. While the volume-variability relationship is thought to derive from both being positively correlated with the arrival rate of new information, the relationship between volume and price changes has not yet been adequately explained.

The purpose of this dissertation is to analyze the relationship between stock prices and trading volume in a manner that is consistent with the generally accepted theories regarding asset pricing and market efficiency. The results of this analysis provide insight into the appropriate methods for modeling the joint relationship between prices and volume. The first step in this process will be to develop a plausible definition of relevant information that is likely to affect everyone's portfolio of stocks to some degree. Then, drawing upon the earlier literature, two types of representative investors will be characterized, with each being motivated to trade by different considerations. The interaction of these traders will be analyzed in a simple framework where investors revise their demand to hold shares of equity securities based on new information regarding the expected prospects for stocks in current and future periods.

\(^4\)See Beaver (1968).

\(^5\)See Lakonishok and Smidt (1984) and Richardson, Sefcik and Thompson (1986) for some examples of this literature.
The major result of the analysis demonstrates that prices and trading volume are jointly determined conditional on the arrival of new information, and that the positive correlation between volume and the direction of the price change arises because each is correlated with a common underlying variable. This variable is the flow of new information to the market, and its implications for stock price changes in both current and future periods. The analysis further shows that the appropriate manner in which to model the joint determination of prices and trading volume is by examining the relationship between changes in stock prices and volume. This will provide the direction for the empirical analysis into the time series characteristics of stock prices and trading volume, which begins in Part 2.

The work presented here is designed to overcome some of the difficulties encountered by previous studies of the relationship between securities prices and trading volume. One such difficulty arises due to the assumption that volume is positively correlated with the arrival rate of new information, which is generally regarded as an unobservable variable. By modeling the relationship between a diversified portfolio of stocks and trading volume, a definition of information that is measurable can be constructed, allowing for the relationship between volume and information to be formally tested.

While the model presented here is consistent with Ross' appeal for a framework that allows for investor opinions to change in a rational manner, the most important result that obtains from the analysis is that it provides a direction for the subsequent empirical investigation into the time series relationship of prices and volume. The implications of the model serve to underscore an important issue that must be addressed by future researchers who seek to reconcile the gap between the asset-pricing literature and the efficient-markets interpretation of asset markets. The current models of the manner in
which information impacts the prices and expected returns of capital assets are incomplete because they fail to recognize that trade between investors is an important mechanism by which new information becomes impounded into the prices of assets. When information arrives in the marketplace and traders revise their demand to hold shares of an asset, not only does a new price result from the interaction of these investors, but a level of trading volume is determined simultaneously along with the new price. While Parts 2 and 3 of this dissertation examine the empirical implications of the joint determination of price and volume, it is left to future research to explore the theoretical implications of this issue.

The remainder of this dissertation is organized as follows: Section 1.2 presents a review of the literature on stock prices and trading volume; Section 1.3 presents a discussion of the likely causes for the observed positive correlation between stock price changes and trading volume; and Section 1.4 incorporates the major points from the discussion into a formal model of stock prices and volume. The empirical exploration into the time series behavior of stock prices and volume begins in Part 2, which documents that stock prices and trading volume on the NYSE were cointegrated between 1962-1986, with the link between the two series being severed following the crash of October, 1987. Modeling stock prices, trading volume and an instrument for the information set using an error-correction model explains over 6% of the variation in monthly stock returns. Part 3 demonstrates that knowledge of the cointegrating relationship between stock prices and volume could have been used to forecast stock returns from 1978-1990. Out-of-sample forecasts from the ECM are computed and compared with forecasts from other competing models. The results indicate that several models outperform a buy and hold strategy, even when transactions costs are taken into account.
1.2. A Review of the Price-Volume Literature

Most studies into the relationship between stock prices and trading volume have focused on one or both of the following characteristics of asset prices and volume:

1. Large price movements are associated with higher trading volume, or
2. Trading volume tends to be higher during periods when prices are generally rising than during periods when prices are generally declining.

Empirical evidence supports the existence of a positive relationship between trading volume and some measure of price variability, such as the absolute value or square of the price change. The literature offers several reasons why trading volume and price variability might be related. First, if investors have heterogenous prior beliefs regarding the value of an asset, the release of new information is likely to generate diverse interpretations as to the implications of the news. This will lead to large price changes and an increase in trading volume as their diversity of opinion is impounded into the price of the asset. Second, if investors use price movements as information on which to make trading decisions, then large price movements will lead to a higher volume of trade. Third, if secondary markets are not perfectly liquid, large buy or sell orders will cause price changes due to temporary imbalances of supply and demand. Finally, the "mixture of distributions" hypothesis proposes that daily price changes are sampled from a set of distributions with different variances, where the variances are positively related to the arrival rate of new information. If this new information causes investors to rebalance their holdings, then volume and the variance of the price change will be positively correlated. The positive correlation between trading volume and price variability has been found in equity, debt, futures, foreign currency, and commodity markets, and is generally regarded as an empirical fact.
The second characteristic is frequently interpreted as implying the existence of a positive relationship between trading volume and the change in price \textit{per se}. The literature is less clear as to why volume might be higher on positive price changes than on negative changes, but several plausible explanations have been offered. First, optimistic investors might form their expectations in a manner that is different from pessimistic investors. Thus, the price-volume relationship might reflect behavioral differences between investors with dissimilar expectations. Second, the fact that it is more costly to establish a short position in equity markets than a long position could lead to an asymmetric price-volume relationship, because the higher cost would inhibit some investors from short selling. The empirical evidence shows that the positive correlation between price changes and volume is present in stock and bond markets, where short selling is more costly, but is absent in futures and options markets, where the costs of going short are no greater than the cost of establishing a long position.

Sections 1.2.A. and 1.2.B. below present a detailed review of the theoretical and empirical evidence regarding the relationship between price variability and volume, and price changes and volume, respectively. Section 1.3 offers new explanations that may account for the observation that volume is higher during periods of rising prices than periods when prices are generally declining. Section 1.4 incorporates the key elements from the discussion in Section 1.3 into a formal model. Empirical evidence regarding the relationship between stock prices and trading volume on the NYSE and AMEX from 1962-1991 is presented beginning in Part 2.
A. The Relationship Between Trading Volume and Price Variability

One explanation for the positive relationship between price variability and trading volume focuses on the dispersion of investors' expectations prior to the release of new information. If investors have heterogeneous prior expectations regarding the value of an asset, then the release of new information may result in diverse interpretations of the significance of the news. This, in turn, should lead to an increase in the variability of subsequent price changes, as well as a higher level of trading volume, as their diverse opinions become impounded into the price of the asset. The theoretical evidence on this issue is mixed, however.

Beaver (1968) seems to have been the first to suggest using volume to test investors' reactions to the release of information. Beaver argues that the magnitude of the price and volume reaction to information reflects the extent to which investors disagree regarding the interpretation of the information, as well as the degree to which the information changed their prior expectations. Verrechia (1981) takes exception to Beaver's assertion that trading volume is increasing in investor disagreement. He argues that while the absence of a volume reaction to the release of new information implies that there is total consensus among investors, the presence of a volume reaction does not imply disagreement.

In a later work, Holthausen and Verrechia (1990) identify two effects of information releases: an informedness effect, which measures the degree to which traders become more knowledgeable, and a consensus effect, which reflects the extent to which traders agree regarding the interpretation of the information. They show that while the variance of the price change is increasing in both informedness and consensus, trading volume is increasing in informedness but decreasing in consensus. Thus, an increase in
informedness contributes to a positive correlation between price variability and volume, but an increase in consensus causes price variability and volume to move in opposite directions.

Copeland (1976) also examines the relationship between price changes and trading volume with respect to the manner in which investors become informed. He constructs a "sequential arrival of information" model, in which investors become informed one at a time, and trade with other investors who have not yet received the information. In his model, new information has a prolonged effect on asset prices and trading volume which lasts until all traders become informed. The price change and trading volume when the next trader becomes informed is determined by both the previous pattern of who has been informed, and whether the next trader is an optimist or a pessimist. One objection to Copeland's model is that investors do not become informed by observing price and volume changes caused by the information dissemination process. Another objection is that Copeland's model yields the counterintuitive result that trading volume is highest when traders are in total agreement regarding new information.

Jennings and Barry (1983) extend the sequential arrival of information model to allow for speculation by informed traders. Their analysis also predicts a positive correlation between trading volume and the absolute value of the price change for a given transaction, but the hypothesized relationship between volume and price variability for the entire trading day is ambiguous. Sankaran and Kazemi (1991) apply the noisy rational expectations framework to a simple model of futures prices. They demonstrate that unless investors are extremely risk tolerant, greater differences in information will increase the correlation between the volume of trade and the magnitude of price changes.

Admati and Pfleiderer (1988) develop a model of intraday trading in a market with both liquidity and informed traders. They show that both types of traders want to trade
when the market is "thick": i.e., when their trades will have the least effect on prices. An increase in the diversity of the signals received by informed investors is shown to increase competition among traders, which leads to a higher concentration of trading at the open and at the close. This has a positive effect on both volume and price variability at the beginning and end of the trading day.

Another potential explanation for the positive correlation between price variability and transactions volume is the wide variety of trading strategies that call for buying stocks when their prices rise and selling stocks when their prices fall. To traders who subscribe to these "positive feedback" strategies, price changes convey information regarding the expected future value of an asset. If a larger change in price is presumed to convey a stronger signal, and generates a stronger response on the part of investors, then these strategies would contribute to the positive correlation between trading volume and the variance of the price change.

Among these strategies are technical analysis trading rules that attempt to identify trends in a time series of prices and recommend buying when the trend is increasing and selling when the trend is decreasing. Another example would be stop-loss orders that automatically reverse a transaction when price changes by a predetermined amount. Assets purchased on margin often have to be sold to meet margin calls when the decline in the price of the asset causes the trader's equity position to fall below the legal maintenance margin. Such selling further exacerbates the decline in price while generating an increase in trading volume.

DeLong, Shleifer, Summers and Waldmann (1990) develop a model where rational speculators place orders to trade in anticipation of the trend-chasing behavior of positive feedback traders. In their model, the interaction between rational speculators and positive feedback traders provides a destabilizing effect which initially drives prices away from
fundamental values. Prices revert back to fundamentals in a long-run sense, and price changes are more variable than they would have been in the absence of speculation. Although the authors do not model volume specifically, it is obvious that the implementation of these strategies increases the volume of trade as well.

The price variability-volume relationship may also be caused by the liquidity effects resulting from orders to buy or sell quantities of securities that are large relative to the outstanding supply. If buyers must incur extra costs to accept a large quantity of securities, there may be a temporary decline in price to reflect this liquidity premium (also known as a price pressure, or distribution effect). Kraus and Stoll (1972) examine all block trades (10,000 shares or more) on the NYSE for a fifteen month period and provide evidence of a price pressure effect. They find that for a day in which there has been a block transaction, the average closing stock price is .71% higher than the block price from earlier in the trading day.

Harris and Gurel (1986) argue that because block trades may also convey information regarding the future prospects of the firm, the results of Kraus and Stoll's study are also consistent with several other price response hypotheses. In order to distinguish among the various hypotheses, Harris and Gurel look at trading surrounding changes in the composition of the S&P 500 list of stocks. According to Standard and Poor's, "judgments as to the investment appeal of the stocks do not enter into the selection process." Changes in the composition of the S&P 500 are therefore based on publicly available information only, which implies that these changes should not reveal any new information to the market. The addition and deletion of firms to the S&P 500 list of stocks are likely to cause shifts in investor demand, however, especially among index funds that attempt to mimic the composition of the S&P 500. Thus, studying the effect of listing changes on prices and volume can identify the existence of price pressures in the
absence of new information. Harris and Gurel find a three percent abnormal return associated with the announcement that a firm is to be included in the S&P 500 list, but the return is almost completely reversed within two weeks. This provides clear evidence that large shifts in investor demand and the trading volume that accompanies such shifts can affect the variability of stock prices. The supply and demand effects found in imperfect capital markets are therefore likely to contribute to the positive correlation between the variance of price changes and trading volume.

Another explanation for the positive relationship between volume and price variability comes from research into the distribution of asset prices. The "mixture of distributions" hypothesis (MDH) asserts that daily price changes are sampled from a set of distributions with different variances, where the variances are dependent on the volume of trade for each transaction. Clark (1973) was the first to suggest that the conditional variance of price changes was a function of transaction volume. He shows that daily price changes are normally distributed when conditioned on volume.

In a study closely related to the work of Clark, Epps and Epps (1976) develop a model in which they assume that there is a positive correlation between the extent to which traders disagree and the absolute value of the change in their reservation prices. The authors also assume that disagreement and the level of trading volume are positively related. A higher level of disagreement is thus shown to imply increasing volume as well as price changes of greater magnitude. Epps and Epps demonstrate that the variance of the price change is conditional upon the volume of each transaction. Transaction price changes are thus mixtures of distributions, with volume as the mixing variable. The predictions of their model are consistent with Clark's finding that the leptokurtosis in the distribution of daily price changes mostly disappears when the changes are grouped by volume levels.
Tauchen and Pitts (1983) model the daily price change and trading volume as mixtures of independent normal distributions, where the mixing variable is the number of equilibrium market clearings per day. An increase in the number of daily equilibria implies a greater flow of information to the market, which leads to a greater change in price as well as a higher level of trading volume. In their model it is the (unobserved) flow of information variable that ties the price change and volume together.

The empirical work in this area is almost exclusively concerned with daily price and volume data, and is largely supportive of the conclusion that price variability and volume are positively correlated. In early research, Granger and Morgenstern (1963) found no relation between an SEC price index and trading volume on the NYSE. Godfrey, Granger, and Morgenstern (1964) also concluded that trading volume and price changes are unrelated. Ying (1966) examined the S&P 500 price index and NYSE trading volume and concluded that higher levels of trading volume do correspond to larger price changes, however.

In subsequent research, Crouch (1970) finds a positive correlation between the absolute value of daily price changes and trading volume for both market indices and individual stocks. Clark (1973) finds that the square of the daily price change is correlated with daily volume in the cotton futures market. Morgan (1976) finds that the variance of the daily price changes is positively related to trading volume for a small sample of stocks, and provides support for the contention of Clark, Epps and Epps, and Tauchen and Pitts that the distribution of stock price changes and volume are adequately described by the MDH. Westerfield (1977) examines a sample of daily price changes and volumes for a sample of 315 stocks and concludes that volume and price variability are positively related. Tauchen and Pitts (1983) find that volume and the variance of price changes are
positively correlated in the Treasury bill futures market, and Grammatikos and Saunders (1986) find the same relationship in foreign currency futures.

Most recently, Jain and Joh (1988) document a strong positive correlation between contemporaneous trading volume and the absolute value of returns using hourly volume on the NYSE and hourly returns on the S&P 500 index. Lamoureux and Lastrapes (1990) examine daily returns for a sample of twenty stocks and show that GARCH effects disappear when volume is included in the conditional variance equation. The implication is that daily trading volume has significant explanatory power regarding the variance of daily returns.

In a rare deviation from the use of high frequency data, Schwert (1989) documents a contemporaneous correlation between volatility and volume in monthly stock returns. Gallant, Rossi and Tauchen (1992) undertake the most comprehensive empirical investigation to date into the relationship of stock price variability and trading volume. They examine daily NYSE trading volume and the return to the S&P 500 index from 1928 to 1987, and find a strong positive correlation between conditional price volatility and volume. Price changes and volume appear to be related in a nonlinear fashion, with large price changes preceding large changes in volume.

Wiggins (1992) provides evidence that it does indeed "take volume to move prices." He examines a sample of firms that do not trade on a day when the percentage return to the stock market exceeds two percent in absolute value. Wiggins finds that revisions in the bid-ask quotations posted by specialists are insufficient to compensate for the market-wide information reflected in the price changes of all other stocks. Furthermore, the higher the level of trading volume subsequent to the non-trading day, the faster prices adjust to the new information. Wiggins concludes that trade plays a distinctive role in the transmission of public information into stock prices.
A preponderance of the theoretical and empirical evidence on the relationship between trading volume and price variability supports the hypothesis that trading volume is positively correlated with the variance and magnitude of changes in the prices of financial assets.

B. The Relationship Between Trading Volume and the Direction of the Price Change

The second price-volume relationship considered concerns the observation that periods of rising prices are usually associated with higher trading volume than periods when prices are generally declining. Some of the theories that purport to explain this phenomenon suggest that there may be intrinsic differences in the way optimistic and pessimistic investors assess the impact of new information on the prices of risky assets. These differences may result in a higher volume of trade when favorable sentiment outweighs negative opinion in financial markets. 

Epps (1975) develops a model that predicts the volume generated by a transaction that results in a rise in price will exceed the volume accompanying a price decline of the same magnitude. His result depends upon two somewhat restrictive assumptions. The first of these is that an information shock changes an asset's expected end of period value and expected variance of return proportionately. This is shown to imply that optimistic investors will perceive any asset to be riskier than would a pessimistic investor. The demand curve for an optimist is thus steeper than the demand curve of a pessimist, which yields the result that an optimist will desire to transact in a greater number of shares than a pessimist. The second assumption Epps employs is that investors tend to favor information that reinforces their existing opinion of the value and risk of an asset. Hence,
investors with favorable expectations tend to ignore slightly negative information and investors with unfavorable expectations are inclined to disregard slightly positive information. The premise that otherwise rational investors will selectively disregard pertinent information casts doubt on the validity of Epps' analysis.

Karpoff (1986) constructs a theory of trading volume in which traders revise their demand prices in response to new information as well as investor-specific idiosyncrasies. His parsimonious representation of the manner in which traders revise their expectations and randomly encounter trading partners yields several implications that are consistent with the empirical evidence on volume. Among these are the existence of positive levels of trading volume in the absence of the release of new information. Karpoff's model also predicts that exchange volume will increase proportionately with the number of outstanding units of the asset, and decrease with a higher level of transactions costs.

The prediction from Karpoff's model of greatest relevance to this study is that trading volume will increase when the price expectation of a non-owner of the security exceeds that of an owner. An objection to Karpoff's analysis arises, however, because this result obtains due to the restriction that investors can own at most one unit of the asset. Thus, everyone who currently owns the asset can only be a seller, and all non-owners can only become buyers. Nonetheless, Karpoff's work provides interesting insights into the relationship between price changes and trading volume.

Other studies have derived an asymmetric volume response to positive and negative price changes by either excluding short sales from the analysis or incorporating the higher costs of selling short into the model. Copeland's (1976) sequential information arrival model precludes traders from short selling and predicts that when traders disagree regarding the significance of new information, the trading volume generated by an optimist will exceed that of a pessimist.
Jennings, Starks and Fellingham (1981) extend Copeland's model to allow for short sales by pessimistic investors. Their analysis also includes costly margin requirements that restrict some investors' decisions to sell short. They demonstrate that for a given change in price, an investor with a short position in the risky asset will alter his portfolio holdings less than an individual with a long position. Their model predicts that volume on a price increase will exceed volume on a price decrease.

Karpoff (1988) builds on the insight that institutional rules that raise the cost of selling short might account for the positive correlation between trading volume and price changes. He demonstrates that the covariance of price change and trading volume will be positive when the variance of shifts in transaction demand is greater than the variance of shifts in transaction supply. Karpoff asserts that this condition should be satisfied whenever the cost of selling short exceeds the cost of establishing a long position.

Ying (1966) provides some of the earliest empirical evidence on stock price movements and trading volume. His data consist of six years of daily observations on the S&P 500 composite index and trading volume on the NYSE. Ying concludes that light volume is usually accompanied by a fall in price, and heavy volume is usually accompanied by a rise in price. He also finds evidence supporting the positive correlation between volume and price variability.

In subsequent empirical work related to the relationship between price changes and trading volume, Rogalski (1978) conducts an investigation into the question of whether security prices and volume are causally related in the sense of Granger (1969) and Sims (1972). He examines monthly returns and volume for a sample of ten stocks, and also looks at a price-volume series for the warrants of these firms. Rogalski first "prewhitens" each price and volume series, which entails removing the component in each series which can be predicted from its own past history. He then examines the cross correlations for
the filtered series and finds in all cases that only contemporaneous price changes are correlated with volume. Because none of the lead or lagged correlations are significant, Rogalski cannot determine if price causes volume, volume causes price, or price and volume are simultaneously causing each other.

Smirlock and Starks (1988) view Granger causality tests as a natural vehicle for providing insight into how information arrives in securities markets. If all investors were to receive information simultaneously, then past price changes should not be useful in forecasting volume. If, on the other hand, investors receive information sequentially and trade following each information arrival, then past price changes should be related to contemporaneous volume. To distinguish between these two hypotheses, the authors examine forty-nine days of price and volume data for the common stock of a sample of 300 large firms. They find evidence of causality running from the absolute value of the price change to volume as well as from volume to the absolute value of the price change, but only for a relatively small percentage of the firms in their sample. They interpret their results as providing weak support for both hypotheses. In an earlier study that uses transactions data, Smirlock and Starks (1985) find that volume is higher on price upticks than on price downticks on a day when there is a known information arrival. When there is no known information arrival, however, they conclude that volume can sometimes be higher on price downticks.

Antoniewicz (1992) confirms the findings of previous studies by documenting a positive association between contemporaneous returns and volume. She also finds a positive relationship between lagged volume and current returns using both causality tests and bivariate vector autoregression. Her findings that large volume precedes large changes in price contradicts the conclusions of Gallant, Rossi, and Tauchen (1992), however, who document that large volumes tend to follow large price movements.
Lakonishok and Smidt (1986) hypothesize that if tax-loss selling influences trading volume, the end of the year would be characterized by a negative correlation between volume and past price changes. The authors examine monthly returns and volume on the NYSE and AMEX from 1971-1982. They find that the volume of a portfolio of "loser" stocks is higher than normal in December. The tendency of winners to have higher abnormal volume than losers for every month of the year, including December, leads them to conclude that tax considerations are probably not a major factor in the determination of trading volume, however.

Ferris, Haugen and Makhija (1988) introduce a new methodology designed to provide a direct test of the tax-loss selling hypothesis vs. the "disposition effect": the tendency of investors to hold losers too long and avoid realizing losses (which implies a positive correlation between price changes and volume). Their sample consists of the thirty smallest stocks that were listed on the CRSP tapes from December, 1981 to January, 1985. After removing the effect of trading volume for the overall stock market, they define eight ranges of past stock prices for each firm and group each firm's measure of abnormal volume into the range that the firm's stock price was in on the day corresponding to that level of volume. Their finding that a higher level of abnormal volume is associated with higher stock price ranges, even during December, is interpreted as clear evidence in favor of the disposition hypothesis. Their method for removing the effect of market volume is suspect, however, due to the size of the firms chosen for their sample. The thirty smallest stocks on the CRSP tapes are probably subject to a nonsynchronous trading problem. Thus, merely removing the effect of contemporaneous stock market volume is likely to be an insufficient adjustment.
1.3. The Determinants of the Differential Volume Effect

In the following section, the factors that are most likely responsible for the positive correlation between stock prices and trading volume are identified and discussed. Some of these have been previously mentioned in the literature, although not always in relation to the same issue with which this study is concerned. Some of the contributing factors are discerned from existing empirical evidence, while others have their roots in behavioral psychology, which offers alternative explanations for the way rational agents make decisions under uncertainty. Other probable factors arise from the institutional design of financial markets, and the behavioral constraints that arise when investors perceive certain trading strategies to be more risky than others. The key points that emerge from the discussion in Sections 1.3.A.-1.3.D. are formalized into a model of stock price changes and trading volume, which is presented in Section 1.4. For definitional convenience, the hypothesis that trading volume is higher during periods of rising prices is hereafter referred to as the differential volume effect.

A. The Constraints Facing Short Sellers

Jennings, Starks and Fellingham (1981) and Karpoff (1988) both observe that selling short entails greater transactions costs than going long, and that this is likely to contribute to the differential volume effect in equity markets. Optimistic investors who desire to speculate on individual securities are more likely to implement their strategies in equity markets than are pessimistic investors who face the higher costs of selling short. Traders who desire to take negative positions will place orders where the costs of speculation are lower, such as the options market. The thin trading in equity markets
during periods of predominantly negative sentiment is likely due in part to the increased use of derivative securities by investors desiring to profit from their expectations of negative future price changes.

In addition to the higher costs of downside speculation in equity markets, there are behavioral and institutional constraints that preclude certain groups of investors from selling short. If these investors have a significant impact on the price formation process in capital markets, then their reluctance to sell short could be another factor contributing to the differential volume effect. Assume for the moment that traders have no restrictions on their access to investment capital. This would theoretically allow them to purchase an unlimited amount of shares when their expectations are strongly optimistic. The quantity of shares they can sell when their expectations are negative, however, will be limited to the number of shares they previously held, if aversion to risk constrains them from selling short. If a substantial number of investors are bound by the various constraints against short selling, this would create a measurable asymmetry between the quantity of shares that investors desire to hold during periods of favorable sentiment and the number of shares that would be offered for sale when pessimistic opinion prevails in the market.

Behaviorally, many investors are constrained against selling short because they perceive a short position to be inherently more risky than a long position. Strictly speaking, this is correct, since a buyer of stock can at most lose his entire investment, whereas a short seller who does not cover his position with a stop-loss order could lose his initial investment many times over. The perception that short selling involves excessive risk is likely to be enhanced by the various complexities involved in taking a short position relative to simply buying or selling stock. An example of one such complexity is the previously mentioned need to cover one's position with a stop-loss order. This provides protection against the possibility that the shares of stock sold short increase dramatically in
value during a time when the investor is either distracted from following the market closely, or unable to communicate with his stockbroker. By way of contrast, a market or limit order to buy or sell stock is not usually supplemented with similar instructions. The fact that the shares sold short are actually borrowed from another investor is an additional facet of short selling that may appear prohibitively confusing or complicated. Additionally, the responsibility for paying dividends to the investor whose shares were borrowed represents yet another complication that might discourage many investors from including short sales in their overall portfolio strategies.

The constraint against short selling stemming from risk aversion also applies to professional money managers, who face what might be termed "moral" constraints that prevent them from taking short positions (as well as numerous other strategies generally associated with excessive risk). The Chartered Financial Analyst (CFA) course of study, for example, places a strong emphasis on defining the professional and ethical responsibilities of the analyst to the client. This necessitates developing an understanding of the long-term goals of each individual client, and constructing a portfolio of securities that is commensurate with that client's profile. The CFA code of ethics states: "The financial analyst shall, when making an investment recommendation or taking an investment action for a specific portfolio or client, consider its appropriateness and suitability for such portfolio or client." For investors whose wealth is sufficient to attract the attention of top money managers, preservation of capital is often as important as the rate of capital appreciation. The best way to achieve this goal, of course, is by minimizing the client's exposure to excessive risks. It is doubtful, therefore, that many of these investors are routinely placed into short positions by their money managers.

Certain classes of investors are also precluded from short selling due to the nature of specific institutional constraints. There are over 2,500 mutual funds registered with the
SEC, the vast majority of which invest primarily in common stock. Establishing a mutual fund involves filing a prospectus with the SEC which details the primary objectives of the fund. Only a very small percentage of these are organized for the express purpose of capitalizing on pessimistic expectations through short sales. Another small percentage of funds (usually known as hedge funds) acknowledge that investments generally regarded as high risk, such as options and short sales, will constitute a considerable portion of the fund's position. By and large, most mutual funds invest in stocks merely by buying and selling, with hundreds of these devoted to simply mimicking the composition of some market index. The existence of these institutional constraints implies that there are hundreds of billions of dollars invested in stock mutual funds that are precluded from being involved in any short sales transactions. The combined effect of the various constraints prohibiting certain classes of investors from short selling are thus likely to be factors that contribute to the differential volume effect.

B. The Disposition Effect

The theory of choice under uncertainty developed by Kahneman and Tversky (1979), known as prospect theory, provides additional evidence that may help to explain the differential volume effect. Prospect theory can be viewed as an alternative to utility theory, which evolved from the logical analysis of decision-making under uncertainty, and provides a normative model of an idealized decision maker. Prospect theory, on the other hand, is a descriptive model of actual behavior. Kahneman and Tversky have shown that prospect theory can account for preferences that are considered anomalous under utility theory, yet systematically arise in both experimental and survey evidence.
The implication of prospect theory that may offer insights into the causes of the differential volume effect has been termed the "disposition effect" in a paper by Shefrin and Statman (1985). This is best described as the tendency for investors to sell assets with positive price changes too soon, and to hold assets with negative price changes longer than would be prescribed by a model of strictly rational choice.\(^6\) If investors display a greater preference for selling stocks with positive returns rather than those with negative returns, the differential volume effect may be partially caused by the market-wide manifestation of this behavior.

