The Nonlinear Behavior of Stock Prices:
The Impact of Firm Size, Seasonality, and Trading Frequency

Debra Ann Skaradzinski

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Douglas M. Patterson, Chair
Richard Ashley
Don M. Chance
Randall S. Billingsley
George Emir Morgan

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(ABSTRACT)

Statistically significant prediction of stock price changes requires security returns' correlation with, or dependence upon, some variable(s) across time. Since a security's past return is commonly employed in forecasting, and because the lack of lower-order correlation does not guarantee higher-order independence, nonlinear testing that focuses on higher-order moments of stock return distributions may reveal exploitable stock return dependencies.

This dissertation fits AR models to TAQ data sampled at ten-minute intervals for 20 small-capitalization, 20 mid-capitalization, and 20 large-capitalization NYSE securities, for the years 1993, 1995, 1997, 1999 and 2001. The Hinich Patterson Bicovariance statistic (to reveal nonlinear and linear autocorrelation) is computed for each of the 1243 trading days for each of the 60 securities. This statistic is examined to see if it is more or less likely to occur in securities with differing market capitalization, at various calendar periods, in conjunction with trading volume, or instances of changing investor sentiment, as evidenced by the put-call ratio.

There is a statistically significant difference in the level and incidence of nonlinear behavior for the different-sized portfolios. Large-cap stocks exhibit the highest level and greatest incidence of nonlinear behavior, followed by mid-cap stocks, and then small-cap stocks. These differences are most pronounced at the beginning of decade and remain significant throughout the decade. For all size portfolios, nonlinear correlation increases throughout the decade, while linear correlation decreases.

Statistical significance between the nonlinear or the linear test statistics and trading volume occur on a year-by-year basis only for small-cap stocks. There is sporadic seasonality significance for all portfolios over the decade, but only the small-cap portfolio consistently exhibits a notable "December effect". The average nonlinear statistic for small-cap stocks is larger in December than for other months of the year. The fourth quarter of the year for small-cap stocks also exhibits significantly higher levels of nonlinearity.

An OLS regression of the put/call ratio to proxy for investor sentiment against the H and C statistic was run from October 1995 through December 2001. There are instances of sporadic correlations among the different portfolios, indicating this relationship is more dynamic than previously imagined.

In memory of my father,
Eugene Anthony Skaradzinski

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CHAPTER I: INTRODUCTION

The question of whether or not a security's price change can be predicted is one of the most engrossing questions in finance, and one that has provoked a vast amount of research in the discipline. While this study does not attempt to resolve the issue, it is primarily motivated by the question. For a security's returns to be forecast in a statistically meaningful manner the returns must necessarily have a correlation with, or a dependence upon, some variable(s) 0across time. These variables may be past realizations of the security's own returns, or potential factors such as dividend yields, the earnings price ratio, or trading volume. This dependence, however, violates the conditions of the simple random walk model of stock price behavior that Fama described in 1965: a security's returns are independent of each other, and the return distribution parameters remain the same, through time, with or without conditioning information.

The research subsequent to Fama's assertion focused on whether the random walk was a useful and realistic probability model of a security's return-generating mechanism. Studies that examined lower-order dependence of returns rejected a strict version of the random walk due to time-varying parameters (Conrad and Kaul, 1981), sampling dependence (Lo and MacKinlay, 1988, 1990a), or parameter changes due to conditional information (Engle 1982, Bollerslev 1986). However, because the lack of correlation between returns does not guarantee the independence of returns, recent studies use more sophisticated tests of independence and focus on higher-order moments. Securities whose returns display higher-order dependence are said to exhibit nonlinear behavior.

The research on the nonlinear behavior of security prices can be roughly divided into two categories: *tests* of whether or not stock returns exhibit nonlinearity, and *models* of nonlinear stock price behavior. The tests for nonlinear behavior include the Engle Lagrange Multiplier (1982), the McLeod-Li (1983), the Keenan (1985), Tsay (1986), BDS/BDLS (1987/1996), Hinich Bispectral (1982), and the Hinich and Patterson Bicovariance (1995). Common models of nonlinear behavior include the bilinear model (Granger and Anderson, 1978), the ARCH/GARCH models of Engle (1982) and Bollerslev (1986), the threshold autoregressive models (Tong: 1983, 1990), and neural networks (White 1989).

This paper is an empirical application that can arguably be placed in the above “test” category, in that it utilizes the Hinich Patterson Bicovariance (HP) test to see precisely *when* nonlinear behavior occurs. There is a surprisingly small amount of work completed on the subject. The tests employed heretofore have been used as blunt instruments, providing a yes/no response to whether or not a price series, over a long period of time, exhibits nonlinear behavior. However, recent work (Hinich and Patterson 1989, 1995, 1998; Patterson and Ashley 2000; Ammermann 1999; Ammermann and Patterson 2001) indicates that the nonlinear behavior of security returns is not a chronic state, but rather a series of episodic occurrences. It has yet to be investigated whether or not these episodes occur in conjunction with any other market-wide or individual-security events commonly associated with stock price behavior.