In prospect theory, decision makers begin with what Kahneman and Tversky refer to as the "editing phase." This entails framing a choice in terms of a potential gain or loss relative to a fixed reference point. In the second stage, known as the evaluation phase, decision makers employ an S-shaped valuation function, which is analogous to a utility function defined on the domain of both gains and losses. The distinguishing feature of the valuation function is that it is concave in the region of gains, but convex in the region of losses. Decision makers are thus risk averse in the domain of gains, but risk seeking in the domain of losses. It is this risk seeking behavior when confronted with losses that causes investors to hold onto their losing stocks longer than would be optimal under utility theory, and might therefore contribute to the low trading volume observed during periods of declining prices.

Thaler (1984) has constructed a framework known as mental accounting in which decision makers segregate different types of gambles into different accounts, and then apply prospect theoretic decision rules to each account. In Thaler's model decision makers tend to ignore any possible interaction between the accounts. For example, when

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a stock is purchased, an investor opens up a new mental account in the name of that stock. The natural reference point for framing future decisions regarding this stock is the original purchase price. A running score is then kept on this account indicating gains or losses relative to the reference point. The tendency of decision makers to seek pride and avoid regret (other features of prospect theory) account for their reluctance to sell shares of stock at a loss to obtain a capital loss for tax purposes, or just cut their losses in general. Decision makers display a compulsion to retain ownership of an asset until its value exceeds the original point of reference. Instead of taking their entire portfolio into consideration when making investment decisions, investors tend to think of each asset separately.

Practitioners have long maintained that one of the most difficult aspects of professional money management is convincing a client to take a loss. The following quotation from Grossi (1982) handbook for stockbrokers illustrates this point:

Many clients, however, will not sell anything at a loss. They don't want to give up the hope of making money on a particular investment, or perhaps they want to get even before they get out. The "getevenitis" disease has probably wrought more destruction on investment portfolios than anything else. Rather than recovering to an original entry price, many investments plunge sickeningly to even deeper losses. Investors are also reluctant to accept and realize losses because the very act of doing so proves that their first judgment was wrong . . .

The theoretical work of Shefrin and Statman (1985) and Thaler (1984), in conjunction with the anecdotal evidence provided by Gross (1982), provides support for the hypothesis that investors resist selling at loss, even when it may be optimal to do so. Additionally, Ferris, Haugen and Makhija (1988) find that for a sample of small firms,
trading volume is higher when the stock of these firms is trading at or near its highest price range. Taken together, the evidence implies that the expected volume of trade generated by investors with optimistic expectations may be greater than the volume generated by investors when pessimistic sentiment prevails in financial markets. The disposition effect is therefore likely to be another factor contributing to the differential volume effect.

C. Positive Feedback Trading Strategies

The prevalence of "positive feedback" trading strategies in securities markets is likely to magnify the causes of the differential volume effect discussed in sections 1.3.A. and 1.3.B. above. Positive feedback investors are those who buy securities when prices rise and sell when prices fall. There are many forms of investor behavior that constitute positive feedback trading. Stop-loss orders, where investors place orders to sell contingent on a price decline of a predetermined magnitude, are one type of positive feedback strategy. Investors who sell assets to meet margin calls when their equity position deteriorates due to a decline in the market price of the underlying asset are another example of positive feedback traders.

Perhaps the best-known example of positive feedback trading results from "extrapolative expectations," which is the tendency for investors to project current circumstances further into the future than is rational when forming expectations. This overweighting of recent events in the formation of expectations is another key characteristic of Kahneman and Tversky's prospect theoretic model of choice under uncertainty. Keynes (1936, page 148) also made note of the propensity of investors to place too much emphasis on the recent past:
It would be foolish, in forming our expectations, to attach great weight to matters which are very uncertain. It is reasonable, therefore, to be guided to a considerable degree by the facts about which we feel somewhat confident, even though they may be less decisively relevant to the issue than other facts about which our knowledge is vague and scanty. For this reason the facts of the existing situation enter, in a sense disproportionately, into the formation of our long-term expectations; our usual practice being to take the existing situation and to project it into the future, modified only to the extent that we have more or less definite reasons for expecting a change.

There is also considerable survey evidence regarding the tendency of investors to extrapolate expectations of current price changes into the future. Case and Shiller (1988) find that home buyers in cities where house prices have risen rapidly expect greater future price appreciation than buyers in cities where prices have been stagnant or have fallen. Additionally, Shiller (1988) surveys investors following the stock market crash of October, 1987. Among investors who were sellers of stock during and after the crash, the most frequently cited reason for selling was that the large decline in stock prices on that day made them fear even further declines.

The tendency of investors to extrapolate the present situation into the future may account for the popularity of the many technical analysis indicators that attempt to identify trends in securities prices by comparing a time series plot of a security's price against a plot of a moving average of its price. Price moving averages of various lag lengths are also compared against each other in an attempt to predict future price trends. Investors who make trading decisions based on the behavior of these indicators obviously believe that studying the recent past behavior of securities prices can yield information regarding

\[7\text{See Pring (1985) for a discussion of how technical analysts use price moving averages to identify trends in securities prices.}\]
the future performance of financial securities. For example, moving averages of certain lag lengths $L_1$ and $L_2$ are constructed, where $L_1 < L_2$. If the moving average of shorter length ($L_1$) rises above the longer moving average ($L_2$), this is interpreted as a signal to buy the security. That is, a buy signal is triggered when

$$\frac{1}{L_1} \sum_{i=1}^{L_1} P_{t-i} > \frac{1}{L_2} \sum_{j=1}^{L_2} P_{t-j}.$$

Conversely, a sell signal is issued when the short moving average falls below the long moving average. In the special case of $L_1 = 1$, the short moving average is just the time series of the price of the security.

Trading volume is frequently used along with the price moving average rule when deciding whether to buy or sell securities. An example of the manner in which volume might be used would be to buy when:

$$\frac{1}{L_1} \sum_{i=1}^{L_1} P_{t-i} > \frac{1}{L_2} \sum_{j=1}^{L_2} P_{t-j} \text{ and } \frac{1}{L_3} \sum_{k=1}^{L_3} V_{t-k} > \frac{1}{L_4} \sum_{l=1}^{L_4} V_{t-l}$$

where the lag length $L_3 < L_4$. As was the case with the price moving average rule, $L_3 = 1$ means that the short moving average is just the time series of volume itself. Among practitioners of technical analysis, some of the more commonly used lag lengths with daily data are $L_1 = 1$, $L_2 = 150$, $L_3 = 1$, and $L_4 = 10$.\(^8\)

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\(^8\)See Weinstein (1988) for a more detailed discussion of the use of price and volume moving averages.
The classical efficient markets view regarding the practice of technical analysis is that investors who base strategies on past price changes are really just trading on "noise," because last period's information is already fully incorporated into today's prices. The activities of noise traders in the marketplace merely incorporates their noisy expectations into asset prices, with the end result being that prices can temporarily deviate from fundamental value. Friedman (1953) and Fama (1965) both argue against the long-term survival of such traders in the market. They point out that in the course of trading, noise traders will encounter rational arbitrageurs who trade against them and drive prices back towards fundamentals. Investors with consistently mistaken expectations will lose money to rational speculators and eventually be driven from the market. Therefore, noise traders cannot affect prices to any great extent, and even if they can, they will not do so for long.

The observations of Friedman and Fama must be interpreted, at least in part, as a rebuttal to one of the most well-known investment analogies ever offered. Keynes (1936, page 157) argues that professional investing is similar to picking out the "six prettiest faces from a hundred photographs," which quickly degenerates into nothing more than "anticipating what average opinion expects the average opinion to be." Keynes goes on to express his doubts regarding the predominance of rational expectations in financial markets:

Investment based on genuine long-term expectation is so difficult today as to be scarcely practicable. He who attempts it must surely lead much more laborious days and run greater risks than he who tries to guess better than the crowd how the crowd will behave; and, given equal intelligence, he may make more disastrous mistakes. There is no clear evidence from experience that the investment policy which is socially advantageous coincides with that which is most profitable.
Recently, the view that noise traders are not surviving and that rational speculation always serves to stabilize prices has been questioned in a series of papers by Delong, Shleifer, Summers and Waldmann (1990a, 1990b, 1991). These authors assert that there are factors that limit the extent to which arbitrage can eliminate the misperceptions of noise traders. In particular, arbitrageurs are likely to be risk averse, and to have relatively short investment horizons. The presence of noise traders introduces an additional risk into the market, however, above and beyond the fundamental risk normally associated with holding risky assets. This is the risk that their mistaken beliefs will not revert to the mean for an appreciable length of time, and in the interim may become even more extreme. If technical analysis indicators are nothing more than noise, but the erroneous beliefs they engender have the capacity to move prices away from fundamental value for an extended period of time, then arbitrageurs with short horizons may not always be willing to step in and take an offsetting position. The analysis of Delong, et. al. also points out that while arbitrageurs may be reluctant to bear the risk created by the presence of noise traders, the noise traders themselves are unknowingly exposed to it. This increased exposure to risk, combined with the reluctance of arbitrageurs to trade against them, is shown to imply that noise traders may not only be surviving in financial markets, but they may even earn higher returns than investors who trade solely on fundamental information.

Other authors have advanced the view that some of the strategies employed by technical analysts may lead to their survival in financial markets. Treynor and Ferguson (1985) argue that knowledge of past price patterns alone are not sufficient to earn excess returns. This knowledge may be helpful in exploiting certain nonprice information, however. If an investor who receives information is skilled at assessing: 1) the value of the information in terms of its impact on the price of the stock, 2) the process by which information is transmitted to the market, 3) the probability that the market will receive (or
has received) the information, and 4) a portfolio strategy which permits capitalizing on the information, Treynor and Ferguson assert that knowledge of past price patterns is useful.

The conventional view that the use of moving averages to identify trends in securities prices constitutes nothing more than noise trading was fostered by the belief that stock prices were adequately described by a random walk process, and that future returns to stocks were completely unpredictable. Recent empirical work by DeBondt and Thaler (1985, 1987), Poterba and Summers (1987), Lo and MacKinlay (1988, 1990), and Fama and French (1988) document that time series of stock prices are characterized by substantial reversion to the mean over long time horizons. These studies demonstrate that stock returns contain a predictable component that is economically significant. It is interesting to note that the manner in which technical analysts use price moving averages to identify turning points in stock price trends is consistent with the empirical evidence on mean reversion. The securities with returns that have substantially underperformed the market for an appreciable period of time do tend to outperform the market in subsequent periods, but only at long time horizons. Additionally, securities with returns that have exceeded the market averages for a substantial period of time have a greater than fifty percent chance of underperforming in the next long-term period. Recall that one of the popular technical analysis rules calls for buying (selling) stocks when their price was above (below) their 150-day moving average. Thus, if stock returns only revert to (and subsequently under- or over-shoot) their mean in the long run, the use of short-term price moving averages could be used to identify stocks whose returns were likely to stay above or below their long-term averages in the near term. One could argue, therefore, that the

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9DeBondt and Thaler (1985) provide evidence that it takes thirty-six months on average for stock returns to revert to their long-term mean values. Fama and French (1988a) demonstrate that predictable price variation due to mean reversion accounts for 25-40% of the variation in stock returns over 3-5 year time horizons.
survival of technical analysts in financial markets may be due in part to their exploitation of the recently discovered phenomenon of mean reversion (which continues to confound strict proponents of market efficiency). In a recent paper Jegadeesh and Titman (1993) find that "relative strength" investing strategies, which call for buying winners and selling losers, yield significant excess returns for 3- to 12-month holding periods. There exist compelling theoretical and empirical reasons, therefore, to accept the view that positive feedback traders may not only be surviving in financial markets, but that they pose considerable competition for investors who trade solely on fundamental information.

The presence of positive feedback traders can be shown to magnify the differential volume effect, provided some of the previously discussed causes of the effect are valid. Assume for moment that the disposition effect provides an adequate description of the way investors behave when faced with the decision to sell stock. Recall that the disposition effect implies that investors display a greater preference for selling stocks with positive returns than negative returns. A positive price change last period causes positive feedback traders to revise their demand price of the asset even higher, since they interpret last period's price change as being relevant in determining this period's price. The disposition effect predicts that previous owners of the asset are more willing to sell now that the asset has increased in value. The interaction of the increase in demand to hold shares by positive feedback traders and the increased willingness to sell predicted by the disposition effect leads to continued positive price changes on higher volume. This serves to magnify the positive correlation between price changes and trading volume predicted by the disposition effect alone.

This argument is easily extended to include the constraints against short selling described in section 1.3.A. above. If last period's price change was negative, positive feedback traders interpret that as unfavorable information regarding the expected change
in price in the current period, and revise their demand price even lower. Current owners of the asset who will not sell short are constrained to only sell their existing inventory of shares. Positive feedback traders who are non-owners of the security and will not sell short would have no means of capitalizing on their negative expectations in the equity market this period. Volume is therefore predicted to be lower during periods of declining prices in the presence of positive feedback traders. If investors use past price patterns as information on which to base their trading decisions this period, then these positive feedback strategies are likely to interact with other causes of the differential volume effect and lead to an enhancement of the effect.

D. Are Stock Prices and Trading Volume Determined by a Set of Common Factors?

Recall that the mixture of distributions hypothesis (MDH) proposes that price variability and trading volume are positively related because they are each correlated with a common underlying variable. As the arrival rate of information to the market increases, the MDH predicts that both volume and the variance of price changes increase. Whether the information itself is likely to be interpreted as favorable or unfavorable for the underlying asset is irrelevant. The arrival of information is an unobservable variable, however, and tests of the MDH frequently employ trading volume as a proxy for the rate of information arrival. Until a plausible measure of the quantity of information can be constructed, it is doubtful that the MDH can be tested definitively. This section explores the possibility that the positive relationship between price changes and volume may also be due to each being correlated with a common underlying variable.
The differential volume hypothesis asserts that trading volume during periods of rising prices is likely to exceed volume during periods when prices are generally declining. Sections 1.3.A.-1.3.C. above develop several plausible explanations for this phenomenon. If markets are efficient, and the price of any asset is a reasonable approximation of its "true" value given the information set currently available, then only new, unanticipated information should cause investors to revise their demand prices, and thus their quantities demanded, of the asset. When new information is favorable, the price of the asset should rise as investors bid up its price as they attempt to acquire more of the asset. Conversely, unfavorable information is likely to result in a fall in the price of the asset, as investors revise their demand prices downward and attempt to sell the overvalued asset. For any market that is efficient in the way information becomes impounded into the prices of assets, the differential volume hypothesis would seem to imply that price changes and trading volume are each positively correlated with the flow of information to the market, and the implications for current and future asset returns that are conveyed when unanticipated information arrives in the market.

For the case of individual assets, any empirical test to determine whether volume is actually correlated with the flow of information would seem to encounter a problem similar to the one that confronts tests of the MDH. Exactly how to measure information for an individual asset is not immediately clear. If we consider the relationship between prices and volume for the overall market of stocks, however, it becomes easier to define a measure of relevant information. Once we identify the type of information that is likely to affect a diversified portfolio of stocks, then we can design a test of the extent to which stock prices and trading volume respond to the information. Arriving at a definition of relevant information for the overall stock market requires a brief review of some well-established theory, as well as a summary of recent empirical evidence.
The existing theory regarding the effect of diversification on the variance of returns to a portfolio of assets and the accompanying literature on asset pricing implies that the aggregate stock market should only respond to changes in information that pertain to overall market conditions that affect security returns but cannot be avoided via diversification.\textsuperscript{10} The indices usually employed to track the changes in wealth that result from changes in stock prices are themselves value-weighted portfolios of securities, such as the S&P 500 or the NYSE index. For such well-diversified portfolios, the random effects resulting from firm-specific information should tend to cancel each other out in the long run. Thus, theory would suggest that the long-term performance of the major stock market indices should only reflect the influences of the undiversifiable factors that determine the performance of financial securities. In order to be consistent with terminology used previously in the literature, this paper will refer to such information as \textit{systematic} information.

The empirical observation that the prices of financial assets tend to move together through time further suggests the existence of some common underlying influences. The identity of the systematic factors that are related to the performance of the U.S. stock market has been thoroughly researched in the recent academic literature. The results of these studies support the view that the prices of financial assets are related to the current and future state of the macroeconomy.

Chen, Roll, and Ross (1986) propose a set of macroeconomic state variables that are likely to be related to the return to U.S. stocks. These variables are the monthly growth rate of industrial production, unanticipated inflation, the yield spread, and the slope of the term structure. The authors regress the monthly returns of twenty size-based

\textsuperscript{10}See Markowitz (1959), Sharpe (1964), Lintner (1965), Mossin (1976) and Ross (1976).
stock portfolios on monthly values of the macroeconomic variables, and find each to be significantly related to the return to each portfolio. When the NYSE index is included in the regressions along with the various macroeconomic factors, its effect in explaining stock returns is insignificant. The authors therefore conclude that a multi-factor macroeconomic model does a better job of explaining equity returns than a single-factor CAPM.

While Chen, Roll and Ross address the relationship between changes in relative prices and macroeconomic factors, Keim and Stambaugh (1986) examine the level of stock prices and the levels of a different set of variables designed to capture macroeconomic conditions. Their set of predetermined variables include the yield spread between long-term low-grade corporate debt and short-term Treasury bills, a detrended price series of the S&P 500 Composite Index, and a stock index designed to capture the extra sensitivity of small firms to changes in expected future risk premiums. Keim and Stambaugh find that all three variables are significant in predicting future stock returns.

Fama and French (1989) test the hypothesis that expected returns on stocks and bonds vary inversely with the business cycle. They find that the dividend yield on the NYSE and the default spread on corporate bonds capture similar variation in expected stock and bond returns, and that these variables appear to be related to economic conditions that span several business cycles. The slope of the term structure, however, appears to capture variation in expected returns that is related to short-term business cycles. Their results support the hypothesis that expected returns on stocks and bonds are lower when economic conditions are strong, and higher when conditions are weak. Thus, future returns to financial securities are shown to be partially forecastable from the levels of current macroeconomic state variables.
Fama (1990) identifies three factors that are likely to account for the time-varying expected returns documented in previous studies. These are unanticipated shocks to expected cash flows, the predictable variation in discount rates, and shocks to discount rates. Fama argues that future growth rates of industrial production should be highly correlated with future cash flows to businesses, and that if the stock market is efficient, and thus forward-looking, contemporaneous stock returns should be related to the future growth of industrial production. Fama finds that the change in industrial production for a given month is related to up to ten lags of monthly returns. He also shows that regressions of longer-horizon returns on future production growth rates have higher explanatory power than regressions using short-term returns. Fama finds that the term spread, default spread, and dividend yield on the stock market can also be used to predict returns to the stock market. He maintains that these variables are likely to capture the variation (both anticipated and unanticipated) in discount factors.

Balvers, Cosimano and McDonald (1990) assert that the intertemporal relationship between stock returns and industrial production is also consistent with multiperiod asset pricing models such as Breeden's (1979) consumption CAPM. The time-variation and predictability of expected returns on stocks may be partially explained by the intertemporal consumption desires of investors who attempt to "smooth" consumption into future periods. Since industrial production is serially correlated, it is somewhat predictable. Investors associate higher future growth of industrial production with greater consumption opportunities, and implicitly adjust their required rate of return for financial assets as they attempt to maximize their utility by smoothing their lifetime consumption patterns. When investors anticipate lower output in the next period they will attempt to transfer wealth into the future by saving. This increased demand for financial securities bids up the prices of assets, which implies that investors will accept a lower required rate
of return. The predictability of output and the linkage between output and returns implies that returns will have a predictable component. The empirical results reported in Balvers, et. al. lend support to the hypothesis that stock returns are partially forecastable.

Chen (1991) takes a step toward integrating all of the work discussed thus far. First, he confirms that the default spread, the term spread, the one-month T-bill rate, the lagged growth rate of industrial production and the dividend-price ratio are all important determinants of future returns to the stock market. He then documents that these same variables are related to the recent and future growth of GNP as well. Chen interprets this as evidence that the expected excess market return is negatively related to the recent growth of GNP and positively related to its future growth. His work further reinforces the notion that returns in an efficient market may be predictable based on state variable forecasts of the future health of the macroeconomy.

The theoretical considerations that motivate the differential volume hypothesis, in conjunction with the strong empirical evidence relating the macroeconomic information set to the behavior of stock prices, implies that trading volume should also be positively correlated with certain state variables. Since trading is the mechanism by which new information becomes impounded into prices, the evidence would seem to suggest that prices and volume are jointly determined based on the information content of the macroeconomic state variables, as well as any other information investors may consider relevant to the return of a diversified portfolio of assets. This raises the interesting possibility that including volume into an analysis of stock prices and instruments for the macroeconomic state variables could improve upon forecasts of future stock returns that are based on state variables alone. An empirical exploration into the implications of this issue regarding the predictability of stock returns is presented beginning in Part 3 of this dissertation.
The conclusions of this section, then, are that rational traders operating in informationally efficient markets are likely to monitor the current and future state of the macroeconomy, and that they will revise their expectations of the prospects for equity securities as far into the future as they can comfortably forecast. The prices of stocks and the accompanying volume of trade are predicted to be increasing in the quality of the macroeconomic signal. The discussion presented in Sections 1.3.A - 1.3.C. indicate that in addition to expectations regarding future macroeconomic conditions, the relevant information set may also contain a backward-looking component due to the presence of positive feedback traders and other factors likely to contribute to the differential volume effect.
1.4. A Model of Stock Prices and Trading Volume

This section presents a simple analytical example which demonstrates that stock prices and trading volume can each be expressed as a function of the information signals received by traders in capital markets. Part 2 uses this result to show that if stock prices and trading volume are both related to a set of common factors (i.e., the information set), they may share a common stochastic trend. One way to test the hypothesis that the joint determination of stock prices and volume is driven by the same set of forces, therefore, is to test each series for the presence of a common stochastic trend.

The example analyzes the interaction of two groups of traders over two time periods. The asset traded can be thought of as a diversified portfolio of equity securities (like an index fund based on the S&P 500 or the NYSE index). Agents who revise their demand to hold shares of the asset based on the information available in securities markets are referred to as information traders. They observe a signal \( \psi \) regarding the expected return to holding shares in the equity fund, and revise their demand prices based on this signal. Traders who choose not to become informed, but bring orders to the market due to life-cycle liquidity needs (or other uninformed motivations, such as noise trading), are referred to as liquidity traders. There are a total of \( i \) information traders and \( l \) liquidity traders. Following the arrival of information in the marketplace, expressions for the equilibrium price of the asset and the level of trading volume will be derived. The time series implications for stock prices and trading volume based on these expressions will be analyzed beginning in Part 2.

The assumptions underlying the analysis are those typically employed in models of this type. The available supply of shares of the equity fund are assumed to be fixed and infinitely divisible. The determination of the equilibrium number of shares in existence is
exogenous to the model. It is assumed that the information signal is revealed simultaneously and costlessly to all agents, and potential differences in information traders' abilities to interpret the signal are not considered. There are no taxes or transactions costs. The number of liquidity traders is assumed to be sufficiently large in relation to the number of information traders so that the demand price revisions of these traders always results in the market clearing: i.e., information traders can buy up all the shares they demand or sell all the shares they desire to supply. Each trader is assumed to have a linear, downward sloping demand curve to hold shares of the equity fund. The slope and intercept term of both groups of traders' demand curves are assumed to be equal for simplicity.

In time period one, last period's information is fully incorporated in the price of the equity fund, but next period's information has yet to be revealed. Thus, liquidity and information traders have the same demand to hold shares:

\[ D_{1}^{L,J} = \alpha - \beta P, \beta > 0. \] (1.1)

In time period two, information traders observe a signal \( \psi \) regarding the expected return to holding shares in the equity fund, and appropriately revise their demand prices. This corresponds to a shift in their demand curves by the amount of the signal:

\[ D_{2}^{I} = \alpha - \beta P + \psi. \] (1.2)

Liquidity traders demand to hold shares remains unchanged, however. An expression for the total demand to hold shares by any one group of traders can be obtained by summing
across the demands of the individual traders. The total demand of liquidity and information traders in time period two can be expressed as:

\[ \sum_{l=1}^{L} D_{2}^{L} = ID_{2}^{L}, \text{and} \sum_{i=1}^{I} D_{2}^{I} = iD_{2}^{I}. \] (1.3)

Equilibrium requires that the total demand to hold shares equals the total supply of shares:

\[ ID_{2}^{I} + iD_{2}^{I} = S. \] (1.4)

Substituting in from Equations (1.1) and (1.2) and rearranging Equation (1.4) gives an expression for the equilibrium price of the asset in time period two:

\[ P_{2}^{e} = \frac{\alpha}{\beta} + \psi \left[ \frac{i}{\beta(1+i)} \right]. \] (1.5)

Notice that the expression for the price of the asset is linear in the information parameter, \( \psi \). Next an expression for trading volume must be derived. In this example, with the number of shares outstanding assumed to be fixed, volume can be expressed as the change in holdings by either liquidity or information traders. Equivalently, this is the number of shares transferred from one group of traders to the other. The total holdings of liquidity traders in period one can be expressed as:

\[ H_{1}^{L} = l(\alpha - \beta P) = l \left[ \frac{S}{1+i} \right]. \] (1.6)
An expression for the total holdings of liquidity traders in period two is given by:

$$H_2^L = I(\alpha - \beta P) = I \left[ \frac{S - \psi l}{l + i} \right].$$  \hfill (1.7)

Trading volume can then be expressed as the change in holdings by liquidity traders, which is obtained by subtracting Equation (1.6) from Equation (1.7):

$$V = \Delta H^L = |H_2^L - H_1^L| = |\psi| \left[ \frac{ll}{l + i} \right].$$ \hfill (1.8)

Equations (1.5) and (1.8) demonstrate that, in a simple supply and demand framework, asset prices and trading volume are both functions of the information signals received by traders in efficient capital markets. While asset prices are linearly related to the information parameter, the expression for trading volume is found to be nonlinear in information. Recall that the discussion on the differential volume effect presented above identifies several factors that are likely to contribute to the empirical observation that trading volume on positive price changes exceeds volume when price changes are negative. The finding that volume is nonlinear in information is therefore consistent with that discussion.

This concludes Part 1 of this dissertation. Part 2 presents a discussion of common stochastic trends, and shows that the results of this section may suggest the presence of such a trend in stock prices and trading volume. Although the analysis suggests that only a time series of prices should be linear in information, as a first approximation volume is
treated as if it were also linearly related to $\psi$. Part 2 tests the hypothesis that stock prices and trading volume are related to a set of common factors by testing each series for a common stochastic trend (cointegration). Stock prices and trading volume are then modeled using an error-correction model (ECM), which is the theoretically correct method for modeling cointegrated variables.\textsuperscript{11} Part 3 extends the empirical evidence from Part 2 by constructing out-of-sample forecasts of monthly returns based on the ECM developed in Part 2. These forecasts are compared with forecasts from other methods under a variety of conditions.

\textsuperscript{11} See Engle and Granger (1987).
PART 2:

THE TIME SERIES BEHAVIOR OF STOCK PRICES AND TRADING VOLUME: COINTEGRATION AND ERROR-CORRECTION
2.1 Introduction

One of the many persistent puzzles that remains to be solved in financial economics is the role of trading volume in the determination of asset prices. While considerable attention has been paid to theories of asset prices, our knowledge of trading volume remains surprisingly limited. Much has also been written on the related notion of market efficiency, which is concerned with the extent to which the relevant information set is reflected in asset prices. Developing a better understanding of trading volume should provide insight into empirical tests of asset pricing models as well as the information content of asset prices, because trade between investors is likely to affect the manner in which information becomes impounded into the prices of financial securities.¹ This paper develops and tests the hypothesis that stock prices and trading volume are influenced by a common set of fundamental factors. The implications of this hypothesis for modeling the time series behavior of stock prices and trading volume are also explored.

The potential importance of incorporating trading volume into theoretical and empirical studies of asset pricing is highlighted by the following quote from Ross (1987):

"...There is no serious research as yet on volume data. This is in large part because we have no serious theories that purport to explain the volume of trade... If I had to point to a single priority of business for intertemporal pricing theory, it would be the construction of such a theory..."

¹ See Schwartz (1988) for a discussion of how the prices established in equity markets and the number of shares traded generally differs from the desired theoretical values that would be attained in a frictionless market.
Subsequent to Ross' observation, several new theories of volume have emerged. None of these enjoys the widespread acceptance afforded to the more established theories of asset prices and their information content, however. A possible reason for their lack of acceptance is that the theories of trading volume have failed to yield a spectrum of testable implications as rich as those provided by the literature on asset pricing and market efficiency.

The lack of a comprehensive theory of trading volume does not mean that its importance has been overlooked in the academic literature, however. It has long been thought that trading volume is associated with the arrival of new information. Some empirical studies have recently incorporated an analysis of trading volume in an attempt to assess the information content of investor behavior and corporate announcements. Additionally, a positive correlation between price variability and trading volume has been documented empirically in the literature. Ying (1966), Crouch (1970), Morgan (1976), Westerfield (1977), and Gallant, Rossi, and Tauchen (1992) all find that price variability and trading volume are positively correlated in equity markets. The positive relationship between price variability and volume is thought to derive from each being correlated with the arrival rate of new information. This contention, known as the mixture of distributions hypothesis (MDH), is supported by the findings of Clark (1973), Epps and Epps (1976), and Tauchen and Pitts (1983). One problem with empirical tests of the MDH is that the arrival rate of information is difficult to measure, so trading volume is typically used as a proxy for information arrival.

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2 Among these are Karpoff (1986), Admati and Pfleiderer (1988), and Holthausen and Verrechia (1990).

3 Beaver (1968) was one of the first to recognize the link between information and volume.

4 See Lakonishok and Smidt (1986), Richardson, Sefcik and Thompson (1986) and Ferris, Haugen and Makhija (1988) for some examples.
The positive correlation between stock prices and trading volume has also been well documented in the literature. Ying (1966), Lakonishok and Smidt (1986), Smirlock and Starks (1985, 1988), Ferris, Haugen and Makhija (1988), and Antoniewicz (1992) all provide evidence that volume tends to be higher when stock prices are increasing rather than decreasing. Recent theoretical evidence indicates that the positive relationship between prices and volume may be due to their common correlation with the flow of information to the market. Huffman (1992) conjectures that since prices and volume are generated simultaneously, they may be determined by the same set of underlying forces. He develops a dynamic model where agents with access to different information sets use the equilibrium price of capital to forecast the return to holding capital. Huffman's model shows that both asset prices and trading volume can be highly correlated with a measure of the information content of prices.

For the case of individual assets, any empirical test to determine whether price and volume are actually correlated with information would seem to encounter a problem similar to the one that confronts tests of the MDH. Exactly how to measure information for an individual asset is not immediately clear. Arriving at a definition of information for a portfolio of stocks is somewhat easier, however. Existing theories of asset pricing assert that the long-run return to a diversified portfolio of stocks should only reflect the influences of an unspecified number of undiversifiable factors that collectively comprise "market risk." While the number of factors and their exact identity remains an empirical question, there exists a substantial literature that supports the hypothesis that the expected returns of financial assets are related to the current and future state of the macroeconomy. If these macroeconomic factors constitute the relevant information set

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regarding the expected returns (and therefore prices) of common stocks, then it is plausible to conjecture that they have an effect on the volume of trade as well, since prices and the volume of trade are simultaneously determined in capital markets.

This paper investigates the hypothesis that stock prices and trading volume are determined by a set of common underlying factors. If these factors exhibit a stochastic trend, then this trend should be common to both price and volume. In the terminology of the seminal paper by Engle and Granger (1987), stock prices and trading volume should be cointegrated. A value-weighted index of stock prices is found to be cointegrated with trading volume using data from 1962-1986, which supports the hypothesis that stock prices and volume are jointly determined by a set of common factors. The theoretically correct method for modeling cointegrated variables, known as an error-correction model (ECM), is fit to a time series of stock prices and trading volume using daily, weekly, monthly and quarterly data. An index of the total dividends-per-share paid out to the S&P 500 over the past twelve months is then included into the ECM as an instrument for the information set. This alternative method for modeling the time series behavior of stock prices produces a level of explanatory power similar to other studies which regress monthly stock returns on a set of predetermined variables. Additionally, the ECM of stock returns is found to be well-specified based on other statistical criteria.

The plan for the rest of this paper is as follows. Section 2 discusses the concept of common stochastic trends in financial and economic time series, and shows that the hypothesis of a set of common determining factors in stock prices and trading volume is consistent with Stock and Watson's (1988) "common trends" representation of cointegration. Section 3 presents tests for unit roots and cointegration in a time series of stock prices and trading volume. The importance of cointegration for the modeling of financial time series is discussed in Section 4, which models stock prices and trading
volume using an error-correction model. Section 5 introduces the dividend index as an instrument for the information set hypothesized to be a common determining factor of stock prices and trading volume. Section 6 compares the results of this study to other studies which run predictive-type regressions of monthly stock returns on a set of predetermined variables. Section 7 presents the conclusions of this study.
2.2. Common Stochastic Trends

Many financial time series are known to exhibit stochastic trends. Among these are stock prices, stock price indices, foreign exchange rates, and futures prices. A variable \( y_t \) is said to have a stochastic trend when it must be differenced to induce stationarity, or more formally, if its first difference, \( y_t - y_{t-1} \), has a stationary invertible autoregressive moving average (ARMA) representation plus a deterministic component. Equivalently, if \( y_t \) has a stochastic trend it is said to have a "unit root", or to be integrated of order one (\( y_t \sim I(1) \)). If no differencing is required to induce stationarity, then \( y_t \) is said to be integrated of order zero. Recent research in financial economics has focused on the special case when two or more variables share the same stochastic trend, known as cointegration.\(^6\)

Granger (1986) offers the following explanation of cointegration:

At the least sophisticated level of economic theory lies the belief that certain pairs of economic variables should not diverge from each other by too great an extent, at least in the long run. Thus, such variables may drift apart in the short run according to seasonal factors, but if they continue to be too far apart in the long run, then economic forces, such as a market mechanism or government intervention, will begin to bring them together again.

Engle and Granger (1987) provide the formal definition of cointegration:

\(^6\) Among the financial time series that have been found to be cointegrated are: dividends and stock prices (Campbell and Shiller, 1987), stock prices within the same industry (Cerchi and Havenner, 1988), exchange rates (Baillie and Bollerslev, 1989), and spot and futures prices in foreign exchange markets (Kroner and Sultan, 1991).
DEFINITION. The $n \times 1$ vector of random variables $Y_t$ is said to be cointegrated if:

a) each variable in $Y_t$ has a stochastic trend, and

b) there exists at least one linear combination of $Y_t$ which has no stochastic trend (e.g., $\alpha' Y_t$, where $\alpha'$ is an $n \times 1$ vector).

When the stationary linear combination of cointegrated variables, $\alpha' Y_t$, is equal to its mean value, the system is usually thought of as being in its long-run equilibrium state. Because $\alpha' Y_t$ is stationary, it crosses its mean frequently, which is why the variables in $Y_t$ trend together in the long run. Engle and Granger (1987) show that the vector $Y_t$ is cointegrated if and only if the variables in $Y_t$ can be modeled using an error-correction model (ECM); i.e., $\alpha' Y_t$ belongs as a regressor in the ARMA representation of $\Delta Y_t$.7 Using methods other than an ECM for modeling cointegrated variables may invalidate standard methods of statistical inference based on asymptotic distribution theory.

The interpretation of cointegration of most interest to the central hypothesis of this paper is due to Stock and Watson (1988), sometimes called the "common trends representation." They show that if $Y_t$ is cointegrated, and there are $k$ linearly independent cointegrating vectors ($\alpha'$ in the above definition), then each element of $Y_t$ is a linear function of the same set of $n - k$ stochastic trends, plus a unique residual term which is stationary. For example, if stock prices and trading volume are cointegrated, then:

\begin{align*}
    P_t &= c_1 + S_t + \varepsilon_{1t} \quad (2.1) \\
    V_t &= c_2 + S_t + \varepsilon_{2t} \quad (2.2)
\end{align*}

7 Section 2.3 provides a more complete definition of error-correction models.
where $c_1$ and $c_2$ are constants, $\Delta^2$ is a stochastic trend which is common to prices and volume, and $\varepsilon_{1t}$ and $\varepsilon_{2t}$ are stationary residual terms. One way to test the hypothesis that there is a set of common factors driving the joint determination of stock prices and trading volume, therefore, is to test for the presence of a common stochastic trend. The finding of a common stochastic trend in stock prices and trading volume would provide evidence consistent with the hypothesis they are influenced by the same set of determining factors. Failure to find a common stochastic trend in stock prices and volume would constitute evidence against the hypothesis.

The remainder of this paper presents tests of the hypothesis that stock prices and trading volume are influenced by the same set of fundamental forces. The following section describes the data used in this study, and presents tests for unit roots and cointegration in a time series of stock prices and trading volume. Subsequent sections demonstrate that an ECM of monthly stock returns that incorporates the role of trading volume and the flow of information to the market rivals the explanatory power of alternative methods of modeling the monthly return to stocks.
2.3. Tests for Unit Roots and Cointegration

This section conducts tests for unit roots and cointegration in a time series of stock prices and trading volume. The data chosen for this study were obtained from the Center for Research in Security Prices (CRSP) monthly returns file. A value-weighted index of stock prices is constructed using the month-end value of the CRSP variable \( \text{TOTVAL} \), which is the total market value (in $1000's) of all the securities included in the CRSP database for month \( I \). The price index used in this study is the ratio of \( \text{TOTVAL} \) in month \( I \) divided by \( \text{TOTVAL} \) in month 1 (arbitrarily chosen to be December, 1925). This ratio is the price relative of the market value of all stocks listed on both the NYSE and AMEX. A time series of volume is constructed by summing the trading volume for all firms included in the CRSP monthly returns file for month \( I \). The newly-enhanced volume data provided by CRSP allowed for the construction of a time series of volume spanning 354 consecutive months. Information regarding the total number of shares on the NYSE and AMEX was obtained by summing the total number of shares outstanding in month \( I \) for all firms included in the CRSP monthly file.

Figure 1 presents a graph of the \( \text{TOTVAL} \) price index and the total trading volume obtained from CRSP spanning the 354 months from July, 1962 to December, 1991. Visually, both series appear to progress smoothly through time while rarely returning to a previous value. Although their short-term movements are not always highly correlated, they do trend together in the long run. The dramatic events of October, 1987 are easily identified on the graph, producing a large downward shift in the stock price index and a pronounced peak in the time series of trading volume. Although stock prices seem to resume their previous pattern subsequent to the crash, trading volume assumes entirely
new characteristics. For the last thirty-six months shown on the graph, total trading volume on the NYSE and AMEX almost resembles a white noise process.

In order to establish that stock prices and trading volume are cointegrated, it is first necessary to determine if each series has a unit root, or is integrated of order one \( I(1) \). Once it has been determined that both stock prices and trading volume are \( I(1) \), the test for cointegration is a test of whether there exists a linear combination of the two \( I(1) \) variables that is stationary, or \( I(0) \). Prior to testing each series for a unit root, it is important to remove any deterministic trends from the data.\(^8\) While some of the unit root tests recommend removing trends by regressing each series on a deterministic time trend, Nelson and Kang (1984) demonstrate that this can cause spurious results if the series being examined is actually \( I(1) \). The power of the unit root tests can be significantly increased if any deterministic trends in the data can be identified \textit{a priori}, and removed without resorting to the potentially spurious regression of an \( I(1) \) variable on time.

For the data used in this study, one obvious trend that is deterministically increasing through time is the number of outstanding shares of stock for the firms used in constructing the price index. Notice, however, that the value-weighted price index is implicitly detrended for stock splits and stock dividends by the nature of its construction. A value-weighted index is the ratio of the market value of a portfolio in one time period to its value in some preceding period. Every time a firm in the index splits its shares, the price of the firm's stock declines by a proportionate amount. This ensures that each firm's total market value in the index remains (approximately) the same immediately following any such increases in the total number of shares outstanding. Since the price index used in

\(^8\) Removing deterministic trends from the data is important because their presence can confound the unit root tests, as well as the effects of the common \textit{stochastic} trends in stock prices and trading volume that this study seeks to model explicitly.
this paper is implicitly detrended, the time series of trading volume is detrended in the same manner. Total trading volume on the NYSE and AMEX in month $I$ is divided by the number of shares outstanding on both exchanges in month $I$.\footnote{Other authors who take a time series approach to the study of trading volume also employ various detrending methods. Gallant, Rossi and Tauchen (1992), who examine daily stock prices and trading volume from 1926-1987, reject the turnover method of detrending in favor of a more complicated detrending strategy. They are concerned with the relationship between price changes and volume, however, and thus desire to purge their data of the long-run trends this study seeks to explicitly model. While the method employed here ignores the effect of new equity issues on the price index, it does offer the advantage of simplicity when compared to the methods used in previous studies.} The volume series is now trading volume in month $I$ relative to the total number of shares outstanding, or equivalently, the total turnover of shares on both exchanges. For the remainder of this paper, any mention of the time series of volume refers to the detrended series of share turnover.

Figure 2 shows the graph of the price index (unchanged from Figure 1) and the detrended time series of share turnover. The relationship between the two series appears to have been enhanced by detrending the volume series. Not only is their long-run relationship more pronounced, but the two series possess significant short-run correlations as well. The effect of the October, 1987 stock market crash is the most striking feature in Figure 2, however. Immediately following the crash, the series of share turnover declines to its 1982 level, and exhibits its lowest volatility since the early 1960's. Share turnover remains virtually constant from 1988-1991. Since the events of October, 1987 appear to mark the beginning of a new relationship between stock prices and trading volume, the results of this study will be reported on the 294-month subperiod spanning July, 1962 to December, 1986, as well as the entire 354-month period ending in December, 1991.

We next test for unit roots in the natural logarithms of the $TOTVAL$ price index and the time series of share turnover. The tests we apply are those developed by Phillips and Perron (1988), which involve running regressions of the following form:
where $\hat{u}_t$ and $u_t^*$ could be stationary autoregressive moving average (ARMA) processes with serially correlated variances. In Equation (2.3) the null hypothesis of a unit root, $H_0^1: \hat{\theta} = 1$, is tested against the alternative hypothesis that $Y_t$ is stationary, $H_A^1: \hat{\theta} < 1$, using the adjusted $t$-statistic $Z(t_{\hat{\theta}})$. In Equation (2.4), the null hypothesis of a unit root with a drift term, $H_0^2: \theta' = 1$, is tested against the alternative of stationarity using the adjusted $t$-statistic $Z(t_{\theta'})$. Panel A of Table 1 summarizes the various hypotheses tested by the Phillips-Perron regressions and provides the critical values of the test statistics at the one and five percent levels of significance.

Panel B of Table 1 shows the value of the two test statistics for unit roots calculated for the time series of stock prices and share turnover, using 294 monthly observations from July, 1962 to December, 1986. The statistics from Equations (2.3) and (2.4), $Z(t_{\hat{\theta}})$ and $Z(t_{\theta'})$, both fail to reject the presence of a unit root in the logarithms of stock prices and share turnover at the one and five percent levels of significance. In evaluating the test statistics a lag truncation operator, $I$, had to be chosen, which allows the regression residuals to follow a moving average process of order $I$ (MA($I$)). The statistics were computed for $I = 1, 2, 4, 6, \text{and } 8$. The results for the stock price series were similar for all values of $I$, so only the results for $I = 1$ are reported. The null hypothesis of a unit root in the time series of share turnover was not rejected at the five percent level for any values of $I$, with the results for $I > 4$ providing the best results. The
statistics reported for share turnover therefore allow the regression residuals to follow an MA(6).

Panel D of Table 1 presents the same tests for unit roots in the logarithms of stock prices and share turnover for the entire 354-month period spanning July, 1962 to December, 1991. Following the method described in Perron (1989), the natural log of each variable is first regressed on a dummy variable which takes on a value of zero prior to October, 1987, and a value of one subsequent to the crash. The Phillips-Perron tests for unit roots are then conducted on the residuals from these regressions. In the first regression (see Equation 2.3) reported in Panel D, which restricts the intercept to be zero, the null hypothesis of a unit root is not rejected at the five percent level of significance for either stock prices or share turnover. The next regression (Equation 2.4), which allows for a non-zero intercept, also fails to reject the hypothesis of a unit root for either series.

Panel E of Table 1 presents tests for unit roots in the TOTVAL index and share turnover using monthly data from 1988-1991. While the null hypothesis of a unit root cannot be rejected for the stock price index, the statistic $Z(t_{f})$ rejects the presence of a unit root in share turnover at the one percent level. The overall conclusion from Table 1 is that there is convincing evidence for the presence of a unit root in both stock prices and share turnover from 1962-1986, but only stock prices continue to exhibit $I(1)$ behavior subsequent to October, 1987.

Now that we have concluded that both the time series of stock prices and share turnover exhibit $I(1)$ behavior from 1962-1986, we investigate whether there exists a long-run equilibrium relationship between the two series. Specifically, we conduct a test of the hypothesis that stock prices and share turnover (detrended volume) evolve around a

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10 Panel C of Table 1 provides the critical values of the test statistics when there is a structural break in the time series (see Perron, 1989).
common stochastic trend. If the stochastic trend in stock prices is the same as the stochastic trend in share turnover, then the two series are cointegrated. This would be evidence consistent with the hypothesis regarding the existence of a set of common factors affecting both stock prices and trading volume. Failure to find a common stochastic trend, however, would be evidence against the hypothesis.

In order to test for cointegration between stock prices and share turnover we first estimate the following equation using OLS:

$$V_t = c + \gamma_1 P_t + \hat{\varepsilon}_t$$  \hspace{1cm} (2.5)

where $V_t$ is the natural logarithm of share turnover and $P_t$ is the natural logarithm of the TOTVAL price index, using the 294 monthly observations of both series from July, 1962 to December, 1986.\(^{11}\) The test for cointegration requires testing for a unit root in $\varepsilon_t$. If we reject the hypothesis of a unit root in $\varepsilon_t$, then the regression residuals from Equation (2.5) are a linear combination of two I(1) variables that is I(0), which implies that $P_t$ and $V_t$ are cointegrated. Since the OLS residuals $\hat{\varepsilon}_t$ are constructed to be mean zero, the appropriate test for a unit root should employ Equation (2.3), which excludes an intercept term. The decision regarding rejection of the null hypothesis will therefore be based on the test statistic $Z(t_0)$.

The OLS estimates of $(c, \hat{\gamma}_1)$ are presented in Panel A of Table 2, along with the results from the Phillips-Perron test for a unit root in the regression residuals $\hat{\varepsilon}_t$. The regression of $V_t$ on $P_t$ resembles the type of spurious regression cited by Granger and Newbold (1974), with an $R^2$ of 0.83. The value of the regression coefficient $\hat{\gamma}_1$ is 0.94,

\(^{11}\) Equation (2.5) is usually referred to as the cointegrating regression.
which appears highly significant with a $t$-statistic of 33.89. The results of the regression confirm the visual impression created by Figure 2, which is that the level of trading volume is highly correlated with the level of stock prices in both a short- and long-run sense. The regression residuals from Equation 2.5 ($\hat{e}_t$) exhibit no serial correlation, so the lag truncation operator in the Phillips-Perron test is set at one. Panel A of Table 2 shows that the value of the test statistic $Z(t_0)$ is -5.46, which rejects the hypothesis of a unit root in $\hat{e}_t$ at the one percent level of significance. The regression residuals are a stationary linear combination of two nonstationary variables. We therefore conclude that stock prices and trading volume from 1962-1986 are cointegrated, or equivalently, the two series share a common stochastic trend. This finding is interpreted as support for the hypothesis that stock prices and trading volume are determined by a set of common factors.

In order to test for cointegration over the entire 1962-1991 period, we next estimate the following regression using OLS:

$$V_t = c + \hat{\gamma}_0 d_c + \hat{\gamma}_1 P_t + \hat{\gamma}_2 d_p + \hat{e}_t$$

(2.6)

where $V_t$ is the natural logarithm of share turnover, $P_t$ is the natural logarithm of the $TOTVAL$ price index, and $d_c$ and $d_p$ are dummy variables that allow the regression intercept and slope coefficient on $P_t$ to shift subsequent to October, 1987. Panel B of Table 2 reports the results of the regression given by Equation (2.6) using 354 months of data spanning July, 1962 to December, 1991. The values and significance of the coefficients $c, \hat{\gamma}_1$ are essentially unchanged in Panel B. Additionally, the strong significance of the coefficients $\hat{\gamma}_0, \hat{\gamma}_2$ indicate that both the regression intercept and slope

12 The $t$-statistic is reported merely as a matter of convention. The test statistics from the cointegrating regression do not actually follow a $t$-distribution.
The coefficient on $P_t$ are indeed different subsequent to October, 1987. The residuals from Equation (2.6) are tested for a unit root as in Panel A. The value of $Z(t_{0})$ rejects the presence of a unit root in $\hat{e}_t$ at the one percent level of significance.\(^{13}\) Thus, contrary to the visual evidence presented in Figure 2, the cointegrating relationship between stock prices and trading volume may persist after accounting for the effects of October, 1987. This would lend further support to the hypothesis that stock prices and trading volume are determined by a set of common underlying factors.

In order to more closely examine the relationship between stock prices and trading volume subsequent to October, 1987, the test for cointegration given by Equation (2.5) is re-estimated using data from 1988-1991. Results are reported in Panel C of Table 2. The slope coefficient on the $TOTVAL$ index of -0.58 is of opposite sign as that reported in Panels A and B, indicating that the relationship between stock prices and share turnover is reversed subsequent to October, 1987. Running the Phillips-Perron test for a unit root (Equation 2.3) on the regression residuals results in a statistic of $Z(t_{0}) = -5.49$, which rejects the null of a unit root at the one percent level; i.e., stock prices and share turnover appear to be cointegrated in the 1988-1991 period as well. This result is puzzling, since share turnover was found to be $I(0)$ in the 1988-1991 period, which would mean that it should no longer be a candidate for cointegration with stock prices.

One final test is performed in an attempt to resolve this puzzle. Equation (2.5) is re-estimated as shown below:

\[
P_t = c + \hat{\gamma}_1 V_t + \hat{\epsilon}_t \tag{2.5.a}
\]

\(^{13}\) The critical values used in Panel B of Table 2 are again from Perron (1989), which accounts for the timing of the structural break in the time series.
with the TOTVAL index as the dependent variable and share turnover as the independent variable. The slope coefficient on share turnover is negative (-0.26), confirming that stock prices and share turnover are trending in opposite directions in the 1988-1991 subperiod. Repeating the Phillips-Perron test for a unit root on the regression residuals from Equation (2.5.a) results in a test statistic of \( Z(t_{\theta}) = -2.54 \), which rejects the null hypothesis of a unit root at the five percent level, and is extremely close to rejecting at the one percent level as well. The results of the unit root tests and tests for cointegration from the 1988-1991 subperiod therefore give conflicting results. Although the null hypothesis of a unit root in share turnover is strongly rejected, it is still possible to form a linear combination of stock prices and share turnover which is stationary.\(^{14}\)

\(^{14}\) The contradictory results from the 1988-1991 subperiod may also be due to the paucity of data available subsequent to October, 1987. Forty-eight months of data is likely to be insufficient when testing for a long-run relationship such as cointegration.
2.4. An Error-Correction Model of Stock Prices and Trading Volume

The conclusion that stock prices and trading volume are cointegrated has certain implications for the manner in which their joint relationship should be modeled. For example, the traditional econometric approach to modeling two nonstationary series would be to difference each variable prior to regressing one on the other. If the series are cointegrated, however, this would induce a negative unit root in the regression residuals \((\hat{e}_t \sim I(-1))\), and standard methods of inference based on asymptotic distribution theory become invalid. Of perhaps even more serious consequence, differencing ignores any potential long-run dynamics between the two series. Modeling their relationship in levels is also a misspecification, as explained by Engle and Granger (1987). According to the "Granger Representation Theorem", if \(x_t\) and \(y_t\) are both \(I(1)\) without trends in their mean and are also cointegrated, the appropriate method for modeling \(x_t\) and \(y_t\) is through the use of an "error-correction model" (ECM) of the following form:

\[
\begin{align*}
\Delta y_t &= -\rho_1 \varepsilon_{t-1} + \text{lagged} (\Delta y_t, \Delta x_t) + d_1(B) \nu_{1t} \\
\Delta x_t &= -\rho_2 \varepsilon_{t-1} + \text{lagged} (\Delta y_t, \Delta x_t) + d_2(B) \nu_{2t}
\end{align*}
\]  

(2.7)

where

\[\varepsilon_t = y_t - Z x_t,\]

\(Z\) is the cointegrating parameter (or vector), \(d(B)\) is the backshift operator (such that \(B^k \nu_t = \nu_{t-k}\), i.e., past shocks to the ECM may affect contemporaneous values of the dependent variable), \(\nu_{1t}, \nu_{2t}\) are joint white noise (but may be contemporaneously correlated), and \(|\rho_1| + |\rho_2| \neq 0\). Engle and Granger (1987) show that cointegrated
variables must conform to an ECM of the type shown above. Granger (1986) also asserts that if a valid error-correction representation exists, then the variables must be cointegrated. If this is the case, then successfully modeling stock prices and trading volume using an ECM would imply that they are cointegrated, which provides further evidence in support of the main hypothesis of this paper.

The type of model given by Equation (2.7) is termed "error-correcting" due to the inclusion of the lagged equilibrium error from the cointegrating regression ($\hat{\epsilon}_t$ from Equation 2.5 or 2.6). In this paper, the error-correction term $\hat{\epsilon}_t$ is equal to

$$\hat{\epsilon}_t = \ln V_t - c - \gamma_1 \ln P_t,$$

which is a measure of the distance (or disequilibrium) between the cointegrated variables. Lagged values of $\hat{\epsilon}_t$ are included in the ECM because when cointegrated variables are perturbed away from equilibrium (i.e., $|\hat{\epsilon}_t|$ is large), an adjustment back toward equilibrium is likely in a subsequent period. A large error-correction term therefore predicts a change in one or both of the cointegrated variables which will "correct" the disequilibrium. This correction results in a value of $\hat{\epsilon}_t$ that is closer to zero (or its long-term mean value). The ECM given by Equation (2.7) shows that cointegrated variables have significant relationships in both the short run (lagged $\Delta y_t$, $\Delta x_t$) and the long run (lagged $\hat{\epsilon}_t$). Proper modeling of cointegrated variables therefore requires that both their long- and short-run relationships be taken into account.

Table 3 summarizes the results of several error-correction models fit to the natural logarithms of stock prices and share turnover for the period spanning July, 1962 to December, 1991, as well as the 1962-1986 (pre-crash) subperiod. All the models reported in Table 3 are estimated using maximum likelihood estimation. Results are reported using
daily, weekly, monthly, and quarterly data. Equation (2.8) below shows the ECM of stock prices reported in Panel A:

\[ \Delta P_t = c_1 + \sum_{i=1}^{I} \alpha_i \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{1j} \Delta V_{t-j} + \delta_1 \hat{\epsilon}_{t-1} + \gamma_1 v_{1t-1} + v_{1t}, \]  

(2.8)

which models the contemporaneous return to stocks \( (\Delta P_t) \) as a function of \( I \) lagged returns to the stock market, \( J \) lagged changes in total share turnover \( (\Delta V_t) \), and one lagged error-correction term \( \hat{\epsilon}_{t-1} \), using data from 1962-1986.\(^{15}\) Estimation of the \( \gamma \) parameter allows the regression residuals to follow an MA(1) process. The results reported in Panel A of Table 3 indicate that an ECM captures between 3-5 percent of the variation in stock returns at daily, weekly monthly and quarterly horizons, with adjusted \( R^2 \)s of 0.048, 0.031, 0.042, and 0.028, respectively.\(^{16}\)

Examination of the regression coefficients obtained in Panel A of Table 3 indicates different relationships between stock returns and lagged returns and turnover at different measurement intervals. For example, the coefficient on the first lagged return using daily data is positive and strongly significant, while the same coefficient at monthly horizons is negative and significant. The coefficient on the second lagged return is negative at all horizons, but is only significant in the case of daily data. Similarly, while the first lag of turnover is insignificant in all regressions, the second lag is positive and significant for daily data, but negative and significant for monthly data.

\(^{15}\) The decision on the number of lags of \( P_t \), \( V_t \) and \( \hat{\epsilon}_t \) to include are based on maximizing the Schwarz-Bayes Criterion (SBC). The SBC is a model selection criterion which chooses the specification that results in the highest value of the likelihood function, minus a penalty for over-parameterizing the model. See Judge (1985, page 245) for information on the SBC and other model selection criteria.

\(^{16}\) Note that the first difference of the log of the TOTVAL Price Index is the continuously compounded return to stocks for the time interval specified.
The sign and magnitude of the coefficients also reveal that the relationship between contemporaneous and lagged stock returns at monthly horizons is different when the effect of lagged turnover is taken into consideration. For example, regressing monthly returns on one lag of monthly returns results in a regression coefficient (also the autocorrelation coefficient in a one-variable regression) of approximately 0.03. Panel A of Table 3 reveals that in the presence of lagged turnover and the error-correction term between $P_t$ and $V_t$, the coefficient on the first lagged monthly return is negative and statistically significant.