To answer the question of under what particular circumstances we might observe nonlinear behavior we may begin with three stylized facts in finance: market capitalization matters, calendar effects persist, and the contemporaneous volume/volatility relationship is very strong. These facts are framed as the hypotheses to be tested in this paper:

H_0: *Episodes of nonlinear behavior in security prices occur at random.*

Versus

H_{1A}: *Nonlinearity will appear differently in stocks with varying market capitalizations.*

H_{1B}: *Nonlinearity will tend to cluster at specific calendar points in time.*

H_{1C}: *Nonlinearity will tend to be associated with periods of high volume.*

In a preliminary version of this research, it was noted that days on which a high percentage of stocks in the portfolios exhibited nonlinearity were anecdotally associated with negative information surprises in the market. As it is popularly believed that changes in the put/call ratio can proxy for investor sentiment, an OLS regression of the put/call ratio against the nonlinearity statistic will be used to test the fourth hypothesis:

H_{1D}: *Nonlinearity will tend to be associated with episodes of a “negative surprise” in the market.*

I. A. Size Effects

All finance academicians are familiar with the *Ibbotson* charts of historical stock index prices that appear in introductory textbooks. The *Ibbotson* small-cap portfolio graph exhibits much greater volatility and larger long-run returns than the large-cap portfolio graph. Small-cap stocks are traded less often (by fewer noise traders), are followed by fewer analysts, and have larger bid/ask spreads; these characteristics imply that the return-generating process for small-cap stock prices may be different from that of large-cap stocks (Lo and MacKinlay 1988, 1990a; Fama and French 1992, 1993). Berk (1995) provides a theoretical justification that size-related differences are to be expected, rather than thought of as anomalous, in financial assets. Accordingly, the nonlinear testing in this paper distinguishes between small, mid, and large-cap firms.

I. B. Calendar Effects

The term "calendar effects" refers to the phenomenon that security returns exhibit systematically and significantly different behavior at different points in time (for instance, times of the day, days of the week, months of the year). The discovery that small-cap firms tended to have a higher return in January[1] prompted investigations into calendar anomalies for virtually any period one cares to differentiate. Ariel (1987) documents that average returns for the first and second halves of the month are not equal. French (1980) and Gibbons and Hess (1981) find that returns on Mondays are negative. Harris (1986) documents intra-day variation. Hinich and Patterson (1993) do not find any evidence of a day-of-the-week effect in their tests for nonlinearity, but do find that the opening and close of each day may be significant. This paper examines months of the year, weeks of the year, and days of the week to determine if nonlinearity in stock returns is more or less likely to show up at particular calendar times.

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[1] Rozeff and Kinney (1976) note a “January effect” in equally weighted index returns; Banz (1981) notes that small firms tend to have higher returns than one would expect from mean/variance efficiency; Keim (1983) and Blume and Stambaugh (1983) equate the two: small-cap firms tend to have higher returns in January. As awareness of this phenomenon has become widespread it has abated somewhat, but as the hypothesized reasons for this behavior (tax loss selling and portfolio rebalancing: the selling period, occurring at the end of December, does not match up with the buying period, which happens later in January) remain, so does the anomaly. It has also been reported in other countries.

I. C. The Relation to Volume

There is an extensive literature on the relationship of trading volume to stock returns, especially to the volatility of stock returns. Karpoff (1987) provides a broad review of empirical research on the price/volume relationship, and O'Hara (1995) provides a concise overview of the primary role that volume plays in models of competitive and strategic interactions among traders. Volume can be considered a conditioning variable that increases the precision of a noisy price signal; it serves as a proxy for traders' private and public information sets and objectives. Both McInish and Wood (1991) and Jones *et al* (1994) provide compelling evidence that it is the number of *trades* (the frequency of transactions) rather than the number of *shares* (the size of the transaction) that is important. Because it is strongly contemporaneously linked to volatility and can serve as an indication of disagreement among traders (thus a dis-equilibrium state of pricing) this paper will test to see if trading volume is positively associated with the incidence of nonlinear security return behavior.