Equation (2.9) below shows the ECM reported in Panel B of Table 3:

$$
\Delta V_t = c_2 + \sum_{i=1}^{I} \alpha_{2i} \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{2j} \Delta V_{t-j} + \delta_2 \hat{e}_{t-1} + \gamma_2 \nu_{2t-1} + \nu_{2t}, \tag{2.9}
$$

which models the contemporaneous change in share turnover (1962-1986) as a function of the same explanatory variables used in Equation (2.8). The ECM captures a significantly greater percentage of the variation in $\Delta V_t$ than was the case with $\Delta P_t$, with daily, weekly, monthly and quarterly adjusted $R^2$ of 0.187, 0.090, 0.221, and 0.161, respectively.

Panels C and D of Table 3 report results of the error-correction models of $\Delta P_t$ and $\Delta V_t$ using data from the entire period available on CRSP (July, 1962 to December, 1991). Panel C reports results from Equation (2.10) below, which shows the ECM of $\Delta P_t$:

$$
\Delta P_t = c_1 + c_1 \delta_{t} + \sum_{i=1}^{I} \alpha_{1i} \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{1j} \Delta V_{t-j} + \delta_1 \hat{e}_{t-1} + \gamma_1 \nu_{1t-1} + \nu_{1t}, \tag{2.10}
$$
Equation (2.10) is similar to Equation (2.8), except for the inclusion of dummy variables which allow the regression intercept \((d_e)\) and slope coefficients on lagged changes in stock prices \((d_p)\) and lagged changes in share turnover \((d_v)\) to shift subsequent to October, 1987. Results are reported using daily, weekly, monthly and quarterly data from 1962-1991. The explanatory power of the models reported in Panel C are comparable to those in Panel A. The adjusted R\(^2\) on the daily and monthly models in Panel C rises slightly, while the models which use monthly and quarterly data result in slightly lower adjusted R\(^2\).

Inclusion of the 1987-1991 period produces some results that are materially different than those obtained from fitting the ECM to data from the 1962-1986 period alone, however. For example, the parameter on the error-correction term in the daily ECM \((\delta_1)\) was positive in Panel A, but is negative in Panel C. Additionally, in the monthly model, the coefficient on the first lag of return changes sign once again, to positive, and is statistically insignificant. It is also interesting to note that the values of the slope coefficients on several of the dummy variables indicate that the regression slopes of these variables are diminished, and in some cases completely reversed, in the post-crash period. For example, the dummy coefficients on lags of \(\Delta P_t\) and \(\Delta V_t\) in the daily ECM are of opposite sign in the post-crash period. The positive regression coefficient on the second lag of share turnover also changes to negative subsequent to October, 1987. These results are interpreted as statistical confirmation of the visual impression created by Figure 2, which is that the crash of October, 1987 precipitates a change in the relationship between stock prices and share turnover which persists through 1991.

Panel D of Table 3 reports results of the ECM of share turnover given by Equation (2.11) below:

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\[ \text{No dummy variable is included for the error-correction term because } \varepsilon_t \text{ was estimated using Equation (6), which included a dummy variable for October, 1987. The error-correction term used in Equation (2.10) and Equation (2.11) below is therefore already adjusted for the effects of the 1987 crash.} \]
\[ \Delta V_i = c_2 + c_2^* d_c \sum_{i=1}^{I} \alpha_{2i} \Delta P_{t-i} + \sum_{i=1}^{I} \alpha_{2i}^* d_{P, t-i} + \sum_{j=1}^{J} \beta_{2j} \Delta V_{t-j} + \sum_{j=1}^{J} \beta_{2j}^* d_{V, t-j} + \delta_2 \delta_{t-1} + \gamma_2 \nu_{2t-1} + \nu_{2t} \] (2.11)

Once again, this regression is similar to that given by Equation (2.9), with the inclusion of dummy variables which allow the regression intercept and slope coefficients to shift subsequent to October, 1987. A comparison of Panels B and D of Table 3 indicate that inclusion of the 1987-1991 period increases the adjusted R²'s for the weekly, monthly, and quarterly ECM's. While some regression coefficients are reversed by their post-crash dummy counterparts, the effect is not as pervasive as in the ECM of \( \Delta P_t \). As reported in Panel B, the error-correction model explains a substantially greater percentage of the variation in share turnover than for stock return at all horizons.

Recall that the Granger Representation Theorem states that cointegrated variables must be modeled using an ECM. The statistical significance of the error-correction terms and lagged effects reported in Table 3 indicate that an ECM may provide an alternative methodology for modeling the process generating stock returns. Granger (1986) asserts that the existence of a valid ECM also implies cointegration. If this assertion is correct, the results of Table 3 provide evidence that stock prices and trading volume are cointegrated, or share a common stochastic trend. This provides further support for the hypothesis that stock prices and trading volume are determined by a set of common underlying factors. The results reported in Table 3 also indicate that, when properly modeled, lagged returns to stocks and lagged changes in share turnover are significant determinants of the contemporaneous return to stocks.
2.5. Stock Prices, Trading Volume and Information

Sections 2.3 and 2.4 of this study demonstrate that stock prices and trading volume on the NYSE and AMEX were cointegrated from 1962-1991, and that an error-correction model provides a potentially accurate characterization of their joint time series relationship. These findings are consistent with the hypothesis that stock prices and trading volume are influenced by a common set of fundamental forces. This section provides further evidence in support of this hypothesis by introducing an instrumental variable into the analysis which is likely to be correlated with the factors or information set proposed to be a common determinant of both stock prices and trading volume.

A. Selection of an Instrument for the Information Set

There are several relevant considerations regarding the choice of an appropriate instrument. First, for reasons of parsimony, it would be advantageous if a single variable could be used as a proxy for the information set. Second, the instrument should be acceptable on theoretical grounds, and also be familiar to those who specialize in empirical tests of asset-pricing models. Third, in order to be consistent with the analysis presented thus far, the instrument must have the appropriate time series characteristics; i.e., it must be nonstationary, or integrated of order one, as stock prices and trading volume were found to be in Section 2.3 above. Lastly, and most obviously, the variable must be observable at convenient intervals, and subject to a minimum of measurement error. Based on these considerations, the flow of dividends to the stock market is proposed as an
instrument for the factors or information set hypothesized to be a common determinant of stock prices and trading volume.

At the most basic level, the price of any asset can be conceptualized as the present value of the cash flows it is expected to generate during its lifetime. In a study which tests certain time series implications of this present value relationship, Campbell and Shiller (1987) find that a monthly index of the four-quarter total dividend paid out to the S&P 500 to be nonstationary, and present weak evidence that this index is cointegrated with a time series of stock prices. Dividends therefore possess the necessary time series characteristics to be included as an instrument for the information set. Dividends are also appealing as a proxy for information from a theoretical standpoint, since there is a large literature which implies that a firm's dividend policy may signal information to the market regarding the firm's future prospects.\(^{18}\) Furthermore, the dividend yield on the overall stock market has been shown to have the power to predict monthly returns to stocks, which renders dividends acceptable from the standpoint of empirical asset pricing as well.\(^{19}\) Lastly, the choice of dividends as the information variable allows for a test of Huffman's (1992) model, which uses a measure of the informativeness of the expected dividend as the information factor with which volume and the price of capital are positively correlated.

Data regarding the monthly dividend yield on the Standard and Poor's Index of 500 stocks and the level of the S&P 500 Index from July, 1962 to June, 1991 were obtained

\(^{18}\) See, for example, Bhattacharya (1979), John and Williams (1985), Miller and Rock (1985), Ambarish, John and Williams (1987), Ofer and Thakor (1987), Williams (1988), Kumar (1988), Brennan and Thakor (1990), and John and Lang (1991). These are signalling models regarding the dividend policy of individual firms, of course, and not an aggregate measure of total dividends paid out to the entire market, as used in this study.

\(^{19}\) Fama and French (1988).
from the Wharton Econometrics Forecasting Associates (WEFA) database.\textsuperscript{20} The S&P 500 Index was then multiplied by the S&P 500 dividend yield in order to create a 348-month index of the total dividends paid out to the S&P 500 for the previous twelve month period. Figure 3 shows a graph of the dividend index along with the TOTVAL price index and total share turnover on the NYSE and AMEX.\textsuperscript{21} From the graph it is obvious that the dividend index moves together with stock prices for the entire 29-year period shown, and also moves together with share turnover until the events of October, 1987 result in the sharp downward spike in the turnover series.

\textbf{B. The Time Series Characteristics of the Dividend Index}

Recall from the discussion in Section 2.4 above that the appropriate method for modeling economic and financial data depends upon their time series characteristics. This section therefore examines the time series characteristics of the dividend index. Conducting the Phillips-Perron test for a unit root (Equation 4) on the natural logarithm of the dividend index (with lag truncation operator $l = 4$) results in a test statistic of $Z(t_e) = 0.31$, which fails to reject the null hypothesis of a unit root. The dividend index is therefore nonstationary, or $I(1)$, which means that it is qualified to be cointegrated with stock prices and share turnover.

Because the flow of dividends is hypothesized to be part of a trivariate cointegrated system, the simple test for pairwise cointegration presented in Section 2.3 is

\textsuperscript{20} The author thanks Dr. Marshall Vest and the Department of Economics and Business Research at the University of Arizona for providing access to the WEFA database. The WEFA database did not yet have data for the last six months of 1991 in time for this version of the paper, so only 348 months of data are used in this section.

\textsuperscript{21} The TOTVAL index has been scaled in Figure 3 so all three variables can be conveniently shown together.
no longer the optimal test. We instead use the method described in Johansen (1988), who derives a maximum likelihood estimator for the space of a cointegrated system, as well as a likelihood ratio test for the dimensions of the system. In terms of the framework presented here, information (proxied by dividends) is hypothesized to be the single "common trend" tying stock prices and trading volume together through time. With three cointegrated time series and one common trend, we would expect to find that the dimension of the system is two; i.e., the null hypothesis is that two cointegrating vectors span the space of stock prices, share turnover and dividends.

In order to test the null hypothesis that the space of the cointegrated system is \( \leq 2 \), we use the multivariate likelihood ratio test statistic proposed by Johansen (1989), given by Equation (2.12) below:

\[
-2\ln(Q) = -T \sum_{i=1}^{r} \ln(1 - \Phi_i^*)
\]  

(2.12)

where \( T \) is the number of time series observations (348), \( r \) is the number of cointegrating vectors under the null hypothesis (2 in this case), and \( \Phi_1^*, ..., \Phi_r^* \) are the smallest canonical correlations between the residuals of the regression of \( \Delta X_t \) on \( X_{t-l} \) (where \( l \) is analogous to the lag truncation operator in the Phillips-Perron test; once again we allow for 4th-order autocorrelation, so \( l = 4 \)).\(^{22}\) The likelihood ratio statistic is distributed \( \chi_r^2 \), so a value of the statistic greater than the critical values of a \( \chi_2^2 \) rejects the hypothesis that two cointegrating vectors span the space of the three time series. Failure to reject the null hypothesis that \( r = 2 \) implies that stock prices, trading volume and dividends are all part of the same cointegrated system, which is consistent with the hypothesis that stock prices and trading volume are jointly determined conditional on the prevailing information set.

\(^{22}\) In this case \( X \) is the 348 x 3 matrix of stock prices, share turnover, and dividends.
Table 4 shows the value of the likelihood ratio statistic given by Equation (2.12) along with the corresponding critical values of a $\chi^2_r$ distribution for $r = 0, 1,$ and 2. The null hypotheses of zero or one cointegrating vectors are strongly rejected at the one percent level of significance with values of 68.65 and 12.68, respectively. The null hypothesis that two cointegrating vectors span the space of stock prices, share turnover and dividends results in a test statistic of 0.98, which fails to reject the null at any level of significance. Based on this result we conclude that stock prices, share turnover and dividends are all part of the same cointegrated system. This supports the hypothesis that stock prices and trading volume are influenced by the same set of determining factors, and indicates that the appropriate method for incorporating dividends into the analysis is through the use of an error-correction model.

C. An Error-Correction Model of Stock Prices, Share Turnover and Dividends

This section expands upon the error-correction models reported in Section 2.4 and Table 3 by incorporating the dividend index into the analysis as a proxy for the information set hypothesized to influence the joint determination stock prices and trading volume. This section will focus exclusively on ECM's based on monthly data, which will afford a comparison with other studies which employ similar types of regression analysis. The results of this section are reported in Table 5. The first ECM of stock returns reported uses 294 monthly observations from July, 1962 to December, 1986:

\[
\Delta P_t = c_1 + \alpha_{11}\Delta P_{t-1} + \alpha_{12}\Delta P_{t-2} + \beta_{11}\Delta V_{t-1} + \beta_{12}\Delta V_{t-2} + \\
\lambda_{11}\Delta D_{t-1} + \lambda_{12}\Delta D_{t-2} + \delta_{1}\hat{\epsilon}_{t-1} + \theta_{1}\hat{n}_{t-1} + \gamma_{1}v_{t-1} + v_{lt}
\]  

(2.13)
where $P$ is the natural logarithm of the \textit{TOTVAL} Index, $V$ is the natural logarithm of share turnover, $D$ is the natural logarithm of the dividend index, the $\varepsilon$'s are the regression residuals from the cointegrating regression between stock prices and share turnover (Equation 2.6), the $\eta$'s are the regression residuals from a similar regression of stock prices on the dividend index (not shown), $c$, $\alpha$, $\beta$, $\lambda$, $\delta$, $\theta$ and $\gamma$ are regression coefficients estimated using maximum likelihood estimation, and the $\nu$'s are the regression residuals from Equation (2.13). As in the previously reported ECM's, estimation of the $\gamma$ coefficient allows the regression residuals to follow an MA(1).

The results reported in Panel A of Table 5 show that one lagged return to stocks, the second lagged change in share turnover and one lagged change in the dividend index are significant determinants of the contemporaneous return to stocks. The lagged error-correction term between stock prices and the dividend index ($\hat{\eta}_{t-1}$) and one lagged shock ($\nu_{t-1}$) are also statistically significant.

Inclusion of the dividend index into the ECM raises the adjusted $R^2$ of the model reported in Panel A of Table 3 from 4.2 to 6.5%. The same coefficients which were significant in Table 3 retain their significance in Table 5. It is interesting to note the similarity between the results reported in Panel A and those reported in other studies. The error-correction term between stock prices and dividends ($\hat{\eta}_{t-1}$), estimated as the residuals from the regression of the logarithm of the dividend index on the logarithm of the stock price index, is a close approximation to the monthly dividend yield on the stock market. Fama and French (1988) find that one lag of the market dividend yield explains approximately two percent of the variation in monthly stock returns. Inclusion of the lagged change in the dividend index and $\hat{\eta}_{t-1}$ adds approximately two percent to the explanatory power of the ECM.
Panel B of Table 5 reports the results of an ECM fit to the time series of share turnover given by Equation (14) below:

\[
\Delta V_t = c_2 + \alpha_{21} \Delta P_{t-1} + \alpha_{22} \Delta P_{t-2} + \beta_{21} \Delta V_{t-1} + \beta_{22} \Delta V_{t-2} + \\
\lambda_{21} \Delta D_{t-1} + \lambda_{22} \Delta D_{t-2} + \delta_2 \hat{\varepsilon}_{t-1} + \phi_2 \hat{u}_{t-1} + \gamma_2 \upsilon_{2t-1} + \upsilon_{2t} \tag{2.14}
\]

where all variables are the same as in Equation (2.13), with the exception of \( \hat{u}_t \), which are the regression residuals from the cointegrating regression between dividends and share turnover. As was the case for the ECM of stock prices, the same variables that were significant in Panel B of Table 3 retain their significance in Table 5, with the exception of the second lag of the change in the price index, which becomes marginally insignificant, and the error-correction term between stock prices and turnover, \( \hat{\varepsilon}_{t-1} \), which also loses its significance. The newly-included error-correction term between dividends and turnover is significant at the one percent level, however. Inclusion of the dividend index into the ECM of share turnover increases the adjusted \( R^2 \) of the model from 22 to 26 percent.

Panel C of Table 5 gives the results of the ECM fit to the change in the monthly level of the dividend index, given by Equation (2.15) below:

\[
\Delta D_t = c_3 + \alpha_{31} \Delta P_{t-1} + \alpha_{32} \Delta P_{t-2} + \beta_{31} \Delta V_{t-1} + \beta_{32} \Delta V_{t-2} + \\
\lambda_{31} \Delta D_{t-1} + \lambda_{32} \Delta D_{t-2} + \theta_3 \hat{\eta}_{t-1} + \phi_3 \hat{u}_{t-1} + \gamma_3 \upsilon_{3t-1} + \upsilon_{3t} \tag{2.15}
\]

23 The cointegrating regressions between stock prices and dividends and share turnover and dividends necessary to estimate the additional error-correction terms were conducted in the same manner as Equation (2.6) above.
where all variables are as previously specified. While both lags of the monthly return to stocks and the change in the dividend index are strongly significant, neither lag of the change in share turnover is significant. Additionally, the coefficient on \( \hat{\eta}_{t-1} \), the error-correction term between stock prices and the dividend index, is significant at the five percent level. The explanatory power of the ECM of the dividend index is far greater than the ECM for either stock prices or share turnover, with an adjusted \( R^2 \) of 43 percent.

Panels D through F of Table 5 estimate the same error-correction models as in Panel A through C, using monthly data from July, 1962-June, 1991. Equation (2.16) below shows the ECM of stock prices:

\[
\Delta P_t = c_1 + c_1^* + \sum_{i=1}^{2} \alpha_{1i} \Delta P_{t-i} + \sum_{i=1}^{2} \alpha_{2i} d \Delta P_{t-i} + \sum_{j=1}^{2} \beta_{1j} \Delta V_{t-j} + \sum_{j=1}^{2} \beta_{2j} d \Delta V_{t-j} + \\
\sum_{i=1}^{2} \lambda_{1i} \Delta D_{t-i} + \sum_{i=1}^{2} \lambda_{2i} d \Delta D_{t-i} + \delta_1 \hat{e}_{t-1} + \theta_1 \hat{\eta}_{t-1} + \gamma_1 v_{lt-1} + v_{lt}
\]

(2.16)

where all variables are as previously specified, and the \( d \)'s are dummy variables which allow the regression intercept and slope coefficients to shift subsequent to October, 1987. Results are reported in Panel D of Table 5. While the explanatory power of the regression rises slightly, none of the dummy coefficients in Equation (2.16) are statistically significant. This is surprising, given the visual evidence in Figure 2, which shows a significant structural break in the time series of share turnover beginning in October, 1987. Inclusion of the post-crash period causes lagged returns and lagged changes in the dividend index to lose their significance. The second lagged change in share turnover and \( \hat{\eta}_{t-1} \), the error-correction term between stock prices and dividends, retain their significance.
Panel E of Table 5 reports results from the ECM of share turnover, using monthly data from 1962-1991, and given by Equation (2.17) below:

$$\Delta V_t = c_2 + e_2 + \sum_{i=1}^{2} \alpha_{2i} \Delta P_{t-i} + \sum_{i=1}^{2} \beta_{2j} \Delta V_{t-j} + \sum_{j=1}^{2} \alpha_{2i}^* d_{\Delta P_{t-i}} + \sum_{j=1}^{2} \beta_{2j}^* d_{\Delta V_{t-j}} + \sum_{i=1}^{2} \lambda_{2i} \Delta D_{t-i} + \sum_{i=1}^{2} \lambda_{2i}^* d_{\Delta D_{t-i}} + \delta_2 \hat{e}_{t-1} + \phi_2 \hat{u}_{t-1} + \gamma_2 v_{2t-1} + \nu_{2t}$$

(2.17)

where all variables are as described above. The results in Panel E are similar to those reported in Panel B. The same variables are significant in both panels, with the dummy coefficient on the first lag of share turnover turning up significant at the five percent level. The explanatory power of the model again rises slightly, with an adjusted $R^2$ of 28 percent.

The final ECM reported in Table 5 is fit to the dividend index, again using monthly data from 1962-1991, which is shown below as Equation (2.18):

$$\Delta D_t = c_3 + e_3 + \sum_{i=1}^{2} \alpha_{3i} \Delta P_{t-i} + \sum_{i=1}^{2} \beta_{3j} \Delta V_{t-j} + \sum_{j=1}^{2} \alpha_{3i}^* d_{\Delta P_{t-i}} + \sum_{j=1}^{2} \beta_{3j}^* d_{\Delta V_{t-j}} + \sum_{i=1}^{2} \lambda_{3i} \Delta D_{t-i} + \sum_{i=1}^{2} \lambda_{3i}^* d_{\Delta D_{t-i}} + \theta_3 \hat{h}_{t-1} + \phi_3 \hat{u}_{t-1} + \gamma_3 v_{3t-1} + \nu_{3t}$$

(2.18)

The results of this regression are shown in Panel F of Table 5. Although the second lag of $\Delta P_t$ and $\Delta D_t$ lose their significance, $\hat{h}_{t-1}$ becomes statistically significant when the 1987-1991 years are included. Dummy variables on the first two lags of $\Delta P_t$ and the first lag of
\( \Delta V_t \) are strongly significant. As was the case in Panels D and E, the explanatory power of the ECM rises slightly from the inclusion of the post-crash period.

In order to evaluate the statistical fit of the error-correction models employed above, Panel G of Table 5 presents time series diagnostics on the models presented in the six previous panels. The Bera-Jarque (BJ) statistic, shown below as Equation (2.19), tests for normality in the regression residuals:

\[
BJ = T \left[ \frac{\text{skewness}^2}{6} + \frac{(kurtosis - 3)^2}{24} \right] \sim \chi^2_k \tag{2.19}
\]

where \( T \) is the sample size and \( k \) is the number of parameters estimated in the model. The results reported in Panel G indicate that the Bera-Jarque statistic strongly rejects normality for all the ECM's reported in Table 5.

The next diagnostic reported is Engle's test for ARCH in the regression residuals. This test is performed by capturing the regression residuals from each ECM and regressing the squared residuals on \( n \) lagged squared residuals:

\[
\varepsilon_i^2 = c + \alpha_1 \varepsilon_{i-1}^2 + \alpha_2 \varepsilon_{i-2}^2 + \cdots + \alpha_n \varepsilon_{i-n}^2 \tag{2.20}
\]

Engle (1982) shows that the \( R^2 \) from the above regression multiplied by the sample size is asymptotically distributed \( \chi^2_n \). The null hypothesis of no ARCH is rejected if the value of \( TR^2 \) exceeds the critical value of a chi-square distribution (which indicates significant serial correlation in the squared residuals).
Panel G of Table 5 presents Engle's test for $ARCH$ using regressions with four and eight lagged regression residuals. For the models in Panels A, B and C, which employ monthly data from 1962-1986, the null hypothesis of no $ARCH$ is only rejected for the ECM of the dividend index, and only when eight lagged residuals are employed in the regression. That the ECM of stock prices failed to show significant $ARCH$ effects is surprising, since the serial correlation in the second-moment of stock returns is largely accepted as an empirical fact.\(^{24}\) Testing for $ARCH$ in Panels D, E and F results once again in a failure to reject the null of no $ARCH$ in the ECM of stock prices. The ECM's of both turnover and dividends do exhibit $ARCH$ effects, however, when using the full 1962-1991 period.

The last three diagnostics reported in Panel G of Table 5 involve tests for serial correlation in the regression residuals. The first of these, the Durbin-Watson $H$-statistic, tests for first-order serial correlation when a lagged dependent variable is used as an explanatory regressor. The $H$-statistic is calculated as follows:

$$H = r_1 \sqrt{\frac{T}{1 - T\hat{\nu}(b_1)}}$$

(2.21)

where $r_1$ is the first-order autocorrelation coefficient calculated from the OLS regression residuals, $\hat{\nu}(b_1)$ is the OLS estimate of the variance of the coefficient on the first lagged dependent variable used as a regressor, and $T$ is the sample size. Under the null hypothesis of no serial correlation, $H$ is asymptotically normal with zero mean and unit

---

\(^{24}\) An interesting possibility is that inclusion of trading volume in the ECM subsumes $ARCH$ effects in much the same way as found by Lamoureux and Lastrapes, who find that including volume in the conditional variance equation causes the significance of the $ARCH$ coefficients to diminish and usually vanish.
variance, and is valid even if more than one lag of the dependent variable is used in the regression. Note that $H$ cannot be calculated if $T \hat{h}(b_1) > 1$, which happens to be the case for all the ECM's reported in Table 5. In this case, Durbin (1970) gives an asymptotically equivalent test, which is to regress $\hat{\epsilon}_t$ on $\hat{\epsilon}_{t-1}$ and all other independent variables from the model, including the lagged dependent variables. The significance of the OLS coefficient on $\hat{\epsilon}_{t-1}$ is then evaluated using conventional methods, and the null of no first-order serial correlation is rejected if the t-statistic exceeds the usual critical values. The results of this alternative formulation of the Durbin-Watson $H$ reported in Panel G of Table 5 reveals no significant first-order autocorrelation in the regression residuals for any of the ECM's.

The next test for serial correlation is the Ljung-Box $Q$-statistic, shown below as Equation (2.21):

$$Q = T(T + 2) \sum_{j=1}^{L} \frac{r_j^2}{T-j}$$

where $T$ is the sample size, $L$ is the number of lags of the process being tested, and $r_j$ is the correlation between residual $t$ and residual $t-j$. Ljung and Box (1979) show that the $Q$-statistic is distributed chi-square with $L$ degrees of freedom. A low value of $Q$ fails to reject the null hypothesis of zero autocorrelation in the first $L$ residuals, which indicates a well-specified model. Panel G of Table 5 shows that the $Q$-statistic fails to reject zero autocorrelation in the first six lagged residuals for all the ECM's reported. Only the ECM of share turnover, in both Panels B and E, shows serial correlation at higher lags.

The overall conclusion from this section is that an error-correction model of stock prices, share turnover and dividends (proxying for the information set) provides an adequate fit for all three time series (the Bera-Jarque test notwithstanding, which is known to reject the null of normality too frequently). The ECM seems to capture the serial
correlation in the regression residuals to the point of eliminating ARCH effects. The results reported in Table 5 are interpreted as strong support for the hypothesis that stock prices and trading volume are jointly influenced by the same set of fundamental factors.
2.6. Comparison with Previous Studies

This section compares the explanatory power of the ECM's reported in Table 5 with other studies that estimate predictive-type regressions that purport to explain the variation in monthly stock returns. Table 6 summarizes the results of these other studies by presenting the dependent variable forecasted, the lagged explanatory regressors used in the forecasts, the adjusted R² from the strongest regressions reported in each study, and the time period examined. The adjusted R² from the previous studies range from 0.02 to 0.25. Forecasts based on only one or two lagged economic factors result in regressions with particularly low explanatory power. Ferson and Harvey model the excess return to the equally-weighted CRSP index as a function of five lagged economic factors and a January dummy and obtain an adjusted R² of 14%.

The highest explanatory power reported in Table 9 comes from the study by Conrad and Kaul (1989), who regress the nominal monthly return to the small quintile CRSP portfolio on four lagged weekly returns, allowing the weights of each weekly return to decrease successively.²⁵ Their model captures 25% percent of the variation of returns to a small-firm portfolio from 1962-1986, and over 40% during the 1970's. This indicates that monthly expected returns may be influenced more by the short-term effects modeled by Conrad and Kaul, and less by the longer-term effects represented by macroeconomic factors.

²⁵ Conrad and Kaul also use four dummy variables, one for each week of January.
2.7. Conclusions

This paper hypothesized that stock prices and trading volume are determined by a set of common underlying factors. This representation is consistent with Stock and Watson's (1988) interpretation of common stochastic trends in economic time series. Empirical tests confirm the presence of a common stochastic trend in a time series of stock prices and trading volume. The two variables are found to be cointegrated using monthly data from 1962-1986. The finding of a common stochastic trend is interpreted as evidence consistent with the hypothesis that a common set of underlying factors influences both prices and the volume of trade in equity markets.

The evidence subsequent to October, 1987 is mixed. The unit root tests reported in Panel E of Table 1 indicate that share turnover does not have a unit root subsequent to the crash, and is therefore not qualified to be cointegrated with stock prices. The tests for cointegration reported in Panel C of Table 2 cannot reject the null hypothesis that stock prices and share turnover are cointegrated in the 1988-1991 period as well. These conflicting results may be resolved only when several more years of data become available.

An error-correction model (ECM) of stock prices and trading volume explains 4% of the variation in monthly stock returns, and a similar percentage of the variation of returns at daily and quarterly intervals. Incorporating dividends into the analysis as a proxy for the flow of information to the market increases the explanatory power of the ECM to 6.5%.

The finding that stock prices and trading volume are cointegrated indicates that Stephen Ross' call for a theory of asset prices that accounts for the role of volume is also a promising area for future research. Investigating whether asset prices and trading volume are cointegrated in other markets poses another interesting question. Explaining the
behavior of share turnover in the stock market following the events of October, 1987 is yet another area for future research, especially as more post-crash data become available. Perhaps the most interesting direction for future research that results from this study concerns the application of modern time series analysis to questions of empirical asset pricing. Given the low explanatory power of most studies that investigate the nature of asset prices using cross-sectional regression techniques, further work that employs a time series-based approach may continue to shed light on the process generating returns to assets.

Figure 1: Monthly Values of the TOTVAL Price Index and Total Share Turnover on the NYSE and AMEX, 1962-1991.
Figure 2: Monthly Values of the TOTVAL Price Index and Total Share Turnover on the NYSE and AMEX, 1962-1991.
Table 1

Tests for Unit Roots in the Logarithms of Stock Prices and Share Turnover.

This table presents the tests for unit roots developed by Phillips and Perron (1988). These tests are conducted by running the regressions shown in Panel A using OLS, while allowing the regression residuals to follow a moving average process. The null hypothesis being tested is whether the regression coefficient on $Y_{t-1}$ is equal to one. Failure to reject the null provides evidence that $Y_t$ has a unit root (or stochastic trend). The alternative hypothesis being tested is that the regression coefficient on $Y_{t-1}$ is less than one. Panel B shows the value of the adjusted $t$-statistics obtained by running the regressions shown in Panel A on the natural logarithms of the TOTVAL price index and total share turnover on the NYSE and AMEX using monthly data from 1962-1986. Panel C presents the same regressions as shown in Panel A, with critical values taken from Perron (1989), where the critical values have been adjusted for a structural break in the time series. Panel D presents the results of the tests for unit roots on monthly data from 1962-1991, where the observations have first been regressed on a dummy variable to account for the effects of October, 1987. In both Panels B and D, the null hypothesis of a unit root is rejected if the adjusted $t$-statistics are less than the critical values shown in Panels A or C. Panel E presents unit root tests using monthly data from 1988-1991.

**Panel A:** The following statistics test the various null hypotheses from one of the two regressions shown above. Critical values for the 5% and 1% levels of significance are also provided.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Null Hypothesis</th>
<th>Regression</th>
<th>95% cv's</th>
<th>99% cv's</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z(t_\theta)$</td>
<td>$\theta = 1$</td>
<td>$Y_t = \hat{\theta}Y_{t-1} + \hat{\eta}_t$</td>
<td>-1.95</td>
<td>-2.58</td>
</tr>
<tr>
<td>$Z(t_\delta^*)$</td>
<td>$\delta^* = 1$</td>
<td>$Y_t = \mu^* + \theta Y_{t-1} + u_t^*$</td>
<td>-2.86</td>
<td>-3.43</td>
</tr>
</tbody>
</table>

**Panel B:** Tests for unit roots in the logarithms of stock prices and share turnover using monthly data 1962-1986.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>TOTVAL</th>
<th>Share Turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z(t_\theta)$</td>
<td>2.46</td>
<td>0.67</td>
</tr>
<tr>
<td>$Z(t_\delta^*)$</td>
<td>-0.81</td>
<td>-1.90</td>
</tr>
</tbody>
</table>

*, ** Significant at the one and five percent levels, respectively.
Table 1 (continued)

Panel C: The following statistics test the various null hypotheses from one of the two regressions shown below when there is a structural break in the time series. Critical values for the 5% and 1% levels of significance (Perron, 1989) are also provided.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Null Hypothesis</th>
<th>Regression</th>
<th>95% cv's</th>
<th>99% cv's</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z(t_{\hat{\theta}})$</td>
<td>$\hat{\theta} = 1$</td>
<td>$Y_t = \hat{\theta}Y_{t-1} + \hat{\epsilon}_t$</td>
<td>-3.80</td>
<td>-4.42</td>
</tr>
<tr>
<td>$Z(t_{\theta})$</td>
<td>$\theta = 1$</td>
<td>$Y_t = \mu + \theta Y_{t-1} + \epsilon_t$</td>
<td>-3.85</td>
<td>-4.51</td>
</tr>
</tbody>
</table>

Panel D: Tests for unit roots in the logarithms of stock prices and share turnover using monthly data 1962-1991. The time series of stock prices and share turnover have first been regressed on a dummy variable to account for the effects of October, 1987. The residuals from those regressions are then tested for the presence of a unit root.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>TOTVAL</th>
<th>Share Turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z(t_{\tilde{\theta}})$</td>
<td>-2.39</td>
<td>-2.32</td>
</tr>
<tr>
<td>$Z(t_{\tilde{\theta}})$</td>
<td>-2.59</td>
<td>-2.41</td>
</tr>
</tbody>
</table>

Panel E: Tests for unit roots in the logarithms of stock prices and share turnover using monthly data 1988-1991. The appropriate critical values are once again those given in Panel A.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>TOTVAL</th>
<th>Share Turnover</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z(t_{\tilde{\theta}})$</td>
<td>1.37</td>
<td>-0.63</td>
</tr>
<tr>
<td>$Z(t_{\tilde{\theta}})$</td>
<td>-1.55</td>
<td>-5.06*</td>
</tr>
</tbody>
</table>

* ** Significant at the one and five percent levels, respectively.
The test for cointegration between the natural logarithms of the TOTVAL price index and share turnover on the NYSE and AMEX first involves estimating the cointegrating regression given by Equation (2.5):

\[ V_t = c + \gamma_1 P_t + \hat{\epsilon}_t \]

where \( V_t \) is the natural logarithm of share turnover and \( P_t \) is the natural logarithm of the TOTVAL price index. The Phillips-Perron (1988) test for a unit root is then conducted on the regression residuals from the above regression. Rejection of the null hypothesis of a unit root in the regression residuals provides evidence that there exists a linear combination of the stock price index and share turnover that is stationary; i.e., stock prices and share turnover are cointegrated. The table below reports the regression coefficients from Equations (2.3) and (2.5) and the test statistic \( Z(t_{\theta}) \) for the Phillips-Perron test for a unit root given by Equation (2.3):

\[ \hat{\epsilon}_t = \hat{\theta}\hat{\epsilon}_{t-1} + \hat{n}_t. \]

The null hypothesis of a unit root is rejected if the value of the adjusted \( t \)-statistic is less than the critical values shown in the table. Panel A reports results using monthly data from 1962-1986.

### Panel A. Monthly Data: 1962-1986

<table>
<thead>
<tr>
<th>Regression Coefficient</th>
<th>Value</th>
<th>Test Statistic</th>
<th>95% cv's</th>
<th>99% cv's</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\epsilon} )</td>
<td>-0.062</td>
<td>( t = -0.07 )**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\gamma}_1 )</td>
<td>0.944</td>
<td>( t = 33.89 )**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\theta} )</td>
<td>0.669</td>
<td>( Z(t_{\theta}) = -5.46 )*</td>
<td>-1.95</td>
<td>-2.58</td>
</tr>
</tbody>
</table>

* Rejects the null hypothesis of a unit root at the 1% level of significance.

** Reported as a matter of convention only. The statistics do not follow a \( t \)-distribution.
Table 2 (continued)

Panel B below tests for cointegration between the natural logarithm of share turnover and the TOTVAL price index using monthly data from 1962-1991. The test for cointegration first involves running the regression given by Equation (2.6):

\[ V_t = c + \gamma_0 d_c + \gamma_1 P_t + \gamma_2 d_p + \hat{\epsilon}_t \]

where \( V_t \) is the natural logarithm of share turnover, \( P_t \) is the natural logarithm of the TOTVAL price index, \( d_c \) is a dummy variable that allows the regression intercept to shift subsequent to October, 1987, and \( d_p \) is a dummy variable that allows the slope coefficient on \( P_t \) to shift post-crash. As shown in Panel A, the Phillips-Perron (1988) test for a unit root is then conducted on the regression residuals from the above regression. The critical values shown in Panel B are from Perron (1989), which account for the timing of the structural break in the time series of share turnover and stock prices.

<table>
<thead>
<tr>
<th>Regression Coefficient</th>
<th>Value</th>
<th>Test Statistic</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{c} )</td>
<td>0.014</td>
<td>( t = 0.17 )</td>
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<tr>
<td>( \hat{\gamma}_0 )</td>
<td>8.440</td>
<td>( t = 6.36 )</td>
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<tr>
<td>( \hat{\gamma}_1 )</td>
<td>0.920</td>
<td>( t = 36.93 )</td>
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<td>( \hat{\gamma}_2 )</td>
<td>-2.030</td>
<td>( t = -6.94 )</td>
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<tr>
<td>( \hat{\theta} )</td>
<td>0.634</td>
<td>( Z(t_{\hat{\theta}}) = -5.56 )</td>
<td>-3.80</td>
<td>-4.42</td>
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</tbody>
</table>


<table>
<thead>
<tr>
<th>Regression Coefficient</th>
<th>Value</th>
<th>Test Statistic</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{c} )</td>
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<tr>
<td>( \hat{\gamma}_1 )</td>
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<td>( t = -3.26 )</td>
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<tr>
<td>( \hat{\theta} )</td>
<td>0.132</td>
<td>( Z(t_{\hat{\theta}}) = -5.49 )</td>
<td>-1.95</td>
<td>-2.58</td>
</tr>
</tbody>
</table>

* Rejects the null hypothesis of a unit root at the 1% level of significance.
** Reported as a matter of convention only. The statistics do not follow a t-distribution.
Figure 3. Monthly Values of the USDVAL Price Index, Share Turnover, and an Index of the Total Dividends paid to the S&P 500.
Table 3
Error-Correction Models of the Logarithms of Stock Prices and Share Turnover

Panel A: Error-Correction Models of the TOTVAL Price Index 1962-1986

This panel presents results from the error-correction models of the USDVAL Price Index given by Equation (2.7):

\[ \Delta P_t = c_1 + \sum_{i=1}^{I} \alpha_{i1} \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{j1} \Delta V_{t-j} + \delta_1 \tilde{\epsilon}_{t-1} + \eta_1 \nu_{t-1} + \nu_t \]

where \( P \) is the natural logarithm of the TOTVAL Index, \( V \) is the natural logarithm of share turnover, the \( \epsilon \)'s are the regression residuals from the cointegrating regression (Equation 2.5) also known as the error-correction term, \( c, \alpha, B, \delta \) and \( \gamma \) are regression coefficients estimated using maximum likelihood estimation, \( I \) and \( J \) are the number of lags of \( \Delta P \) and \( \Delta V \) included in each equation, and the \( \nu \)'s are the regression residuals from Equation (13). Estimation of the \( \gamma \)-coefficient allows the regression residuals to follow a moving average process. The \( t \)-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). Results are shown using daily, weekly, monthly and quarterly data from 1962-1986.

<table>
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<tr>
<th></th>
<th>( c_1 )</th>
<th>( \alpha_{11} )</th>
<th>( \alpha_{12} )</th>
<th>( \alpha_{13} )</th>
<th>( \beta_{11} )</th>
<th>( \beta_{12} )</th>
<th>( \beta_{13} )</th>
<th>( \beta_{14} )</th>
<th>( \delta_1 )</th>
<th>( \gamma_1 )</th>
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<tbody>
<tr>
<td>Daily</td>
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<td>0.368</td>
<td>-0.122</td>
<td>0.052</td>
<td>0.009</td>
<td>0.002</td>
<td>0.004</td>
<td>0.002</td>
<td>0.001</td>
<td>0.177</td>
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<td></td>
<td>2.81**</td>
<td>2.86**</td>
<td>-1.74</td>
<td>1.96*</td>
<td>14.91**</td>
<td>1.77</td>
<td>6.62**</td>
<td>2.76**</td>
<td>2.70**</td>
<td>1.375</td>
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<td>adj. ( R^2 )</td>
<td>0.17</td>
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</tr>
<tr>
<td>Weekly</td>
<td>0.001</td>
<td>0.207</td>
<td>-0.016</td>
<td>0.009</td>
<td>-0.002</td>
<td>-0.001</td>
<td>0.17</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>2.26*</td>
<td>0.65</td>
<td>-0.14</td>
<td>1.67</td>
<td>-0.70</td>
<td>-0.75</td>
<td>0.52</td>
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<tr>
<td>adj. ( R^2 )</td>
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</tr>
<tr>
<td>Monthly</td>
<td>0.011</td>
<td>-0.366</td>
<td>-0.206</td>
<td>0.038</td>
<td>0.031</td>
<td>0.081</td>
<td>-0.342</td>
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<tr>
<td></td>
<td>2.91**</td>
<td>-3.21**</td>
<td>-2.66**</td>
<td>1.79</td>
<td>2.18*</td>
<td>3.72**</td>
<td>-2.71**</td>
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<tr>
<td>Quarterly</td>
<td>0.015</td>
<td>0.424</td>
<td>-0.17</td>
<td>0.010</td>
<td>-0.661</td>
<td>0.001</td>
<td>0.455</td>
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<tr>
<td></td>
<td>2.67**</td>
<td>1.90</td>
<td>-1.07</td>
<td>0.17</td>
<td>-1.69</td>
<td>2.30*</td>
<td>2.38*</td>
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<tr>
<td>adj. ( R^2 )</td>
<td>0.28</td>
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</tbody>
</table>

*, ** Significant at the 5% and 1% levels, respectively.
Table 3 (continued)

Panel B: Error-Correction Models of Share Turnover on the NYSE and AMEX 1962-1986

This panel presents error-correction models of the natural logarithm of share turnover on the NYSE and AMEX given by Equation (2.9):

$$\Delta V_t = c_2 + \sum_{i=1}^{I} \alpha_{2i} \Delta P_{t-i} + \sum_{j=1}^{J} \beta_{2j} \Delta V_{t-j} + \delta_{21} \hat{e}_{t-1} + \gamma_2 v_{2t-1} + v_{2t}$$

where all variables and regression coefficients are as described in Panel A above. Results are shown using daily, weekly, monthly and quarterly data from 1962-1986.

<table>
<thead>
<tr>
<th></th>
<th>$c_2$</th>
<th>$\alpha_{21}$</th>
<th>$\alpha_{22}$</th>
<th>$\alpha_{23}$</th>
<th>$\beta_{21}$</th>
<th>$\beta_{22}$</th>
<th>$\beta_{23}$</th>
<th>$\beta_{24}$</th>
<th>$\delta_2$</th>
<th>$\gamma_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Daily</strong></td>
<td>-0.001</td>
<td>2.492</td>
<td>-1.26</td>
<td>0.956</td>
<td>-0.352</td>
<td>-0.351</td>
<td>-0.245</td>
<td>-0.133</td>
<td>-0.021</td>
<td>0.029</td>
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<tr>
<td></td>
<td>t-stat</td>
<td>-0.96</td>
<td>9.42*</td>
<td>-4.66*</td>
<td>-3.61*</td>
<td>-7.21*</td>
<td>-6.56*</td>
<td>-8.71*</td>
<td>-4.44*</td>
<td>-7.56*</td>
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<td>adj. $R^2$</td>
<td>0.187</td>
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<tr>
<td><strong>Weekly</strong></td>
<td>-0.003</td>
<td>0.654</td>
<td>0.467</td>
<td>-0.211</td>
<td>-0.291</td>
<td>0.013</td>
<td>0.013</td>
<td>0.313</td>
<td>1.48</td>
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<tr>
<td></td>
<td>t-stat</td>
<td>-0.661</td>
<td>2.39**</td>
<td>1.33</td>
<td>-0.79</td>
<td>-1.14*</td>
<td></td>
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<td></td>
<td>adj. $R^2$</td>
<td>0.09</td>
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<tr>
<td><strong>Monthly</strong></td>
<td>0.004</td>
<td>0.699</td>
<td>0.547</td>
<td>-0.689</td>
<td>-0.262</td>
<td>-0.171</td>
<td>0.664</td>
<td>-0.225</td>
<td>0.198</td>
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<tr>
<td></td>
<td>t-stat</td>
<td>0.038</td>
<td>2.50*</td>
<td>2.23**</td>
<td>-2.82*</td>
<td>-3.67*</td>
<td>-2.45**</td>
<td>1.01</td>
<td>-3.81*</td>
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<td>adj. $R^2$</td>
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<tr>
<td><strong>Quarterly</strong></td>
<td>0.042</td>
<td>0.008</td>
<td>-0.319</td>
<td>-0.002</td>
<td>-0.322</td>
<td>0.001</td>
<td>0.349</td>
<td>2.68*</td>
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<td></td>
<td>t-stat</td>
<td>2.48**</td>
<td>0.41</td>
<td>-1.22</td>
<td>-0.50</td>
<td>-2.77*</td>
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<td></td>
<td>adj. $R^2$</td>
<td>0.161</td>
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</table>

*, ** Significant at the 1% and 5% levels, respectively.
Panel C: Error-Correction Models of the TOTVAL Price Index 1962-1991

This panel presents results from the error-correction models of the TOTVAL Price Index given by Equation (2.9):

\[
\Delta P_t = c_1 + c_{1i} d_{1i} + \sum_{i=1}^{I} \alpha_{1i} \Delta P_{t-i} + \sum_{i=1}^{I} \alpha_{2i} \Delta d_{1i} + \sum_{j=1}^{J} \beta_{1j} \Delta V_{t-j} + \sum_{j=1}^{J} \beta_{2j} \Delta d_{2j} + \delta_{t-1} + \gamma_{1} v_{t-1} + \epsilon_{t},
\]

where all variables and regression coefficients are as described in Panel A above, with the addition of dummy variables \(d\) that allow the regression intercept and slope coefficients on the lags of \(\Delta P\) and \(\Delta V\) to shift subsequent to October 19, 1987. Results are shown using daily, weekly, monthly and quarterly data from 1962-1991. Coefficient values and \(t\)-statistics on the dummy variables are shown in light type.

<table>
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<tr>
<th></th>
<th>(c_1)</th>
<th>(c_{1i})</th>
<th>(\alpha_{11})</th>
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<th>(\alpha_{13})</th>
<th>(\alpha_{21})</th>
<th>(\alpha_{22})</th>
<th>(\alpha_{23})</th>
<th>(\beta_{11})</th>
<th>(\beta_{12})</th>
<th>(\beta_{13})</th>
<th>(\beta_{21})</th>
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<th>(\beta_{23})</th>
<th>(\delta_t)</th>
<th>(\gamma_1)</th>
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<tr>
<td><strong>Daily</strong></td>
<td>0.001</td>
<td>0.003</td>
<td>0.430</td>
<td>-0.117</td>
<td>-0.164</td>
<td>0.018</td>
<td>0.069</td>
<td>-0.081</td>
<td>0.015</td>
<td>-0.008</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.003</td>
</tr>
<tr>
<td><strong>t-stat</strong></td>
<td>2.50**</td>
<td>0.05</td>
<td>5.45**</td>
<td>-4.48**</td>
<td>-3.10**</td>
<td>0.643</td>
<td>2.87**</td>
<td>-3.14**</td>
<td>1.84</td>
<td>-1.11</td>
<td>6.35**</td>
<td>-3.49**</td>
<td>2.68**</td>
<td>-3.13**</td>
<td>-6.70**</td>
<td>3.02**</td>
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<td><strong>adj. (R^2)</strong></td>
<td>0.19</td>
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<tr>
<td><strong>Weekly</strong></td>
<td>0.002</td>
<td>-0.001</td>
<td>-0.272</td>
<td>0.026</td>
<td>-0.065</td>
<td>0.005</td>
<td>0.010</td>
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<tr>
<td><strong>t-stat</strong></td>
<td>2.53**</td>
<td>-0.49</td>
<td>-2.53**</td>
<td>0.39</td>
<td>-1.05</td>
<td>0.07</td>
<td>2.28**</td>
<td>-0.47</td>
<td>-0.37</td>
<td>0.90</td>
<td>-0.28</td>
<td>1.51</td>
<td>-1.52</td>
<td>-2.96**</td>
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<tr>
<td><strong>adj. (R^2)</strong></td>
<td>0.07</td>
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<tr>
<td><strong>Monthly</strong></td>
<td>0.006</td>
<td>-0.007</td>
<td>0.146</td>
<td>0.376</td>
<td>-0.109</td>
<td>-0.058</td>
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<td>-0.088</td>
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<td><strong>t-stat</strong></td>
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<td>0.705</td>
<td>2.782**</td>
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<td>4.74**</td>
<td>-4.00**</td>
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<td>-1.51</td>
<td>3.38**</td>
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<td><strong>adj. (R^2)</strong></td>
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</tr>
<tr>
<td><strong>Quarterly</strong></td>
<td>0.022</td>
<td>0.023</td>
<td>-0.105</td>
<td>-0.357</td>
<td>0.034</td>
<td>-0.002</td>
<td>-0.002</td>
<td>0.185</td>
<td>-0.025</td>
<td>0.329</td>
<td>0.002</td>
<td>-0.062</td>
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<tr>
<td><strong>t-stat</strong></td>
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<td>0.24</td>
<td>-0.03</td>
<td>-0.029</td>
<td>0.77</td>
<td>-0.46</td>
<td>1.59</td>
<td>2.00**</td>
<td>-0.15</td>
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<tr>
<td><strong>adj. (R^2)</strong></td>
<td>0.17</td>
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</tbody>
</table>

*, **Significant at the 5% and 1% levels, respectively.
Table 3 (continued)


This panel presents results from the error-correction models of Share Turnover given by Equation (2.11):

\[ \Delta V_t = c_2 + c_2^* d_t + \sum_{i=1}^{I} \alpha_{21} \Delta P_{t-i} + \sum_{i=1}^{J} \alpha_{22} \Delta V_{t-i} + \sum_{j=1}^{J} \beta_{21} \Delta V_{t-j} + \sum_{j=1}^{J} \beta_{22} \Delta V_{t-j} + \delta_{2} \hat{e}_{t-1} + \gamma_{2} V_{t-1} + \epsilon_{2t} \]

where all variables and regression coefficients are as described in Panel A above, with the addition of dummy variables (d) that allow the regression intercept and slope coefficients on the lags of \( \Delta P \) and \( \Delta V \) to shift subsequent to October 19, 1987. Results are shown using daily, weekly, monthly and quarterly data from 1962-1991. Coefficient values and t-statistics on the dummy variables are shown in light type.

<table>
<thead>
<tr>
<th></th>
<th>( c_2 )</th>
<th>( c_2^* )</th>
<th>( \alpha_{21} )</th>
<th>( \alpha_{22} )</th>
<th>( \alpha_{23} )</th>
<th>( \beta_{21} )</th>
<th>( \beta_{22} )</th>
<th>( \beta_{23} )</th>
<th>( \beta_{24} )</th>
<th>( \delta_{2} )</th>
<th>( \gamma_{2} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily</td>
<td>0.000</td>
<td>0.002</td>
<td>-0.841</td>
<td>-0.125</td>
<td>1.256</td>
<td>-1.146</td>
<td>-0.665</td>
<td>-0.165</td>
<td>-0.172</td>
<td>-0.318</td>
<td>0.004</td>
</tr>
<tr>
<td>t-stat</td>
<td>0.03</td>
<td>-0.33</td>
<td>-3.969**</td>
<td>-0.24</td>
<td>4.280**</td>
<td>-2.712**</td>
<td>-0.341**</td>
<td>3.202**</td>
<td>-0.163</td>
<td>-5.742**</td>
<td>0.14</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.142</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly</td>
<td>-0.002</td>
<td>-0.006</td>
<td>0.639</td>
<td>0.222</td>
<td>0.454</td>
<td>-0.659</td>
<td>-0.184</td>
<td>-0.077</td>
<td>-0.264</td>
<td>0.007</td>
<td>-0.074</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.60</td>
<td>-0.53</td>
<td>2.26*</td>
<td>0.35</td>
<td>1.47</td>
<td>-1.04</td>
<td>-0.89</td>
<td>-1.11</td>
<td>-4.252**</td>
<td>0.10</td>
<td>-0.99</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.127</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly</td>
<td>-0.001</td>
<td>-0.032</td>
<td>0.702</td>
<td>-0.204</td>
<td>0.589</td>
<td>0.167</td>
<td>-0.257</td>
<td>-1.62</td>
<td>-0.181</td>
<td>-0.016</td>
<td>-0.268</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.07</td>
<td>-1.24</td>
<td>2.59*</td>
<td>-0.39</td>
<td>2.521**</td>
<td>0.31</td>
<td>-3.94</td>
<td>-2.032**</td>
<td>-2.99</td>
<td>-0.092</td>
<td></td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.259</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quarterly</td>
<td>0.030</td>
<td>-0.051</td>
<td>-0.631</td>
<td>0.291</td>
<td>-0.328</td>
<td>0.214</td>
<td>-0.002</td>
<td>0.341</td>
<td>-0.352</td>
<td>0.461</td>
<td>0.001</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.31*</td>
<td>-1.19</td>
<td>-0.10</td>
<td>0.57</td>
<td>-1.18</td>
<td>0.42</td>
<td>-0.02</td>
<td>0.69</td>
<td>-2.542*</td>
<td>1.08</td>
<td>0.16</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.223</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* ** Significant at the 1% and 5% levels, respectively.
Table 4

Likelihood Ratio Statistic for the Number of Cointegrating Vectors Spanning the Space of Stock Prices, Share Turnover and Dividends

In order to test the null hypothesis that the space of the cointegrated system is \( \leq r \), we form the likelihood ratio statistic derived in Johansen (1988), given by Equation (2.12) below:

\[
-2 \ln(Q_r) = -T \sum_{i=1}^{r} \ln(1 - \Phi_i^*)
\]  

(2.12)

where \( T \) is the number of time series observations (348), \( r \) is the number of cointegrating vectors under the null hypothesis (2 in this case), and \( \Phi_1^*, \ldots, \Phi_i^* \) are the smallest canonical correlations between the residuals of the regression of \( \Delta X_t \) on \( X_{t-l} \) (where \( l \) is analogous to the lag truncation operator in the Phillips-Perron test; once again we correct for 4th-order autocorrelation, so \( l = 4 \)). The likelihood ratio statistic is distributed \( \chi_r^2 \), so a value of the statistic greater than the critical values of a \( \chi_r^2 \) rejects the hypothesis that \( r \) cointegrating vectors span the space of the three time series. Failure to reject the null hypothesis that \( r = 2 \) implies that stock prices, trading volume and dividends are all part of the same cointegrated system, which is consistent with the hypothesis that stock prices and trading volume are cointegrated with the flow of dividends to the market (which proxy for the information set in the model).

<table>
<thead>
<tr>
<th>( r )</th>
<th>Test Statistic</th>
<th>Critical Value for a ( \chi_r^2 ) at the 1% level</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>68.65</td>
<td>7.88 *</td>
</tr>
<tr>
<td>1</td>
<td>12.68</td>
<td>10.60 *</td>
</tr>
<tr>
<td>2</td>
<td>0.98</td>
<td>12.80</td>
</tr>
</tbody>
</table>

* Rejects the null hypothesis of \( r \) cointegrating vectors at the 1% level of significance.
Table 5


This panel presents results from the error-correction model of the TOTVAL Price Index given by Equation (2.13):

\[
\Delta P_t = c_1 + \alpha_{11} \Delta P_{t-1} + \alpha_{12} \Delta P_{t-2} + \beta_{11} \Delta V_{t-1} + \beta_{12} \Delta V_{t-2} + \lambda_{11} \Delta D_{t-1} + \lambda_{12} \Delta D_{t-2} + \delta_{1} \hat{\epsilon}_{t-1} + \theta_{1} \hat{\eta}_{t-1} + \gamma_{1} \hat{v}_{t-1} + \nu_t
\]

where \( P \) is the natural logarithm of the TOTVAL Index, \( V \) is the natural logarithm of share turnover, \( D \) is the natural logarithm of the dividend stream to the S&P 500 index of stocks, the \( \epsilon \)'s are the regression residuals from the cointegrating regression between stock prices and share turnover \( \eta \)'s are the regression residuals from the cointegrating regression between stock prices and dividends, \( c, \alpha, \beta, \lambda, \delta, \) and \( \theta \) are regression coefficients estimated using maximum likelihood estimation, and the \( \nu \)'s are the regression residuals from Equation (2.13). Estimation of the \( \gamma \)-coefficients allows the regression residuals to follow a moving average process. The \( t \)-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). Results are shown using monthly data from July, 1962-June, 1986.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>c_1</th>
<th>( \alpha_{11} )</th>
<th>( \alpha_{12} )</th>
<th>( \beta_{11} )</th>
<th>( \beta_{12} )</th>
<th>( \lambda_{11} )</th>
<th>( \lambda_{12} )</th>
<th>( \delta_{1} )</th>
<th>( \theta_{1} )</th>
<th>( \gamma_{1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>0.008</td>
<td>0.215</td>
<td>-0.125</td>
<td>-0.033</td>
<td>-0.039</td>
<td>-0.291</td>
<td>-0.056</td>
<td>0.028</td>
<td>0.018</td>
<td>0.154</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.82*</td>
<td>2.43**</td>
<td>-1.43</td>
<td>-1.82</td>
<td>-2.38**</td>
<td>-2.02**</td>
<td>-0.55</td>
<td>1.83</td>
<td>2.51**</td>
<td>2.23**</td>
</tr>
<tr>
<td>adj. R^2</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
<td>0.065</td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 5 (continued)


Panel B: Error-Correction Model of Share Turnover: 1962-1986

This panel presents results from the error-correction model of Share Turnover given by Equation (2.14):

$$\Delta V_t = c_2 + \alpha_{21} \Delta P_{t-1} + \alpha_{22} \Delta P_{t-2} + \beta_{21} \Delta V_{t-1} + \beta_{22} \Delta V_{t-2} + \lambda_{21} \Delta D_{t-1} + \lambda_{22} \Delta D_{t-2} + \delta_2 \hat{e}_{t-1} + \phi_2 \hat{u}_{t-1} + \gamma_2 D_{t-1} + \nu_t$$

where all variables are as described in Panel A, and the $\hat{u}$'s are the regression residuals from the cointegrating regression between dividends and share turnover.