I. D. Motivation and Preliminary Results

Prior arguments to persuade financial economists that nonlinear modeling is not only useful, but also necessary, support the importance of knowing *when* nonlinearity does or does not occur. A wrongly specified model results in poor and unstable estimates of coefficients, misleading forecasts, and bad insight, regardless of whether it is a linear model applied to nonlinear data, or vice versa. In addition, this research is timely for other reasons. Nonlinear statistical behavior has been documented in virtually all types of financial assets, worldwide.[2] As of yet there has not been any extensive and systematic attempt to determine *why* it occurs at certain times and not others. Also, during this past decade interest and investment in security markets have become widespread, so that the "average person on the street" is more likely than not to have a significant amount of savings in the form of risky assets. (A timely example is the national debate on the privatization of Social Security.) As relatively more individuals risk their endowments, it becomes increasingly imperative, for simply the general welfare, that the

[2] The literature review in this paper focuses on stock indices, with a few exceptions. Nonlinearity has been documented in various countries' security prices, index returns, discount bonds, T-bills, options, futures, forward and spot rates, foreign exchange rates, GNP data, inflation measures, and profitability measures.

behavior of these assets is well understood. And, because many economic time series are in essence proxies for human knowledge, beliefs, and attitudes, various academic disciplines (notably economics, but also finance and accounting) are beginning to fashion laboratory experiments that attempt to model "real-time" human behavior, especially adaptive behavior. This behavior is both interactive and iterative, characteristics that might best be described by nonlinear models.

This study uses the Hinich Patterson Bicovariance (HP) test, which tests for serial dependence at higher (third-order) moments. This third-order measurement can be thought of as a generalized skewness test; these measurements equal zero for zero mean, serially i.i.d. data. One expects non-zero values for the Bicovariance tests in which x_t depends on lagged cross-products, such as $x_{t-i}x_{t-j}$, and higher order terms.

In particular, this study finds some interesting patterns of nonlinear behavior for all the stocks. There is a significant difference in the level and incidence of nonlinear behavior for the different-sized portfolios, with the large-cap stock portfolio exhibiting the highest level and greatest incidence of nonlinear behavior, followed by the mid-cap, and then the small-cap portfolio. For all three portfolios, nonlinear correlation increases throughout the decade, while linear correlation decreases.

The relationship between the nonlinear or the linear test statistics and trading volume is ambiguous. An OLS regression between the average daily level of these statistics and trading volume is supported on a year-by-year basis only for small-cap stocks.

There are sporadic indications of calendar effects for all of the portfolios over the time period, but only the small-cap portfolio consistently exhibits a notable relationship: a "December effect", in which the average nonlinear test statistic is far larger in December than for other months of the year.

In a preliminary version of this research, it was noted that for a portfolio of 61 stocks in 1992, days of high nonlinearity were anecdotally associated with negative information surprises in the market. An OLS regression of the put/call ratio to proxy for investor sentiment against various forms of the H and C statistic was run for this data, and although there are instances of sporadic correlations among the different portfolios, this relation appears to be more dynamic than previously imagined.

This dissertation proceeds as follows: chapter two is a review of time series models and tests, an explanation of the Hinich Patterson test statistic, and a empirical literature review of nonlinear stock price behavior; chapter three is a description of the data and methodology; chapter four is a discussion of the test results; and chapter five is a list of items to pursue with further study.

CHAPTER II: BACKGROUND AND LITERATURE REVIEW

This chapter is subdivided into four parts. The first part is an intuitive overview of nonlinear systems and how they relate to financial markets; the second and third parts describe some nonlinear models and tests that are commonly used in research; and the fourth part reviews the empirical literature.

II. A. Overview

The notion of "nonlinearity" used in this thesis emanates from the study of systems in the physical and biological sciences, as well as in economics and statistics. A "system" is comprised of three parts: an input (or stimulus), one or more operations (functions) on the input, and an output (the resulting response). A linear system has several necessary characteristics, among which are superposition, homogeneity, and a unique equilibrium. To consider superposition, imagine two functions, $f_1(t)$ and $f_2(t)$, that map respectively onto two responses, $y_1(t)$ and $y_2(t)$. For a linear system to obey the criteria of superposition the following must hold:

$$f_1(t) + f_2(t) \rightarrow y_1(t) + y_2(t) \tag{2.1}$$

In other words, the superposition of functions $f_1(t)$ and $f_2(t)$ result in the superposition of the individual responses $y_1(t)$ and $y_2(t)$. Intuitively, this means that the presence of additional operations in the system does not affect the responses of previous operations, and that there are no interactions among these responses to different operations. By way of contrast, the superposition of two or more functions in a nonlinear system would *not* result in the superposition of the individual responses. Thus in a nonlinear system, the above (2.1) might look like this:

$$f_1(t) + f_2(t) \rightarrow y_1(t) + y_2(t) + y_1(t)\, y_2(t) \tag{2.2}$$

Expression (2.2) includes an interaction term, the cross-product of the two responses.

Homogeneity, in this sense, refers to the notion of proportionality, or the preservation of scale. In a linear system, if one applies "n" identical functions to an input, then the ultimate response will equal "n times" the original response. One example of a nonlinear system (in which homogeneity does not hold) is an exponential function.