<table>
<thead>
<tr>
<th>coefficient</th>
<th>$c_2$</th>
<th>$\alpha_{21}$</th>
<th>$\alpha_{22}$</th>
<th>$\beta_{21}$</th>
<th>$\beta_{22}$</th>
<th>$\lambda_{21}$</th>
<th>$\lambda_{22}$</th>
<th>$\delta_2$</th>
<th>$\phi_2$</th>
<th>$\gamma_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t$-stat</td>
<td>-0.27</td>
<td>2.22**</td>
<td>1.87</td>
<td>-4.35*</td>
<td>-3.18*</td>
<td>0.297</td>
<td>1.24</td>
<td>-0.634</td>
<td>3.14*</td>
<td>-1.03</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.260</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* ** Significant at the 1% and 5% levels, respectively.
Table 5 (continued)


This panel presents results from the error-correction model of the Dividend Index given by Equation (2.15):

\[ \Delta D_t = c_3 + \alpha_{31} \Delta P_{t-1} + \alpha_{32} \Delta P_{t-2} + \beta_{31} \Delta V_{t-1} + \beta_{32} \Delta V_{t-2} + \lambda_{31} \Delta D_{t-1} + \lambda_{32} \Delta D_{t-2} + \theta_3 \hat{\eta}_{t-1} + \phi_3 \hat{\nu}_{t-1} + \gamma_3 \nu_{t-1} + \nu_t \]

where all variables are as described in Panels A and B above.

<table>
<thead>
<tr>
<th>( c_3 )</th>
<th>( \alpha_{31} )</th>
<th>( \alpha_{32} )</th>
<th>( \beta_{31} )</th>
<th>( \beta_{32} )</th>
<th>( \lambda_{31} )</th>
<th>( \lambda_{32} )</th>
<th>( \phi_3 )</th>
<th>( \theta_3 )</th>
<th>( \gamma_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.011</td>
<td>-0.161</td>
<td>-0.194</td>
<td>-0.099</td>
<td>-0.004</td>
<td>-0.599</td>
<td>-0.136</td>
<td><strong>0.022</strong></td>
<td><strong>0.022</strong></td>
<td><strong>0.042</strong></td>
</tr>
<tr>
<td><strong>6.58</strong></td>
<td><strong>-3.13</strong></td>
<td><strong>-3.81</strong></td>
<td><strong>-0.93</strong></td>
<td><strong>-0.374</strong></td>
<td><strong>-7.19</strong></td>
<td><strong>-2.29</strong></td>
<td>2.02</td>
<td>1.75</td>
<td>0.62</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.430</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 5 (continued)

<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>This panel presents results from the error-correction model of the TOTVAL index given by Equation (2.16):</td>
</tr>
<tr>
<td>[ \Delta P_t = c_1 + c_1^* + \sum_{i=1}^{2} \alpha_{ji} \Delta P_{t-i} + \sum_{j=1}^{2} \beta_{ji} \Delta V_{t-j} + \sum_{l=1}^{2} \lambda_{li} \Delta D_{t-l} + \delta_{t-1} + \delta_{t-1} + \gamma_{1} u_{t-1} + u_t ]</td>
</tr>
<tr>
<td>where all variables are as described in Panels A and B above, and the ( d )'s are dummy variables which allow the respective coefficients to shift subsequent to October, 1987.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>( c_1 )</th>
<th>( c_1^* )</th>
<th>( \alpha_{11} )</th>
<th>( \alpha_{12} )</th>
<th>( \alpha_{12}^* )</th>
<th>( \beta_{11} )</th>
<th>( \beta_{12} )</th>
<th>( \beta_{12}^* )</th>
<th>( \lambda_1 )</th>
<th>( \lambda_1^* )</th>
<th>( \lambda_{12} )</th>
<th>( \lambda_{12}^* )</th>
<th>( \delta_1 )</th>
<th>( \delta_1^* )</th>
<th>( \gamma_1 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t )-stat</td>
<td>2.57*</td>
<td>-0.62</td>
<td>0.72</td>
<td>1.05</td>
<td>-0.37</td>
<td>-1.33</td>
<td>-0.13</td>
<td>-2.51**</td>
<td>-0.82</td>
<td>-1.50</td>
<td>-0.01</td>
<td>-0.86</td>
<td>1.16</td>
<td>1.48</td>
<td>2.35</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.076</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 5 (continued)


This panel presents results from the error-correction model of Share Turnover given by Equation (2.17):

\[ \Delta V_t = c_2 + c_2^* + \sum_{i=1}^{2} \alpha_{2i} \Delta P_{t-i} + \sum_{i=1}^{2} \alpha_{2i}^* \Delta P_{t-i} + \sum_{j=1}^{2} \beta_{2j} \Delta V_{t-j} + \sum_{j=1}^{2} \beta_{2j}^* \Delta V_{t-j} + \sum_{l=1}^{3} \lambda_{2l} \Delta D_{t-l} + \sum_{l=1}^{3} \lambda_{2l}^* \Delta D_{t-l} + \delta_{2} \delta_{t-1} + \phi_{2} \phi_{t-1} + \gamma_{2} \gamma_{2t-1} + \nu_{2t} \]

where all variables are as described in Panels A and B above, and the \( d \)'s are dummy variables which allow the respective coefficients to shift subsequent to October, 1987.

<table>
<thead>
<tr>
<th>( c_2 )</th>
<th>( c_2^* )</th>
<th>( \alpha_{21} )</th>
<th>( \alpha_{21}^* )</th>
<th>( \alpha_{22} )</th>
<th>( \alpha_{22}^* )</th>
<th>( \beta_{21} )</th>
<th>( \beta_{22} )</th>
<th>( \beta_{22}^* )</th>
<th>( \lambda_{21} )</th>
<th>( \lambda_{21}^* )</th>
<th>( \lambda_{22} )</th>
<th>( \lambda_{22}^* )</th>
<th>( \delta_{2} )</th>
<th>( \phi_{2} )</th>
<th>( \gamma_{2} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>-0.003</td>
<td>-0.030</td>
<td>0.569</td>
<td>-0.185</td>
<td>0.658</td>
<td>-0.633</td>
<td>-0.358</td>
<td>-0.448</td>
<td>-0.224</td>
<td>-0.078</td>
<td>0.198</td>
<td>0.148</td>
<td>0.489</td>
<td>-1.178</td>
<td>-0.203</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.25</td>
<td>-0.89</td>
<td>1.73</td>
<td>-0.25</td>
<td>1.96**</td>
<td>0.91</td>
<td>-3.28*</td>
<td>-2.28**</td>
<td>-2.89*</td>
<td>-0.41</td>
<td>0.39</td>
<td>0.12</td>
<td>1.29</td>
<td>-1.23</td>
<td>-2.20**</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.281</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 5 (continued)


This panel presents results from the error-correction model of the Dividend Index given by Equation (2.18):

\[
\Delta D_t = c_3 + c_3^* + \sum_{i=1}^{2} \alpha_{3i} \Delta P_{t-i} + \sum_{i=1}^{2} \alpha_{3i}^* \Delta P_{t-i} + \sum_{j=1}^{2} \beta_{3j} \Delta V_{t-j} + \sum_{j=1}^{2} \beta_{3j}^* \Delta V_{t-j} + \sum_{l=1}^{2} \lambda_{3l} \Delta D_{t-l} + \sum_{l=1}^{2} \lambda_{3l}^* \Delta D_{t-l} + \theta_3 \hat{\eta}_{t-1} + \phi_3 \hat{\eta}_{t-1} + \gamma_3 \nu_{t-1} + \nu_{3t}
\]

where all variables are as described in Panels A and B above, and the \(d\)'s are dummy variables which allow the respective coefficients to shift subsequent to October, 1987.

<table>
<thead>
<tr>
<th>(c_3)</th>
<th>(c_3^*)</th>
<th>(\alpha_{31})</th>
<th>(\alpha_{31}^*)</th>
<th>(\alpha_{32})</th>
<th>(\beta_{31})</th>
<th>(\beta_{31}^*)</th>
<th>(\beta_{32})</th>
<th>(\beta_{32}^*)</th>
<th>(\lambda_{31})</th>
<th>(\lambda_{31}^*)</th>
<th>(\lambda_{32})</th>
<th>(\lambda_{32}^*)</th>
<th>(\theta_3)</th>
<th>(\phi_3)</th>
<th>(\gamma_3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.008</td>
<td>0.002</td>
<td>-0.236</td>
<td>0.335</td>
<td>-0.034</td>
<td>-0.265</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.037</td>
<td>-0.079</td>
<td>-0.330</td>
<td>-0.173</td>
<td>0.081</td>
<td>0.016</td>
<td>-0.003</td>
<td>0.485</td>
</tr>
<tr>
<td>6.27*</td>
<td>0.72</td>
<td>-4.47*</td>
<td>2.75*</td>
<td>-0.54</td>
<td>-2.24**</td>
<td>-0.08</td>
<td>-2.02**</td>
<td>0.07</td>
<td>-1.01</td>
<td>-0.55</td>
<td>-1.51</td>
<td>-2.25**</td>
<td>0.52</td>
<td>1.74</td>
<td>-0.39</td>
</tr>
</tbody>
</table>

* \( \text{adj. } R^2 = 0.450 \)

* \(, ** \text{ Significant at the 1% and 5% levels, respectively.} \)
Table 5 (continued)


Panel G: Diagnostics on the Error-Correction Models

This panel presents diagnostics on the Error-Correction Models presented in Panels A-F above. The notation below is as follows: BJ stands for the Bera-Jarque test for normality in the regression residuals, which is distributed chi-square with $T$ degrees of freedom; $E(L)$ stands for Engle's test for ARCH in the regression residuals at lag $L$, which is also distributed chi-square with $T$ degrees of freedom; $DW(H)$ stands for the Durbin-Watson $H$-statistic, which tests for first-order serial correlation in the regression residuals when a lagged dependent variable used as an explanatory regressor; in the method employed here, the null of no first-order autocorrelation is rejected if the value of $H$ exceeds the critical value of a $t$-statistic; $Q(L)$ stands for the Ljung-Box $Q$-statistic, which tests the hypothesis that the autocorrelations in the first $L$ regression residuals jointly equal zero.

<table>
<thead>
<tr>
<th>PANEL</th>
<th>$BJ$</th>
<th>$E(4)$</th>
<th>$E(8)$</th>
<th>$DW(H)$</th>
<th>$Q(6)$</th>
<th>$Q(12)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>60.87*</td>
<td>8.58</td>
<td>11.79</td>
<td>0.07</td>
<td>4.30</td>
<td>10.62</td>
</tr>
<tr>
<td>$B$</td>
<td>64.19*</td>
<td>12.50</td>
<td>13.79</td>
<td>1.44</td>
<td>4.91</td>
<td>26.02*</td>
</tr>
<tr>
<td>$C$</td>
<td>53.41*</td>
<td>13.97</td>
<td>18.46**</td>
<td>-1.24</td>
<td>4.82</td>
<td>8.34</td>
</tr>
<tr>
<td>$D$</td>
<td>29.62*</td>
<td>1.53</td>
<td>3.17</td>
<td>-0.69</td>
<td>3.90</td>
<td>9.01</td>
</tr>
<tr>
<td>$E$</td>
<td>70.83*</td>
<td>14.72*</td>
<td>16.18**</td>
<td>0.46</td>
<td>4.40</td>
<td>29.04*</td>
</tr>
<tr>
<td>$F$</td>
<td>66.39*</td>
<td>10.41**</td>
<td>14.23</td>
<td>-1.92</td>
<td>4.18</td>
<td>9.65</td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 6

Predicting Monthly Returns to Stocks: Comparison with Other Studies.

This table reports results from other studies that attempt to explain monthly returns to either the overall market of stocks or a large portfolio of stocks using regressions similar to those shown in Table 4. The study, dependent variable, explanatory regressors, adjusted R-square and time period studied are shown below. The information reported represents the strongest results from each study.

<table>
<thead>
<tr>
<th>Study</th>
<th>Dependent Variable</th>
<th>Explanatory Regressor(s)</th>
<th>$R^2$</th>
<th>Time Period Studied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Keim &amp; Stambaugh 1987</td>
<td>Excess Return to Small Quintile CRSP Portfolio</td>
<td>One lag of monthly return to S&amp;P 500</td>
<td>0.03</td>
<td>1928-1952</td>
</tr>
<tr>
<td>Fama &amp; French 1988</td>
<td>Nominal Return to Value-Weighted CRSP Index</td>
<td>One lag of monthly market dividend yield</td>
<td>0.02</td>
<td>1957-1986</td>
</tr>
<tr>
<td>Fama &amp; French 1989</td>
<td>Nominal Return to Value-Weighted CRSP Index</td>
<td>One lag of monthly market dividend yield and default spread</td>
<td>0.04</td>
<td>1953-1987</td>
</tr>
<tr>
<td>Conrad &amp; Kaul 1989</td>
<td>Nominal Return to Small Quintile CRSP Portfolio</td>
<td>Four lagged weekly returns to small quintile CRSP portfolio and four dummies for each week in January</td>
<td>0.25</td>
<td>1962-1985</td>
</tr>
<tr>
<td>Jegadeesh 1990</td>
<td>Nominal Return to Large Quintile CRSP Portfolio</td>
<td>12 lagged monthly returns and 2 lagged annual returns of large CRSP portfolio</td>
<td>0.13</td>
<td>1929-1982</td>
</tr>
<tr>
<td>Ferson &amp; Harvey 1991</td>
<td>Excess Return to Value-Weighted CRSP Index</td>
<td>One monthly lag of excess return to CRSP equally-weighted index, January dummy, excess return on 3-mo. T-Bill, junk spread, div. yield on S&amp;P 500, and nominal return to 1-mo. T-Bill</td>
<td>0.14</td>
<td>1964-1986</td>
</tr>
</tbody>
</table>
PART 3:

OUT-OF-SAMPLE FORECASTS OF MONTHLY STOCK RETURNS FROM AN ERROR-CORRECTION MODEL: A COMPARISON WITH PREVIOUS METHODS
3.1. Introduction

The question of whether returns to financial securities are predictable from historical information is one of long-standing interest to researchers in financial economics. Evidence regarding the predictability of security returns can provide insight into the process generating returns to assets, as well as the empirical validity of theories that purport to explain the behavior of asset prices in efficient markets. While early research supported the view that asset returns were largely unpredictable, more recent evidence indicates that a substantial percentage of the variation in the returns to assets may be predictable, particularly at longer horizons. This paper presents new evidence regarding the predictability of returns to stocks at monthly intervals.

Part 2 of this dissertation developed and tested the hypothesis that stock prices and trading volume are influenced by a set of common underlying factors. The empirical evidence presented in Part 2 could not reject the hypothesis of a common stochastic trend in a time series of stock prices and trading volume, which was interpreted as evidence consistent with the common factor hypothesis. Inclusion of an index of the aggregate annual dividend paid out to the S&P 500 as an instrument for the (unobservable) common factors resulted in an error-correction model that explained 6.5% of the variation in monthly stock returns. Section 2.6 above showed that this level of explanatory power is comparable with previous studies which model monthly returns as a function of a set of predetermined instruments thought to be correlated with the true information set which should influence the expected returns of financial securities in efficient markets.

Because error-correction models exclusively use lagged regressors to model the time series behavior of cointegrated variables, they are often associated with forecasting models. In Part 3 of this dissertation, the error-correction model (ECM) of stock prices,
trading volume and aggregate dividends from Part 2 is re-written into a forecasting model of monthly stock returns. Out-of-sample forecasts of monthly stock returns from the ECM are calculated and compared to forecasts from other competing models. The various models are evaluated according to both statistical and economic criteria. The results indicate that the simple time-series model of Conrad and Kaul (1989) provides the best forecasts of monthly returns under a variety of conditions.

The structure of this paper is as follows: Section 3.2 presents a review of the literature on the predictability of security returns; Section 3.3 reviews the empirical evidence regarding the time series behavior of stock prices and trading volume presented in Part 2 above, discusses why ECM's might be useful in forecasting financial and economic time series, and presents within-sample results from the ECM forecasting model in various subperiods; Section 3.4 identifies two other forecasting models chosen to compete with the ECM forecasts, and presents within-sample results and diagnostics from these models; Section 3.5 presents the out-of-sample forecasting evidence from each model; Section 3.6 presents the conclusions of this study.
3.2. Review of the Literature

Most of the literature on the predictability of security returns falls into one of two broad categories. The first of these attempts to predict future returns to financial securities from the autocorrelation structure of past returns. The early evidence from studies employing this approach, which focus mostly on the autocorrelations in short-term returns, indicates that security returns are largely unpredictable. This literature is sometimes referred to collectively as the "random walk" literature. More recent work on the autocorrelations in returns indicates that returns at longer horizons contain a substantial predictable component. One of the most interesting issues raised by these studies is whether changes in expected returns represent a rational market response to changes in risk, irrational overreaction to news (a.k.a. speculative bubbles), or some combination of the two.

The second approach to the question of the predictability of security returns examines whether returns can be forecasted from economic variables that may collectively comprise the undiversifiable market factors postulated by theories of asset prices in efficient markets. As with the other branch of the predictability literature, the early evidence finds only a weak relationship between expected returns and macroeconomic factors. The more recent evidence, however, indicates that a substantial percentage of the variation in security returns through time may be related to the current and future state of the macroeconomy.
A. Predicting Stock Returns from the Autocorrelations in Past Returns

One problem with the early literature on the autocorrelation structure of security returns is the lack of an explicit theoretical model to test. For much of the pre-1965 literature, the "null hypothesis" is that investing in securities should be a "fair game." The fair game model implies that investing in securities should present the investor with an equal opportunity of a gain or loss, with the net expectation being a zero gain. The early work of Kendall (1935), Working (1934), Roberts (1959) and Osborne (1959) implies that security returns are consistent with the fair game model and appear to follow a "random walk," where successive price changes are approximately independent.

Until the mid-1980's it was somewhat heretical to even entertain the notion that capital markets exhibited any significant degree of inefficiency. DeBondt and Thaler's (1985) study on investor overreaction presents important new evidence that rekindled interest into this line of inquiry, however. They formally test whether investors overreact to information by hypothesizing that a portfolio of stocks that has experienced extreme negative returns (losers) will subsequently outperform a portfolio of stocks that experienced extreme positive returns (winners) over the same portfolio-formation period. DeBondt and Thaler form winner and loser portfolios of common stocks based on their performance over a 36-month period, and find that the loser portfolios outperform the winner portfolios by twenty-four percent over the subsequent 36 months. This "mean reversion" effect is stronger for the losers than for the winners, with the majority of the reversion taking place in January of the second and third years. In a subsequent study,

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1 The original fair game model is attributed to the work of Bachelier (1900).

2 Fama (1970) provides an excellent review of the early literature on market efficiency and the predictability of security returns.
Debondt and Thaler (1987) present evidence that this effect cannot be attributed to changes in the systematic risk of the portfolios, nor can it be explained by changes in firm size. They conclude that the winner/loser effect is evidence that investors overreact to information.

Lo and MacKinlay (1988) examine the variance ratios of stock portfolios to test whether stock returns actually follow a random walk, which would imply variances that increase linearly through time. They find that the weekly variance ratios of a sample of size-ranked portfolios increase by less than suggested by the random walk hypothesis, which is indicative of positive autocorrelation in portfolio returns over short horizons. Poterba and Summers (1987) find similar positive autocorrelation in short-horizon returns, as well as negative autocorrelations over longer horizons. Their estimates of the long-horizon variance ratios of value-weighted stock portfolios indicate that over fifty percent of the variance of long-horizon returns is due to the transitory, mean-reverting component in returns. Fama and French (1988) present further evidence that stock returns exhibit a slowly mean-reverting component that induces significant predictability in security returns. Regressions of long-horizon returns on prior period returns explain almost forty percent of 3-5 year return variances of small firm portfolios, and twenty-five percent of the variation of returns to large firm portfolios. Fama and French conclude that their results are consistent with both overreaction on the part of investors as well as rational time-varying expected returns.

Chan (1988) presents a significant challenge to DeBondt and Thaler's conclusions that mean reversion indicates overreaction on the part of investors. Chan argues that DeBondt and Thaler's use of betas estimated during the ranking period may underestimate the risk of the losers and overestimate the risk of the winners. Chan adjusts for risk by estimating the test-period betas directly, and finds that the risk-adjusted excess returns
earned by loser portfolios are much smaller than those reported by DeBondt and Thaler. Chan concludes that the returns to a contrarian strategy are likely due to changes in firm risk. Ball and Kothari (1989) present further evidence regarding firm risk and the profits to contrarian investment strategies. They find that when beta is estimated using annual returns, the betas of extreme losers exceed the betas of extreme winners by 0.76 following the portfolio formation period. They conclude that such extreme differences in systematic risk account for the substantial differences in the returns to winner and loser portfolios.

Zarowin (1989) conducts a study similar to DeBondt and Thaler, in which he forms winner/loser portfolios based on changes in earnings instead of cumulative returns. Zarowin finds that the earnings losers outperform the earnings winners over the subsequent 36-month period, which is consistent with the DeBondt and Thaler overreaction hypothesis. He also finds that the poorest earners are significantly smaller than the best earners, however. Moreover, when both groups are matched by size, the return discrepancy disappears entirely. Zarowin therefore concludes that mean reversion for winner/loser portfolios is merely a manifestation of the size effect.

Lo and MacKinlay (1990) present evidence which suggests that less than half of the expected profits from a contrarian investment strategy may be attributed to overreaction. The majority of such profits are found to be caused by cross-correlation effects among securities, where the returns of larger stocks lead the returns to smaller stocks. Lo and MacKinlay therefore conclude that contrarian profits are likely due to a delayed reaction on the part of small firms to common factors in the returns of all securities. Conrad and Kaul (1993) offer further evidence against DeBondt and Thaler's overreaction hypothesis. They argue that single-period returns are inflated due to bid-ask errors, nonsynchronous trading and price discreteness. Techniques such as DeBondt and Thaler's, which cumulate short-horizon returns over long periods, cumulate the "true"
component of returns as well as the component which is upwardly biased. If the common stock of firms in the loser portfolios are lower-priced than those in the winner portfolios, then the upward bias in the loser portfolios will be substantially greater than the winners. This bias will influence the results of all studies which seek to examine the returns to contrarian-based investment strategies.

Chopra, Lakonishok and Ritter (1992) test whether the winner/loser effect is based on investor overreaction, or is mainly a manifestation of a risk and/or size effect. They claim that the market compensation per unit of beta risk estimated from a Sharpe-Lintner market model is biased upwards. They therefore adjust for risk using a market-estimated risk premium. Using monthly returns and five-year portfolio formation periods, they find that extreme losers outperform extreme winners by over nine percent per year. They further conclude that this effect is not a manifestation of the size effect, as argued by Zarowin (1989, 1990).

There is also a substantial literature which explores the time series behavior of security returns without directly addressing questions regarding overreaction and market efficiency. Conrad and Kaul (1988) model weekly returns as an autoregressive process and find that short-horizon returns exhibit frequent mean-reverting behavior. Their Kalman filter technique allows them to forecast weekly returns to size-ranked portfolios using the returns from four previous weeks, while allowing the weights to decline as the weeks become more distant. Regressions of realized returns on expected returns extracted using this method explain up to twenty-six percent of the variation in the weekly returns to small stocks. Because they construct their weekly returns using data from Wednesday close-to-Wednesday close, where firms must trade on both Wednesdays, it is unlikely that the positive short-term autocorrelations they discover result primarily from the well-known nonsynchronous trading effect.
In a subsequent study, Conrad and Kaul (1989) develop a model for monthly expected returns that relies on the rapidly decaying autocorrelations in weekly returns. The mean reversion in weekly returns explains over twenty-five percent of the variation in monthly returns to small-firm portfolios using data from 1962-1986. Their study also uncovers evidence that the variation in monthly expected returns is much larger than previously expected. For the 1970's sub-period, changes in short-horizon expected returns explain over forty percent of the variation in returns to a small-firm portfolio. Curiously, a portfolio of large firms exhibits almost no variation in expected returns.

The positive autocorrelation in short-horizon returns documented by Poterba and Summers (1987), Fama and French (1988), Conrad and Kaul (1988, 1989) and Lo and MacKinlay (1988, 1990) would seem to indicate that buying winners and selling losers in the short-term should also yield positive excess returns. Jegadeesh and Titman (1993) find that these "relative strength" investing strategies yield significant excess returns for 3- to 12-month holding periods. The results of their paper indicate that these returns are not due to the systematic risk of the trading strategies, nor can they be attributed to the lead-lag effects documented by Lo and MacKinlay (1990). The results are consistent with delayed price reactions to firm-specific information, however.

Two main conclusions emerge from this review of the predictability literature based on the autocorrelations in security returns. The first is that stock returns are predictable from historical information. The second is that persuasive arguments exist for both the overreaction hypotheses and the view that time-varying expected returns represent rational responses to changes in risk and other firm characteristics.
B. Forecasting Stock Returns from Economic Variables

The theoretical and empirical evidence regarding the co-movements of the prices of financial assets suggests the existence of some common underlying influences, also known as market or systematic factors. The identity of the systematic factors that are related to the performance of the U.S. stock market has been thoroughly researched in the academic literature. The results of these studies support the view that the prices of financial assets are related to the current and future state of the macroeconomy.

Chen, Roll, and Ross (1986) propose a set of macroeconomic state variables that are likely to be related to the return to U.S. stocks. These variables are the monthly growth rate of industrial production, unanticipated inflation, the yield spread, and the slope of the term structure. The authors regress the monthly returns of twenty size-based stock portfolios on monthly values of the macroeconomic variables, and find each to be significantly related to the return to each portfolio. When the NYSE index is included in the regressions along with the various macroeconomic factors, its effect in explaining stock returns is insignificant. The authors therefore conclude that a multi-factor macroeconomic model does a better job of explaining equity returns than a single-factor CAPM.

Keim and Stambaugh (1986) examine the predictive power of the level of stock prices and the levels of a different set of variables designed to capture macroeconomic conditions. Their set of predetermined variables include the yield spread between long-term low-grade corporate debt and short-term Treasury bills, a detrended price series of

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3 Chen, Roll and Ross (1986) examine the contemporaneous relationship between monthly stock returns and changes in macroeconomic variables. While their study does not address the issue of stock return predictability per se, it is included in the literature review as a cornerstone paper that establishes the link between macroeconomic forces and the stock market.
the S&P 500 Composite Index, and a stock index designed to capture the extra sensitivity of small firms to changes in expected future risk premiums. Keim and Stambaugh find that all three variables are significant in predicting future stock returns.

Fama and French (1989) test the hypothesis that expected returns on stocks and bonds vary inversely with the business cycle. They find that the dividend yield on the NYSE and the default spread on corporate bonds capture similar variation in expected stock and bond returns, and that these variables appear to be related to economic conditions that span several business cycles. The slope of the term structure, however, appears to capture variation in expected returns that is related to short-term business cycles. Their results support the hypothesis that expected returns on stocks and bonds are lower when economic conditions are strong, and higher when conditions are weak. Fama and French show that future returns to financial securities are partially forecastable from the levels of current macroeconomic state variables.

Breen, Glosten and Jagannathan (1989) present evidence that the knowledge of the predictability of stock returns may be used to earn significant economic profits. They use the one-month T-Bill rate to determine when to shift funds between a value-weighted stock index and a portfolio of T-Bills. Using data from 1954-1986, they find that a managed portfolio earns a return two percent higher than the passive index portfolio. Additionally, the managed portfolio exhibits only 60% of the volatility of the passive stock portfolio.

Fama (1990) provides a useful discussion that identifies three likely sources of the time-varying expected returns documented in previous studies. These are unanticipated shocks to expected cash flows, the predictable variation in discount rates, and shocks to discount rates. Fama argues that future growth rates of industrial production should be highly correlated with future cash flows to businesses, and that if the stock market is
efficient, and thus forward-looking, contemporaneous stock returns should be related to the future growth of industrial production. Fama finds that the change in industrial production for a given month is related to up to ten lags of monthly returns. He also shows that regressions of longer-horizon returns on future production growth rates have higher explanatory power than regressions using short-term returns. While the evidence indicates that stock returns forecast industrial production, Fama also finds that the term spread, default spread, and dividend yield on the stock market can be used to predict returns to stocks. He asserts that these variables are likely to capture the variation (both anticipated and unanticipated) in discount factors.

Chen (1991) confirms that the default spread, the term spread, the one-month T-bill rate and the dividend-price ratio are all important determinants of future returns to the stock market. He also finds that the lagged growth rate of industrial production can be used to forecast the monthly return to stocks, a finding not documented in previous studies. Chen finds that these same variables are also related to the recent and future growth of GNP. Chen interprets this as evidence that the expected excess market return is negatively related to the recent growth of GNP and positively related to its future growth. His work further reinforces the notion that returns in an efficient market may be predictable based on state variable forecasts of the future health of the macroeconomy.

Ferson and Harvey (1991) identify an interesting aspect of return predictability that has been overlooked by most previous studies. Instead of exclusively focusing on changes in assets' sensitivities to risk (betas), the authors explicitly model time-varying expected returns as a function of changes in the price of beta risk as well. They conclude that time variation in the expected compensation for beta, as opposed to movements in the betas, captures most of the predicted variation in returns for stock portfolios. They find that the risk premium associated with the stock market is most important in explaining time-
varying returns to stocks, and that the premia associated with the term structure and default spreads are most important for fixed-income securities. Ferson and Harvey interpret their results as supportive of a rational foundation for time variation in expected returns. Ferson and Korajczyk (1993) present evidence that the results of Ferson and Harvey (1991) are sensitive to the sample period employed in their study. When looking at returns over longer horizons, however, they conclude that modeling portfolio returns as a function of time-varying betas and risk premia captures a substantial amount of the predictable variation in returns.

The evidence from the macroeconomic branch of the predictability literature supports the notion that changes in expected returns are rational responses to changes in assets' sensitivity to risk and the market-wide price of risk. While the forecasting power of macroeconomic variables is weak for stock returns at short horizons, the empirical evidence indicates that a substantial percentage of expected returns at long-horizon returns are related to the current and future state of the macroeconomy.
3.3 Cointegration, Error-Correction and Forecasting

Sections 2.1 - 2.2 above develop the hypothesis that stock prices and trading volume are jointly determined conditional on the same set of fundamental factors. The presence of a common stochastic trend (cointegration) in a time series of stock prices and trading volume is shown to be consistent with the hypothesis that a set of common factors influences both stock prices and trading volume. Section 2.3 presents a test of this hypothesis designed to circumvent bothersome questions regarding the exact identity of these factors, which represents a separate area of inquiry in the empirical asset pricing literature. The results of Section 2.3 indicate that stock prices and trading volume are cointegrated. This result is interpreted as support for the hypothesis that a set of common factors influences their joint determination.

In Section 2.4 above, stock prices and trading volume are modeled using the theoretically correct method for modeling cointegrated variables, known as an error-correction model (ECM). An ECM of stock prices and trading volume explains 4% of the variation in monthly stock returns using data from 1962-1986. In Section 2.5 an index of the aggregate flow of dividends is included into the analysis as an instrument for the information set or factors hypothesized to influence volume and price. After demonstrating that stock prices, trading volume and dividends are all part of a trivariate cointegrating system, the dividend index is included into the ECM of stock prices. Equation (2.13) shows the ECM of stock prices, volume and dividends, which is reprinted below for convenience:

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4 Engle and Granger (1987) show that cointegration implies an error-correction model.
\[ \Delta P_t = c_1 + \alpha_{11} \Delta P_{t-1} + \alpha_{12} \Delta P_{t-2} + \beta_{11} \Delta V_{t-1} + \beta_{12} \Delta V_{t-2} + \lambda_{11} \Delta D_{t-1} + \lambda_{12} \Delta D_{t-2} + \delta_1 \tilde{\epsilon}_{t-1} + \theta_1 \tilde{\eta}_{t-1} + \gamma_1 \nu_{t-1} + \nu_t \]  

(2.13)

The estimated regression coefficients, t-statistics and adjusted R\(^2\) from Equation (2.13) are shown in Panel A of Table 5. Inclusion of the dividend index substantially enhances the explanatory power of the ECM. The adjusted R\(^2\) of 6.5\% is comparable to other studies which use macroeconomic variables to forecast monthly returns.\(^5\)

Notice from Equation (2.13) that the explanatory regressors are lagged values of \(\Delta P_t\), \(\Delta V_t\) and \(\Delta D_t\), and the "error-correction" terms \(\tilde{\epsilon}_t\) and \(\tilde{\eta}_t\).\(^6\) Because ECM's model the contemporaneous change in a time series as a function of its own lags and the lagged values of other cointegrated variables, ECM's are often associated with forecasting models. Equation (2.13) would be a true forecasting equation were it not for the fact that \(\tilde{\epsilon}_t\) and \(\tilde{\eta}_t\) are estimated in-sample using twenty-five years of data from 1962-1986. This section develops Equation (2.13) into a forecasting model by using an alternative method for estimating the error-correction terms which will allow for the calculation of out-of-sample forecasts. Equation (2.13) is then re-estimated using these approximations for the error-correction terms. Subsequent sections will compare forecasts from the ECM with forecasts calculated from the predictive models developed in previous studies.

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\(^5\) Table 6 compares the results of regressions that use a model similar to Equation (2.13) with predictive regressions from other studies.

\(^6\) The identity of the regressors in Equation (2.13) are thoroughly explained in Section 2.5.C and Table 5. Equation (2.13) models the continuously compounded monthly return to stocks as a function of last month's return to the market, last month's change in share turnover, two monthly lags of the change in the flow of dividends to the market and the error-correction terms, which are the pairwise stationary linear combinations of the cointegrated variables used in the analysis. The \(d's\) are dummy variables which allow all the regression coefficients to shift subsequent to October, 1987.
As discussed in Section 2.4 above, the test for cointegration (or a common stochastic trend) between two nonstationary time series first involves regressing one series on the other. If the residuals from this regression are stationary, then the series are cointegrated. Intuitively, this implies that the stochastic trend in one series explains the stochastic trend in the other, so that the quality of nonstationarity is not passed on to the regression residuals. The residuals from this regression are known as the error-correction term. For example, the error-correction term between the natural logarithm of the stock price index and share turnover is equal to:

\[ \hat{\varepsilon}_t = \ln V_t - c - \hat{\gamma} \ln P_t \]  

where \( c \) is the regression intercept and \( \hat{\gamma} \) is the regression coefficient estimated in the regression of the natural log of share turnover on the natural log of the \( TOTVAL \) price index. Note that the natural logarithm of the share turnover-to-price ratio \( (T/P) \) provides a reasonable approximation to the error-correction term, \( \hat{\varepsilon}_t \):

\[ \frac{T}{P} = \ln \left[ \frac{V_t}{P_t} \right] = \ln V_t - \ln P_t = \hat{\varepsilon}_t. \]  

The closer \( c \) is to zero and \( \hat{\gamma} \) is to 1.0, the better is the approximation.

Equation (2.13) also uses the lagged error-correction term between stock prices and dividends, \( \hat{\eta}_t \), as an explanatory regressor. As was the case with the turnover to price ratio, the natural log of the dividend-price ratio provides a reasonable approximation to \( \hat{\eta}_t \):
Fama and French (1988) show that one lag of the monthly dividend-price ratio explains two percent of the monthly return to stocks. The discussion below provides insight into why ratios such as $T/P$ and $D/P$ should have the power to predict future returns to stocks.

Section 2.4 explains why the error-correction term can be used to forecast future values of cointegrated variables. If cointegrated variables drift apart in the short run, long-run economic forces act to bring them together again. Cointegrated time series are in equilibrium when the value of one series is "close to" the other. Thus, when the error-correction term is large in one period, implying that one or both of the cointegrated variables are far from equilibrium, it can be predicted that one or both of the variables will change in a subsequent time period, resulting in a smaller value of the error-correction term. The tendency for cointegrated variables to move together in the long run ensures that the error-correction term never becomes too large for too long.

The dividend-to-price and turnover-to-price ratios have the power to forecast future returns to stocks because they are the stationary ratios of nonstationary cointegrated series: stock prices and either dividends or trading volume. Whenever the ratio strays from its long-term mean value, it implies that one of the series has changed without a corresponding change in the other. Because cointegrated variables never stray too far from one another in the long run, the corresponding change in the other variable is likely to occur in a subsequent time period.

Figure 4 presents a graph of the natural logarithm of the share turnover-to-price ratio given by Equation (3.2). Visually, the ratio exhibits frequent mean-reverting behavior, crossing its long-term average (1962-1986) of -0.80 over 80 times in the 294
months spanning July, 1962 to December, 1986. Subsequent to October, 1987, however, the ratio declines precipitously to an historical low, where it appears to resume its short-term mean-reverting behavior. Figure 4 allows for a visual interpretation of the predictive power of the turnover-to-price ratio. Whenever the ratio is substantially above or below its long-term mean value, it forecasts a change in either stock prices or trading volume (or both) as economic forces draw each series back into their long-run equilibrium relationship.

Figure 5 presents a graph of the natural logarithm of the dividend-to-price ratio given by Equation (3.3). This ratio also exhibits mean-reverting behavior, although at longer horizons than the turnover-to-price ratio. The dividend-to-price ratio only crosses its long-term mean ten times in the 1962-1986 period. The graph therefore provides the intuition for Fama and French's finding that dividend yield forecasts a greater percentage of the variation in stock returns at longer horizons: when the $D/P$ ratio strays from its mean, it forecasts a change in one or both of the cointegrated series sometime in the future. Figure 5 shows that the reversion to the mean predicted by cointegration occurs at longer horizons. We would therefore expect a value of dividend yield which was far from its mean value to forecast a long-horizon change in stock prices (and returns).

The ECM given by Equation (2.13) can therefore be re-written into a forecasting model by substituting $T/P$ and $D/P$ for $\hat{e}_t$ and $\hat{\eta}_t$, respectively. Equation (3.4) below shows the model which will be used to obtain out-of-sample forecasts of monthly stock returns:

$$
R_t = c + \alpha_1 \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \beta_1 \Delta V_{t-1} + \beta_2 \Delta V_{t-2} + \\
\lambda_1 \Delta D_{t-1} + \delta (T/P)_{t-1} + \theta (D/P)_{t-1} + \nu_t
$$

\hspace{1cm} (3.4)
where \( R_t \) is the monthly return to the \( TOTVAL \) index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, and all remaining variables are the same as in Equation (2.13).

Table 7 reports results within-sample results from the estimation of Equation (3.4) in five different subperiods, as well as a panel of time series diagnostics on each subperiod. Panel A presents results using data from 1962-1986. The forecasting model exhibits only half the explanatory power of the ECM shown in Panel A of Table 5, with an adjusted \( R^2 \) of 3%. The statistical significance of the first lag of the change in the \( TOTVAL \) index and the first lag of the change in the dividend index are both markedly diminished. Additionally, the first lag of the dividend-price ratio is also statistically insignificant. The model is obviously sensitive to the substitution of \( T/P \) and \( D/P \) for the error-correction terms \( \hat{e}_t \) and \( \hat{\eta}_t \). The time series diagnostics reported in Table 7 are the same as reported in Table 5. Even with the low explanatory power of the model, the only diagnostic which raises a flag is the Bera-Jarque statistic, which rejects the null of normality in the regression residuals. The residuals exhibit no \( ARCH \) effects or serial correlation at any of the lag lengths tested.

Panel B estimates the forecasting model over the 1962-1991 period, with the inclusion of dummy variables which allow the regression coefficients to shift subsequent to October, 1987. This model is shown below as Equation (3.5):

\[
R_t = c + c^* + \alpha_1 \Delta P_{t-1} + \alpha_1 d_{\Delta P_{t-1}} + \alpha_2 D_{t-2} + \alpha_2 d_{\Delta D_{t-2}} + \beta_1 \Delta V_{t-1} + \beta_1 d_{\Delta V_{t-1}} + \beta_2 \Delta V_{t-2} + \\
\beta_2 d_{\Delta V_{t-2}} + \lambda_1 \Delta D_{t-1} + \lambda_1 d_{\Delta D_{t-1}} + \delta(T/P)_{t-1} + \delta d_{(T/P)_{t-1}} + \theta(D/P)_{t-1} + \theta d_{(D/P)_{t-1}} + v_t
\]
where all variables are as given by Equation (3.4), and the \( d' \)s are the dummy variables. The coefficient values obtained from estimating Equation (3.5) are not substantively different from those presented in Panel A. The significance of the dummy coefficient on the regression intercept is sufficient to capture most of the effects of October, 1987, with the coefficient on the dividend-to-price ratio dummy also turning up significant. The explanatory power of the model more than doubles to 8% due to the inclusion of the 1987-1991 period. The time series diagnostics are also similar to those reported in Panel A, with the exception of the \( Q^2 \) statistic, which indicates significant serial correlation in the squared residuals.

Panels C and D of Table 7 report results from the 1963-1977 and 1975-1989 subperiods, respectively. While the regression coefficients are not markedly different from those reported in Panels A and B, the explanatory power of the forecasting model from the 1975-1989 period is ten times greater than that from the 1963-1977 period. The time series diagnostics indicate some ARCH effects in the earlier subperiod, as well as significant serial correlation in the squared residuals. The only significant diagnostics from the 1975-1989 period is once again the Bera-Jarque statistic, which rejects the normality of the regression residuals for almost every model presented in this paper.

Panel E of Table 7 reports results of the forecasting model from the 1988-1991 subperiod. The adjusted \( R^2 \) indicates that the model has virtually no explanatory power subsequent to 1987. The only variable which is statistically significant is the dividend-to-price ratio. Surprisingly, the Bera-Jarque statistic does not reject the normality of the residuals for the 1988-1991 subperiod.\(^7\)

\(^7\) Monthly returns are known to be close to normally distributed (see Fama, 1976). The inability of the forecasting model to capture any significant variation in monthly returns means that the distribution of the regression residuals in Panel E closely resembles that of the dependent variable, which is the monthly return to the NYSE and AMEX universe of stocks.
The overall conclusion from Table 7 is that the forecasting model has weak power to capture the variation in the monthly return to stocks. The explanatory power of the model is best in the 1975-1989 period. The next section presents within-sample results from two competing forecasting models. Subsequent sections compare the ability of the various models to forecast monthly returns based on both statistical and economic criteria.
3.4. Two Alternative Forecasting Models

This section discusses the other forecasting models chosen to compete with the ECM forecasting model presented in Section 3.3 above. As the literature review points out, the two main branches of research into the predictability of security returns focus on forecasting returns from either the time series behavior of past returns or a predetermined set of macroeconomic instruments. One representative model from each approach is introduced below, along with the same within-sample statistics and time series diagnostics presented for the ECM forecasting model in Section 3.3.

A. The Macroeconomic Forecasting Model

Section 3.2.A. reviews the academic literature on predicting stock returns from macroeconomic variables believed to be correlated with the undiversifiable or systematic risk factors which should determine the expected returns to financial securities in efficient markets. The main factors usually employed in these studies are the dividend yield on the overall market of stocks; a measure of output, usually the growth rate of industrial production or GNP; some measure of inflation, such as the CPI; and various measures of interest rates, either in level or spread form, usually computed as the difference between the yield on long- and short-term bonds of a constant risk class.

The following monthly time series of macroeconomic variables are obtained from the WEFA database: the yield on government bonds with one and ten years to maturity; the average yield on corporate bonds rated BAA and AAA; the dividend yield on the S&P 500; the CPI; and a seasonally-adjusted index of industrial production. The difference between the yield on long- and short-term government bonds is taken, and renamed
TERM, which will be used to proxy for the slope of the term structure. Similarly, the difference between the yield on BAA and AAA corporate bonds is taken and called DEF for the default spread, which will serve as a measure of the risk premium demanded by investors to hold corporate bonds of greater default risk.

Table 8 presents the results of Phillips-Perron tests for unit roots in the levels of all the macroeconomic variables, as well as the first differences of the CPI and industrial production, which are thought to be nonstationary in level form. In all cases, 348 months of data are used from 1962-1990. Surprisingly, the only variable for which the null hypothesis of a unit root can be rejected is the variable TERM. The null of a unit root is also rejected for the first difference of the CPI and IP. This finding brings up the interesting possibility that the low explanatory power of previous studies into the time series relationship between security returns and macroeconomic factors is partially due to the econometric misspecification of using nonstationary instruments to explain returns, which are covariance stationary. This conjecture is further supported by running the Johansen test on the 294 x 7 matrix of stock prices, share turnover, the CPI, default spread, yield on 1-year government bonds, yield on BAA corporate bonds and dividend yield on the S&P 500, using monthly data from 1962-1986. The results cannot reject the null hypothesis of six cointegrating vectors for the seven time series, which is consistent with the existence of one common stochastic trend tying all seven series together. For the remainder of this study, we will merely make note of this fact, and recommend that a further exploration into modeling the joint time series behavior of security returns and macroeconomic variables may prove a fruitful area for future research. In order to make the macroeconomic forecasting model comparable with the previous literature, as well as to contrast forecasts based on time series methods with other methods, the macroeconomic variables will be incorporated into a forecasting model in a manner that is consistent with their previous treatment in the literature.
Various combinations of the term and default spreads, dividend yield, and the change in the CPI and the index of industrial production are incorporated into regressions of the following form:

\[ R_t = \beta Z_{t-1} + u_t \]

where \( R_t \) is the monthly return to the \( TOTVAL \) index, and \( Z_{t-1} \) is the matrix of predetermined information variables. The data used in this initial attempt on specifying the best forecasting model spans the 1962-1986 period. Based on the Schwarz-Bayes Criterion and a battery of time series diagnostics on the regression residuals, the model which provides the best fit to the data is:

\[ R_t = c + \varphi TERM_{t-1} + \pi DEF_{t-1} + \omega \Delta CPI_{t-1} + u_t \]  

(3.6)

Table 9 presents results from the estimation of Equation (3.6) over four different subperiods. Panel A, which uses data from 1962-1986, shows that DEF and \( \Delta CPI \) are statistically significant, with an adjusted \( R^2 \) of nine percent. The Durbin-Watson statistic shows no first-order autocorrelation in the regression residuals, and the \( Q \)-statistic shows no evidence of significant autocorrelation at higher lags. The \( Q^2 \) shows significant autocorrelation in the squared residuals, however, and Engle's test for \( ARCH \) detects the presence of time-dependent heteroskedasticity as well. As expected, the Bera-Jarque statistic strongly rejects the null of normality in the residuals.

9 Consistent with the findings of Fama and French (1989), dividend yield is found to be collinear with the default spread. Including \( TERM \) and \( DEF \) and excluding dividend yield results in a better specified model. Industrial production is found to be insignificant in all models.
Panels B-D present results from the 1962-1990, 1963-1977, and 1975-1989 subperiods, respectively. The default spread is statistically significant in all periods, while dividend yield anomalously turns up insignificant in the 1975-1989 period. The explanatory power of the macroeconomic model is strongest for the 1963-1977 period, with an adjusted $R^2$ of fifteen percent.

B. A Time Series Forecasting Model

The literature review and the results presented in Table 6 indicate that the time series model of Conrad and Kaul (1989) has the greatest within-sample explanatory power for predicting the monthly return to a portfolio of stocks. Conrad and Kaul hypothesize that one reason lagged monthly returns have such low power to explain future returns is that there is information being lost by averaging over the individual weekly returns for a given month. Instead of placing equal weight on lagged weekly returns, they estimate the following ARMA(1,1) model:

$$R_t^w = c + \phi R_{t-1}^w + \alpha_t^w - \theta \alpha_{t-1}^w$$  \hspace{1cm} (3.7)

where $R_t^w$ is the weekly return to a portfolio of stocks. Their estimates for the expected return in a given month are then based on the past four weekly returns:

$$E_{t-4}(R_t^m) = \pi_1 R_{t-4}^w + \pi_2 R_{t-5}^w + \pi_3 R_{t-6}^w + \pi_4 R_{t-7}^w$$  \hspace{1cm} (3.8)

where the weight placed on week $i$ is:
\[ \pi_i = \theta^i (\theta - \phi)(1 + \phi^2 + \phi^3) \quad i = 1, 2, 3, 4 . \] 

This allows for the greatest weight to be placed on the most recent week, with the weights declining geometrically through week 7.

Table 10 presents results from the estimation of Equation (3.7) over the same four subperiods as reported for the macroeconomic forecasting model in Table 9. Panel A gives results from the 1962-1986 period. The value of the coefficients \( \phi \) and \( \theta \) are 0.341 and 0.281, respectively. These values are comparable to those obtained by Conrad and Kaul for their next-to-largest quintile portfolio of stocks over the same time period (0.465 and 0.257, respectively). Conrad and Kaul do not estimate their model using returns to an aggregate market index, so a direct comparison of the coefficient values is not possible.\(^{10}\) The adjusted R\(^2\) reported in Panel A of 17 percent indicates that the Conrad and Kaul model captures significantly greater variation in weekly returns than either the ECM or the macroeconomic model can capture for monthly returns. While autocorrelation in the regression residuals is not a problem, the \( Q^2 \)-statistic detects significant autocorrelation in the squared residuals. Interestingly, while the ECM and macroeconomic model apparently captured ARCH effects, the Conrad and Kaul model does not. Once again, the Bera-Jarque statistic can reject normality of the regression residuals.

The results of Panel B, which estimate Equation (3.7) over the entire 1962-1990 period, are similar to those reported in Panel A. The \( Q \)-statistic detects some autocorrelation in the regression residuals when twelve lags are used. The explanatory power of the model is slightly increased. Panel C reports results from the 1963-1977

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\(^{10}\) The values of the coefficients obtained in this study are likely to deviate slightly from those obtained by Conrad and Kaul because they also include four dummy variables in their analysis, one for each week of January. This study omits the January dummies in order to focus on the time series characteristics of their model.
subperiod. Interestingly, none of the regression coefficients are significant at conventional levels, but the model still captures 12 percent of the variation in weekly returns. Panel D shows that the model provides the best fit in the 1975-1989 period, with an adjusted $R^2$ of 20%. The results from the time series diagnostics are similar in all panels: while autocorrelation in the residuals is not a problem, the $Q^2$ detects significant autocorrelation in the squared residuals. Engle's test also rejects the null of no $ARCH$ for all subperiods.
3.5 Forecasting Monthly Returns to Stocks: the Out-of-Sample Evidence

This section computes out-of-sample forecasts of monthly stock returns from the ECM, macroeconomic, and Conrad and Kaul forecasting model. For point of comparison, a fourth "naive" model will also be used, where next month's forecast is simply last months' return to the market. The forecasts from each model will be compared to each other according to their statistical characteristics as well as their ability to generate economic profits under a variety of conditions.

A. Computation of the Forecasts

One-month ahead forecasts from each model are calculated from January, 1978 to December, 1990 according to the following method. A fifteen-year within-sample period is used for initial estimation of the parameters from each model. The first of these periods spans January, 1963 to December, 1977. The parameters from each model are then used to generate one-month ahead forecasts of the return to the TOTVAL index. The forecasts use information through the last day of month $t$ to generate the forecast for month $t+1$. After the first twelve forecasts are generated, the parameters from each model are re-estimated by dropping off the most distant year and adding the next year. For the 1979 forecasts, therefore, the estimation period is January, 1964 to December, 1978. These parameters are then used to produce one-month ahead forecasts for the twelve months of 1979. This procedure is followed repetitively, with the last estimation period spanning January, 1975 to December, 1989. The final forecast generated is for the return for the month of December, 1990. This procedure results in a total of 156 forecasts from each model.
Figure 6 shows a plot of the one-month ahead ECM forecasts vs. the actual return to all NYSE and AMEX stocks included in the \textit{TOTVAL} index. The forecasts tend to be centered around the mean return, only occasionally mimicking the true return. As shown in Table 11, the ECM forecasts have only a weak positive correlation with the true return, with a correlation coefficient of 0.149.

Figure 7 plots the monthly macroeconomic forecasts against the return to the \textit{TOTVAL} index. While this model yields promising forecasts in the 1978-1982 period, the forecasts smooth out considerably from 1983-1990. Recall from Panel D of Table 9 that the macroeconomic model had the poorest fit to the data in the 1975-1989 subperiod. Table 11 shows that the correlation coefficient between the macroeconomic forecasts and the true return is weakly positive at 0.114.

Figure 8 plots the monthly forecasts from the Conrad and Kaul model against the return to the \textit{TOTVAL} index. At first glance the forecasts appear to exhibit little significant variation with the underlying return. Re-scaling Figure 8 so that the true return and the forecasts each have their own scale in Figure 9 reveals that the Conrad and Kaul forecasts are highly correlated with the direction of the true return, but not its magnitude. This is confirmed by the results of Table 11, which reports the correlation coefficient between the Conrad and Kaul forecasts and the true return as an amazingly strong 0.728.

The final model to be evaluated is a naive, or "random walk" model, which will forecast next month's return to stocks as equal to last month's return. Figure 10 presents a plot of these forecasts, which is obviously the true return shifted one period forward in time. Table 11 reports that this model has a correlation coefficient of only 0.063 with the true return to the \textit{TOTVAL} index.

One method for evaluating the statistical fit of out-of-sample forecasts is by examining some measure of the deviation between the forecast and the series being
predicted. Figure 11 presents a graph of the cumulative mean absolute forecast deviations from each of the forecasts, computed as:

$$\sum_{t=1}^{156} \left| Y_{t}^{\text{actual}} - Y_{t}^{\text{predicted}} \right|.$$ 

From the graph it is clear that the random walk model is the worst performer of the group. The forecast errors from the remaining three models are comparable, with the Conrad and Kaul model yielding the lowest cumulative forecast deviations. Figure 12 presents a graph of the cumulative squared forecast deviations, which places more weight on deviations between the forecast and the underlying series. These were computed as:

$$\sum_{t=1}^{156} \left( Y_{t}^{\text{actual}} - Y_{t}^{\text{predicted}} \right)^2.$$ 

Once again, the random walk forecasting model is clearly the worst performer. As in Figure 11, the ECM and Conrad and Kaul models remain close until 1988, when the errors in the ECM model become more pronounced. Figures 11 and 12 indicate that the Conrad and Kaul model forecasts reasonably well even after October, 1987.

**B. Trading Rules from the Forecasts**

This section establishes trading rules based on the forecasts from each model. The monthly return to the TOVAL index will represent the return to holding equity securities, with the only other alternative investment being T-bills with three months to maturity.
Four fictitious accounts are created with an initial endowment of $1000 each which is completely invested in either stocks or bills depending upon the forecast for January, 1978. The cumulative wealth from each strategy is then tracked under two different sets of trading rules.

Under the first set of rules, the fictitious investors will move their total wealth into bills if the forecast for stocks is negative, and will invest completely in stocks if the forecast indicates a positive return for the coming month. This trading rule will be termed "monthly rebalancing" since it has the potential to generate the most trades. This rule is first tested with no transactions costs, and then with a transactions cost of one percent of the investors' total wealth every time there is a switch from equities to bills or vice versa.

Under the second trading rule, investors will only trade when the model forecasts a plus or minus one percent change in the return to the TOTVAL index. Under this rule, the investor will not switch out of equities until a negative one percent forecast is generated, and will not switch back into equities until a positive one percent forecast is generated. This trading rule will be called the "one percent filter." It will also be evaluated with and without transactions costs.

Table 12 reports the number of trades generated from each forecasting model under both the monthly rebalancing and one percent filter rules. Under the monthly rebalancing rules, the Conrad and Kaul model trades 86 times in 156 months. The random walk model generates 71 trading signals, and the ECM trades 46 times. The macroeconomic model only generates trading signals 10 times. Figure 13 presents a graph of the cumulative wealth generated by the four models with no transactions costs for trading between equities and bills. A buy and hold portfolio is also included, which represents the return to investing the $1000 in the TOTVAL index and not trading. The final dollar amounts which accrue to each strategy are also shown in Table 13.
Under the monthly rebalancing rule with no transactions costs, the Conrad and Kaul forecasts generate a final portfolio wealth of $25,778, which is almost six times that of the nearest competitor, which, anomalously, is the random walk model. A buy and hold portfolio yields an ending dollar value of $3,301. Figure 14 shows a graph of the cumulative wealth to the forecasting strategies when a one percent transactions cost is deducted each time there is a switch from one investment vehicle to another. Once again, as also shown in Table 13, the Conrad and Kaul strategy dominates all the others with a final dollar wealth of $10,958. All the other models fail to beat a buy and hold in the presence of transactions costs.

Figure 15 and Panel B of Table 13 show the cumulative wealth to the four strategies when trading occurs only after a plus or minus one percent forecast is generated. Once again the Conrad and Kaul model wins, this time only beating the macroeconomic strategy by less than $1,000. The ECM and random walk models fail to outperform a buy and hold strategy. The final scenario uses the one percent filter and deducts a one percent transactions cost for trading. As in the other cases, the Conrad and Kaul model performs the best, generating a final dollar value of $4,569. Referring back to Table 12, we see that their model only generated two trades, switching to bills before a significant market downturn, and switching back just in time to catch the bull market of 1982. The 65 trades generated by the random walk model result in a significant underperformance, with a final portfolio wealth of $1,279. Under this last and most realistic scenario, both the macroeconomic and Conrad and Kaul models beat the buy and hold strategy.
3.6 Conclusions

This study developed the ECM presented in Part 2 into a forecasting model, and compared its out-of-sample forecasting power with other models drawn from the literature on the predictability of security returns. The competing models chosen were a macroeconomic model, developed over many studies and attributed to many different authors, and a time series model recently proposed by Conrad and Kaul. A naive or random walk model, as well as a simple buy and hold strategy were also entered into the forecasting contest.

The results indicate that the time series model of Conrad and Kaul generated amazingly accurate forecasts of monthly returns, with a correlation of 0.728 with the true return to the universe of NYSE and AMEX stocks from January, 1978 to December, 1990. The dollar value generated by following the recommendations from this strategy exceeded that produced from a buy and hold strategy by $1,268 under realistic investment conditions. The annualized return to the Conrad and Kaul strategy yielded an annual return 2.8% greater than the buy and hold under the one percent filter rule with a one percent transactions cost.

The results of this study suggest two areas for future research. One is to extend the data used in this study to investigate the possibility that the strong performance of the Conrad and Kaul is specific to the sample period used. If their model was found to generate superior forecasts over longer horizons than the thirteen years employed in this study, it would seem to vindicate those who study the past patterns of stock prices and returns in an attempt to generate excess investment returns. The second area for future research is to ascertain to what degree other lagged effects, such as macroeconomic variables, volume and dividends can further enhance the Conrad and Kaul forecasts.
Figure 4: Natural Logarithm of the Share Turnover to Price Ratio: 1962-1991.
Total Dividends to the S&P 500 Relative to the TOTVAL Index: 1962-1991

Figure 5: Natural Logarithm of the Total Dividends to the S/P 500 Relative to the TOTVAL Index: 1962-1991.
Table 7
Within-Sample Properties of the ECM Forecasting Model

Panel A: 1962-1986

This panel presents within-sample results from the ECM forecasting model given by Equation (3.4):

\[ R_t = c + \alpha_1 \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \beta_1 \Delta V_{t-1} + \beta_2 \Delta V_{t-2} + \lambda_1 \Delta D_{t-1} + \delta(T/P)_{t-1} + \theta(D/P)_{t-1} + \nu_t \]

where \( R \) is the discrete return to the TOTVAL index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, and all other variables are as described in Table 5. The lower panel reports time series diagnostics as described in Panel G of Table 5.

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*, ** Significant at the 1% and 5% levels, respectively.
Table 7 (continued)
Within-Sample Properties of the ECM Forecasting Model


This panel presents within-sample results from the ECM forecasting model given by Equation (3.5):

\[ R_t = c + c' + \alpha_1 \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \alpha_2^* \Delta P_{t-2} + \beta_1 \Delta V_{t-1} + \beta_1^* \Delta V_{t-1} + \beta_2 \Delta V_{t-2} + \beta_2^* \Delta V_{t-2} + \]

\[ \lambda_1 \Delta D_{t-1} + \lambda_1^* \Delta D_{t-1} + \delta(T/P)_{t-1} + \delta^* (T/P)_{t-1} + \theta(D/P)_{t-1} + \theta^* (D/P)_{t-1} + \nu_t \]

where \( R \) is the discrete return to the TOTVAL index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, the \( d \)'s are dummy variables which allow the respective coefficients to shift subsequent to October, 1987, and all other variables are as described in Table 5. The lower panel reports time series diagnostics as described in Panel G of Table 5.

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</tr>
<tr>
<td>( Q^2(6) )</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>( Q^2(12) )</td>
<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

\* \* Significant at the 1% and 5% levels, respectively.
Table 7 (continued)
Within-Sample Properties of the ECM Forecasting Model

Panel C: 1963-1977

This panel presents within-sample results from the ECM forecasting model given by Equation (3.4):

\[ R_t = c + \alpha_1 \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \beta_1 \Delta V_{t-1} + \beta_2 \Delta V_{t-2} + \lambda_1 \Delta D_{t-1} + \delta (T/P)_{t-1} + \theta (D/P)_{t-1} + \nu_t \]

where \( R \) is the discrete return to the TOTVAL index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, and all other variables are as described in Table 5. The lower panel reports time series diagnostics as described in Panel G of Table 5.

<table>
<thead>
<tr>
<th>( )</th>
<th>( c )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \lambda_1 )</th>
<th>( \delta )</th>
<th>( \theta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>coefficient</td>
<td>0.111</td>
<td>0.205</td>
<td>-0.069</td>
<td>-0.032</td>
<td>-0.029</td>
<td>-0.234</td>
<td>0.015</td>
<td>0.052</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.40**</td>
<td>1.81</td>
<td>-0.59</td>
<td>-1.51</td>
<td>-1.51</td>
<td>-1.39</td>
<td>0.97</td>
<td>2.21**</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.02</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( BJ )</th>
<th>( E(4) )</th>
<th>( E(8) )</th>
<th>( DW(H) )</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 24.23^* )</td>
<td>( 16.16^* )</td>
<td>( 16.97^{**} )</td>
<td>0.39</td>
<td>3.92</td>
<td>9.61</td>
<td>25.44*</td>
<td>35.70*</td>
</tr>
</tbody>
</table>

* ** Significant at the 1% and 5% levels, respectively.
Table 7 (continued)
Within-Sample Properties of the ECM Forecasting Model

Panel D: 1975-1989

This panel presents within-sample results from the ECM forecasting model given by Equation (3.5):

\[ R_t = c + c^* + \alpha_1 \Delta P_{t-1} + \alpha_1^* \Delta \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \alpha_2^* \Delta \Delta P_{t-2} + \beta_1 \Delta V_{t-1} + \beta_1^* \Delta \Delta V_{t-1} + \beta_2 \Delta V_{t-2} + \beta_2^* \Delta \Delta V_{t-2} + \]
\[ \lambda_1 \Delta D_{t-1} + \lambda_1^* \Delta \Delta D_{t-1} + \delta(T/P)_{t-1} + \delta^* (T/P)_{t-1} + \theta(D/P)_{t-1} + \theta^* (D/P)_{t-1} + \nu_t \]

where \( R \) is the discrete return to the TOTVAL index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, the \( d's \) are dummy variables which allow the respective coefficients to shift subsequent to October, 1987, and all other variables are as described in Table 5. The lower panel reports time series diagnostics as described in Panel G of Table 5.

<table>
<thead>
<tr>
<th>coefficient</th>
<th>c</th>
<th>c*</th>
<th>( \alpha_1 )</th>
<th>( \alpha_1^* )</th>
<th>( \alpha_2 )</th>
<th>( \alpha_2^* )</th>
<th>( \beta_1 )</th>
<th>( \beta_1^* )</th>
<th>( \beta_2 )</th>
<th>( \beta_2^* )</th>
<th>( \lambda_1 )</th>
<th>( \lambda_1^* )</th>
<th>( \delta )</th>
<th>( \delta^* )</th>
<th>( \theta )</th>
<th>( \theta^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-stat</td>
<td>0.22</td>
<td>7.22*</td>
<td>-0.14</td>
<td>0.64</td>
<td>-0.29</td>
<td>-1.22</td>
<td>-0.55</td>
<td>-1.96**</td>
<td>-0.05</td>
<td>-0.07</td>
<td>-1.59</td>
<td>1.65</td>
<td>-1.63</td>
<td>-0.41</td>
<td>5.07*</td>
<td></td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.21</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BJ</th>
<th>E(4)</th>
<th>E(8)</th>
<th>DW(H)</th>
<th>Q(6)</th>
<th>Q(12)</th>
<th>Q^2(6)</th>
<th>Q^2(12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>41.89*</td>
<td>2.52</td>
<td>7.65</td>
<td>-1.55</td>
<td>8.52</td>
<td>13.92</td>
<td>5.67</td>
<td>7.78</td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 7 (continued)
Within-Sample Properties of the ECM Forecasting Model


This panel presents within-sample results from the ECM forecasting model given by Equation (3.4):

\[ R_t = c + \alpha_1 \Delta P_{t-1} + \alpha_2 \Delta P_{t-2} + \beta_1 \Delta T_{t-1} + \beta_2 \Delta T_{t-2} + \lambda_1 \Delta D_{t-1} + \delta(T/P)_{t-1} + \theta(D/P)_{t-1} + \nu_t \]

where \( R \) is the discrete return to the TOTVAL index, \( T/P \) is the natural logarithm of the turnover-to-price ratio, \( D/P \) is the natural logarithm of the dividend-to-price ratio, and all other variables are as described in Table 5. The lower panel reports time series diagnostics as described in Panel G of Table 5.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>( c )</th>
<th>( \alpha_1 )</th>
<th>( \alpha_2 )</th>
<th>( \beta_1 )</th>
<th>( \beta_2 )</th>
<th>( \lambda_1 )</th>
<th>( \delta )</th>
<th>( \theta )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>0.595</td>
<td>0.195</td>
<td>0.079</td>
<td>-0.044</td>
<td>-0.019</td>
<td>-0.177</td>
<td>0.023</td>
<td>0.260</td>
</tr>
<tr>
<td>t-stat</td>
<td>1.99**</td>
<td>0.86</td>
<td>0.35</td>
<td>-0.72</td>
<td>-0.34</td>
<td>-0.62</td>
<td>0.57</td>
<td>1.99**</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>BJ</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>E(4)</td>
<td></td>
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</tr>
<tr>
<td>E(8)</td>
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<td></td>
</tr>
<tr>
<td>DW(H)</td>
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<tr>
<td>Q(6)</td>
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<tr>
<td>Q(12)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Q^2(6)</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Q^2(12)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at the 1% and 5% levels, respectively.
Table 8

Tests for Unit Roots in the Macroeconomic Time Series

This table presents the Phillips-Perron tests for unit roots in the levels of the following macroeconomic time series: GOVT1, the yield on government bonds with one year to maturity; GOVT10, the yield on government bonds with ten years to maturity; BAA, the average yield on corporate bonds rated BAA; AAA, the average yield on corporate bonds rated AAA; and YIELD, the dividend-to-price ratio for the S&P 500 list of stocks. The CPI and IP (seasonally-adjusted industrial production) are tested for unit roots in both their levels and first differences. The data span the 348 month period from January, 1962 to December, 1990. A significant test statistic rejects the null hypothesis of a unit root.

<table>
<thead>
<tr>
<th>Variable</th>
<th>( Z(t_0) )</th>
<th>( Z(t_1) )</th>
<th>( Z(\phi_i) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>GOVT1</td>
<td>0.129</td>
<td>-2.561</td>
<td>3.470</td>
</tr>
<tr>
<td>GOVT10</td>
<td>0.645</td>
<td>-2.038</td>
<td>2.576</td>
</tr>
<tr>
<td>AAA</td>
<td>1.023</td>
<td>-2.051</td>
<td>3.024</td>
</tr>
<tr>
<td>BAA</td>
<td>1.049</td>
<td>-1.879</td>
<td>2.754</td>
</tr>
<tr>
<td>YIELD</td>
<td>-0.160</td>
<td>-1.907</td>
<td>1.828</td>
</tr>
<tr>
<td>TERM</td>
<td>-2.979*</td>
<td>-3.380**</td>
<td>5.690**</td>
</tr>
<tr>
<td>DEF</td>
<td>-0.660</td>
<td>-2.351</td>
<td>2.814</td>
</tr>
<tr>
<td>CPI</td>
<td>11.480</td>
<td>1.078</td>
<td>6.260*</td>
</tr>
<tr>
<td>ΔCPI</td>
<td>-3.170*</td>
<td>-6.483*</td>
<td>42.842*</td>
</tr>
<tr>
<td>IP</td>
<td>3.668</td>
<td>-2.105</td>
<td>9.457*</td>
</tr>
<tr>
<td>ΔIP</td>
<td>-8.523*</td>
<td>-9.349*</td>
<td>91.52*</td>
</tr>
</tbody>
</table>

*, ** Significant at the one and five percent levels, respectively.
Table 9
Within-Sample Estimates of the Macroeconomic Forecasting Model

Panel A: 1962-1986

This panel presents results from the macroeconomic forecasting model of stock returns given by Equation (3.6) using data from 1962-1986:

\[ R_t = c + \varphi \text{TERM}_{t-1} + \pi \text{DEF}_{t-1} + \omega \Delta \text{CPI}_{t-1} + u_t \]

where \( R \) is the monthly return to the TOTVAL Index, \( \text{TERM} \) is the difference between the yield on government securities with ten years to maturity and one year to maturity, \( \text{DEF} \) is the difference between the yield on BAA rated corporate bonds and AAA rated corporate bonds, \( \Delta \text{CPI} \) is the change in the level of the consumer price index, and the \( u \)'s are the regression residuals. Equation (3.6) is estimated using maximum likelihood estimation. Results are shown using monthly data from July, 1962-December, 1986. The \( t \)-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). The Durbin-Watson statistic tests for first-order serial correlation in the regression residuals. The \( Q(L) \)- and \( Q(L) \)-squared statistics test the null hypothesis that the autocorrelations of the first \( L \) regression residuals are jointly equal to zero, and are distributed chi-square with \( L \) degrees of freedom. Engle's test (E) is a Lagrange-Multiplier test for ARCH effects in the regression residuals. The Bera-Jarque statistic tests for normality in the regression residuals and is also distributed chi-square with \( L \) degrees of freedom.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>( c )</th>
<th>( \varphi )</th>
<th>( \pi )</th>
<th>( \omega )</th>
<th>DW</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
<th>( E(4) )</th>
<th>( E(8) )</th>
<th>BJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-stat</td>
<td>-0.18</td>
<td>1.35</td>
<td>2.83*</td>
<td>-2.85*</td>
<td>-0.49</td>
<td>6.56</td>
<td>12.94</td>
<td>23.34**</td>
<td>33.54**</td>
<td>18.66*</td>
<td>19.20*</td>
<td>72.60*</td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.09</td>
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</tr>
</tbody>
</table>

* ** Significant at the 1% and 5% levels, respectively.
Table 9 (continued)
Within-Sample Estimates of the Macroeconomic Forecasting Model


<table>
<thead>
<tr>
<th></th>
<th>c</th>
<th>φ</th>
<th>π</th>
<th>σ</th>
<th>DW</th>
<th>Q(6)</th>
<th>Q(12)</th>
<th>Q²(6)</th>
<th>Q²(12)</th>
<th>E(4)</th>
<th>E(8)</th>
<th>BJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>coeff.</td>
<td>-0.001</td>
<td>0.002</td>
<td>0.016</td>
<td>-2.598</td>
<td>1.95</td>
<td>6.96</td>
<td>11.26</td>
<td>4.85</td>
<td>10.36</td>
<td>4.26</td>
<td>5.05</td>
<td>20.55*</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.13</td>
<td>0.63</td>
<td>2.96*</td>
<td>-3.22*</td>
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</tr>
<tr>
<td>adj. R²</td>
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</tr>
</tbody>
</table>

Panel C: 1963-1977

<table>
<thead>
<tr>
<th></th>
<th>c</th>
<th>φ</th>
<th>π</th>
<th>σ</th>
<th>DW</th>
<th>Q(6)</th>
<th>Q(12)</th>
<th>Q²(6)</th>
<th>Q²(12)</th>
<th>E(4)</th>
<th>E(8)</th>
<th>BJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>coeff.</td>
<td>-0.003</td>
<td>0.005</td>
<td>0.025</td>
<td>-2.259</td>
<td>-1.46</td>
<td>5.70</td>
<td>13.24</td>
<td>15.85**</td>
<td>32.66*</td>
<td>13.86*</td>
<td>14.58</td>
<td>21.78</td>
</tr>
<tr>
<td>t-stat</td>
<td>-0.33</td>
<td>1.66</td>
<td>2.45**</td>
<td>-3.96*</td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>adj. R²</td>
<td>0.15</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 9 (continued)
Within-Sample Estimates of the Macroeconomic Forecasting Model

Panel D: 1975-1989

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>$c$</th>
<th>$\varphi$</th>
<th>$\pi$</th>
<th>$\sigma$</th>
<th>$DW$</th>
<th>$Q(6)$</th>
<th>$Q(12)$</th>
<th>$Q^2(6)$</th>
<th>$Q^2(12)$</th>
<th>$E(4)$</th>
<th>$E(8)$</th>
<th>$RJ$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t$-stat</td>
<td>-0.07</td>
<td>0.07</td>
<td>1.99**</td>
<td>-0.66</td>
<td></td>
<td>9.70</td>
<td>11.98</td>
<td>1.08</td>
<td>4.25</td>
<td>1.90</td>
<td>2.81</td>
<td>56.34*</td>
</tr>
<tr>
<td>adj. $R^2$</td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 10
Within-Sample Estimates of an ARMA(1,1) Fit to the Weekly Return to the TOTVAL Index

Panel A: 1962-1986

This panel presents results from the ARMA(1,1) model of stock returns given by Equation (3.7) using data from 1962-1986:

\[ R_t^w = c + \phi R_{t-1}^w + \alpha_t^w - \theta \alpha_{t-1}^w \]

where \( R \) is the monthly return to the TOTVAL index, and the \( \alpha \)'s are the regression residuals. Equation (3.7) is estimated using maximum likelihood estimation. Results are shown using monthly data from July, 1962-December, 1986. The \( t \)-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). The Durbin-Watson statistic tests for first-order serial correlation in the regression residuals. The \( Q(L) \) and \( Q^2(L) \)-squared statistics test the null hypothesis that the autocorrelations of the first \( L \) regression residuals are jointly equal to zero, and are distributed chi-square with \( L \) degrees of freedom. Engle's test (E) is a Lagrange-Multiplier test for ARCH effects in the regression residuals. The Bera-Jarque statistic tests for normality in the regression residuals and is also distributed chi-square with \( L \) degrees of freedom.

<table>
<thead>
<tr>
<th>( c )</th>
<th>( \phi )</th>
<th>( \theta )</th>
<th>( DW(H) )</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
<th>E(4)</th>
<th>E(8)</th>
<th>BJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>0.341</td>
<td>0.281</td>
<td>-0.36</td>
<td>2.69</td>
<td>13.52</td>
<td>31.87*</td>
<td>43.86*</td>
<td>144.73*</td>
<td>209.33*</td>
<td>70.21*</td>
</tr>
<tr>
<td>t-stat</td>
<td>2.67**</td>
<td>6.80*</td>
<td>8.40*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
| adj. \( R^2 \) | 0.17

*, ** Significant at the 1% and 5% levels, respectively.
Table 10 (continued)
Within-Sample Estimates of an ARMA(1,1) Fit to the Weekly Return to the TOTVAL Index

Panel B: 1962-1990

This panel presents results from the ARMA(1,1) model of stock returns given by Equation (3.7) using data from 1962-1990:

\[ R_t = c + \phi R_{t-1} + \alpha_t - \beta \alpha_{t-1} \]

where \( R \) is the monthly return to the TOTVAL Index, and the \( \alpha \)'s are the regression residuals. Equation (3.7) is estimated using maximum likelihood estimation. Results are shown using monthly data from July, 1962-December, 1990. The t-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). The Durbin-Watson statistic tests for first-order serial correlation in the regression residuals. The Q(L)- and Q(L)-squared statistics test the null hypothesis that the autocorrelations of the first \( L \) regression residuals are jointly equal to zero, and are distributed chi-square with \( L \) degrees of freedom. Engle's test (E) is a Lagrange-Multiplier test for ARCH effects in the regression residuals. The Bera-Jarque statistic tests for normality in the regression residuals and is also distributed chi-square with \( L \) degrees of freedom.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>( c )</th>
<th>( \phi )</th>
<th>( \theta )</th>
<th>( DW(H) )</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
<th>( E(4) )</th>
<th>( E(8) )</th>
<th>( BJ )</th>
</tr>
</thead>
<tbody>
<tr>
<td>t-stat</td>
<td>2.67**</td>
<td>6.50*</td>
<td>8.60*</td>
<td>-0.77</td>
<td>9.19</td>
<td>22.10**</td>
<td>136.87*</td>
<td>210.04*</td>
<td>55.48*</td>
<td>106.14*</td>
<td>264.27*</td>
</tr>
<tr>
<td>\text{adj. } R^2</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*, ** Significant at the 1% and 5% levels, respectively.
Table 10 (continued)
Within-Sample Estimates of an ARMA(1,1) Fit to the Weekly Return to the TOTVAL Index

Panel C: 1963-1977
This panel presents results from the ARMA(1,1) model of stock returns given by Equation (3.7) using data from 1963-1977:

\[ R_t^w = c + \phi R_{t-1}^w + \alpha_t^w - \theta \alpha_{t-1}^w \]

where \( R \) is the monthly return to the TOTVAL Index, and the \( \alpha \)'s are the regression residuals. Equation (3.7) is estimated using maximum likelihood estimation. Results are shown using monthly data from July, 1962-December, 1990. The t-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). The Durbin-Watson statistic tests for first-order serial correlation in the regression residuals. The Q(L)- and Q(L)-squared statistics test the null hypothesis that the autocorrelations of the first L regression residuals are jointly equal to zero, and are distributed chi-square with L degrees of freedom. Engle's test (E) is a Lagrange-Multiplier test for ARCH effects in the regression residuals. The Bera-Jarque statistic tests for normality in the regression residuals and is also distributed chi-square with \( L \) degrees of freedom.

<table>
<thead>
<tr>
<th>( c )</th>
<th>( \phi )</th>
<th>( \theta )</th>
<th>( DW(H) )</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
<th>( E(4) )</th>
<th>( E(8) )</th>
<th>( BJ )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.001</td>
<td>0.617</td>
<td>0.663</td>
<td>0.85</td>
<td>2.89</td>
<td>15.23</td>
<td>34.94*</td>
<td>61.62*</td>
<td>130.60*</td>
<td>204.44*</td>
<td>24.65*</td>
</tr>
</tbody>
</table>

* \( t \)-stat, ** \( R \)-squared.

*, ** Significant at the 1% and 5% levels, respectively.
Table 10 (continued)
Within-Sample Estimates of an ARMA(1,1) Fit to the Weekly Return to the TOTVAL Index

Panel D: 1975-1989

This panel presents results from the ARMA(1,1) model of stock returns given by Equation (3.7) using data from 1975-1989:

\[ R_t^w = c + \phi R_{t-1}^w + \alpha_t^w - \theta \alpha_{t-1}^w \]

where \( R \) is the monthly return to the TOTVAL Index, and the \( \alpha \)'s are the regression residuals. Equation (3.7) is estimated using maximum likelihood estimation. Results are shown using monthly data from July, 1962-December, 1990. The \( t \)-statistics are shown below the value of the regression coefficients and test the null hypothesis that a coefficient is significantly different from zero. Standard errors are computed using the method of White (1980). The Durbin-Watson statistic tests for first-order serial correlation in the regression residuals. The \( Q(L) \)- and \( Q(L)^2 \)-squared statistics test the null hypothesis that the autocorrelations of the first \( L \) regression residuals are jointly equal to zero, and are distributed chi-square with \( L \) degrees of freedom. Engle's test (E) is a Lagrange-Multiplier test for ARCH effects in the regression residuals. The Bera-Jarque statistic tests for normality in the regression residuals and is also distributed chi-square with \( L \) degrees of freedom.

<table>
<thead>
<tr>
<th>( c )</th>
<th>( \phi )</th>
<th>( \theta )</th>
<th>( DW(H) )</th>
<th>( Q(6) )</th>
<th>( Q(12) )</th>
<th>( Q^2(6) )</th>
<th>( Q^2(12) )</th>
<th>( E(4) )</th>
<th>( E(8) )</th>
<th>( BJ )</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.002</td>
<td>0.098</td>
<td>0.035</td>
<td>0.92</td>
<td>9.51</td>
<td>16.69</td>
<td>31.87*</td>
<td>43.86*</td>
<td>10.65**</td>
<td>29.68*</td>
<td>33.74*</td>
</tr>
<tr>
<td>2.77**</td>
<td>2.00**</td>
<td>0.50</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\*, ** Significant at the 1% and 5% levels, respectively.
Figure 6: Monthly Return to the TOTVAL Price Index vs. ECM Forecasts
Figure 7: Monthly Return to the TOTVAL Price Index vs. Macroeconomic Forecasts
Figure 8: Monthly Return to the TOTVAL Price Index vs. Conrad and Kaul Forecasts
Figure 8: Monthly Return to the TOTVAL Price Index vs. Conrad and Kaul Forecasts with Separate Scaling.
Figure 10: Monthly Return to the TOTVAL Price Index vs. Random Walk Forecasts
Figure 11: Cumulative Mean Absolute Forecast Deviations.
Figure 12: Cumulative Squared Forecast Deviations
Figure 13: Cumulative Portfolio Wealth with Monthly Rebalancing and No Transactions Costs
Figure 14: Cumulative Portfolio Wealth with Monthly Rebalancing and a One Percent Transactions Cost
Figure 15: Cumulative Portfolio Wealth with a One Percent Filter Rule and No Transactions Costs
Figure 16: Cumulative Portfolio Wealth with a One Percent Filter Rule and a One Percent Transactions Cost
Table 11

Correlation of the Forecasts with the Monthly Return to the \textit{TOTVAL} Index

This table presents the correlation coefficient of the forecasts from the four competing models with the actual monthly return to the \textit{TOTVAL} index. Data ranges from January, 1978 to December, 1990.

<table>
<thead>
<tr>
<th>Forecasting Model</th>
<th>Correlation with Actual Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM</td>
<td>0.149</td>
</tr>
<tr>
<td>Macroeconomic</td>
<td>0.114</td>
</tr>
<tr>
<td>Conrad &amp; Kaul</td>
<td>0.728</td>
</tr>
<tr>
<td>Random Walk</td>
<td>0.063</td>
</tr>
</tbody>
</table>
Table 12

Number of Trades Generated by the Competing Forecasts

This table presents the number of trades generated by each forecasting model during the 156-month period spanning January, 1978 to December, 1990. The number of trades under the monthly rebalancing rule as well as the one percent filter rule are recorded.

<table>
<thead>
<tr>
<th>Forecasting Model</th>
<th>Monthly Rebalancing</th>
<th>One Percent Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM</td>
<td>46</td>
<td>12</td>
</tr>
<tr>
<td>Macroeconomic</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>Conrad &amp; Kaul</td>
<td>86</td>
<td>2</td>
</tr>
<tr>
<td>Random Walk</td>
<td>71</td>
<td>65</td>
</tr>
</tbody>
</table>
Table 13

Cumulative Wealth Generated by the Competing Forecasts

This table presents the dollar wealth generated from each of the trading rules for the 156-month period spanning January, 1978 to December, 1990.

Panel A: Monthly Rebalancing

<table>
<thead>
<tr>
<th>Forecasting Model</th>
<th>No Transactions Costs</th>
<th>Transactions Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM</td>
<td>$4,085</td>
<td>$3,239</td>
</tr>
<tr>
<td>Macroeconomic</td>
<td>$3,270</td>
<td>$2,957</td>
</tr>
<tr>
<td>Conrad &amp; Kaul</td>
<td>$25,778</td>
<td>$10,958</td>
</tr>
<tr>
<td>Random Walk</td>
<td>$4,694</td>
<td>$2,313</td>
</tr>
<tr>
<td>Buy and Hold</td>
<td>$3,301</td>
<td>$3,301</td>
</tr>
</tbody>
</table>

Panel B: One Percent Filter

<table>
<thead>
<tr>
<th>Forecasting Model</th>
<th>No Transactions Costs</th>
<th>Transactions Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECM</td>
<td>$3,086</td>
<td>$2,714</td>
</tr>
<tr>
<td>Macroeconomic</td>
<td>$3,786</td>
<td>$3,641</td>
</tr>
<tr>
<td>Conrad &amp; Kaul</td>
<td>$4,656</td>
<td>$4,569</td>
</tr>
<tr>
<td>Random Walk</td>
<td>$2,418</td>
<td>$1,279</td>
</tr>
<tr>
<td>Buy and Hold</td>
<td>$3,301</td>
<td>$3,301</td>
</tr>
</tbody>
</table>
References