In a paper that develops a theory of and the motivation for nonlinear modeling of economic data, Lye and Martin (1994, pgs 73-75) note that linear models have been traditionally preferred because they have been considered to be more tractable than nonlinear models. Researchers dealt with nonlinearity by transforming data via a filter, or by transforming a nonlinear model into an approximate linear model via a Taylor series expansion. Lye and Martin caution against employing these methods in finance and economics by outlining several reasons to explain why using an approximate linear model (and assuming that errors are normally distributed) is inadequate. Some of these reasons are: 1) the decision to make a risky investment is determined by the trade-off (the relationship) between the mean and the variance, thus both moments must be considered. While the distribution of the conditional variance is normal, the joint distribution of the mean and conditional variance is not; 2) certain nonlinear models (and ARCH models are good at this) are better than linear models at capturing the behavior of outliers, overreactions, and the "bunching" of similar observations, although ARCH models capture only a small portion of the leptokurtosis prevalent in asset returns (Engle 1982, Hsieh 1989); 3) the response to information is asymmetric (Engle and Ng, 1993) and periodic cycles are skewed (De Long and Summers, 1986) indicating dependence at higher moments; 4) linear systems, by definition, exhibit "reversibility": a shock to a system at equilibrium can be cancelled out by the application of an equal and opposite shock, restoring the initial equilibrium—in the real world, certain basic macroeconomic shocks cause the system itself to change and thus can not be reversed; 5) nonlinear systems are characterized by multiple equilibria, which give rise to multiple modes, which give rise to distributional considerations---this problem has been especially noted in exchange rates, 6) simulated experiments (Blatt, 1983) show that linear models can not capture the known instability in nonlinear systems. Also, the precision, and thus the reliability, of classical OLS regression (as well as two-and three-stage least squares analysis) depends on the assumption of linearity, which is shown in the empirical literature discussed below to be violated often enough so as to make parameter estimates suspect.

In his own remarks to motivate a movement away from approximate linear modeling and towards more precise nonlinear modeling, Benhabib (1991) argues that economic time series often exhibit irregular periods and amplitudes, fluctuating rates of change, and activity that evolves in overlapping waves. Also, economic time series occasionally respond to intermittent exogeneities that may be unimportant most of the time, but are every now and then very important.

Brock (2000) proposes that in an uncertain world, arbitrage has only a limited ability to rectify imprecise information. Agents work with approximate models, which result in errors that accumulate until the errors reach a critical point, and then the model self corrects. He suggests that nonlinear modeling may be able to capture this activity, as well as reconcile two opposing versions of security price behavior: Fama's (1970) efficient market, where prices adjust quickly to information and for all intents and purposes follow a random walk; and Schiller's (1984) and De Long's *et al* (1990) inefficient market characterized by irrational psychology and sentiment.

II. B. Models of Nonlinear Behavior

There are an infinite number of possible nonlinear models (whatever is "not linear") but only about a dozen or so are very commonly used in finance and economics. Several of the more familiar ones are described below, and for convenience, are sub-classified into three categories: 1) parametric models that do not model conditional heteroskedasticity, 2) parametric models that do model conditional heteroskedasticity, and 3) nonparametric models. The notation below is for the most part taken from Campbell *et al* (1997). To select a model for one's own use, the general consensus in the literature appears to be to test several models and choose the one that gives the best out-of-sample forecast.

II. B. 1. Non-ARCH parametric models

One of the simplest models, developed by Robinson (1979), is a nonlinear moving average model:

$$(2.3) \qquad x_t = \varepsilon_t + \alpha\varepsilon_{t-1}\varepsilon_{t-2} \qquad \varepsilon \sim N, \text{iid}$$

If the $\varepsilon_{t-1}, \varepsilon_{t-2}$ are uncorrelated, this reduces to a linear moving average model. Granger and Anderson (1978) develop the bilinear model

$$(2.4) \qquad x_t = \alpha\, x_{t-1}\varepsilon_{t-1} + \varepsilon_t \qquad \varepsilon \sim N, \text{iid}$$

Weiss (1986b) notes that both least squares and maximum likelihood will give identical estimates for the bilinear model and that it is very easy to compute. The drawback of the bilinear model is that if there are any ARCH effects (described below) present, it is difficult to distinguish between the two.

Priestley (1980) develops a class of "state-dependent models" in which the average observation in a time series is going to represent the outcome of one state or another. These models are useful for time series that at some point undergo what may be referred to as an intervention, a jump process, a structural break, or a change in regime. Two common examples are threshold auto-regression (TAR) models (developed by Tong and Lim, 1980) and a Markov switching regime:

$$(2.5) \qquad x_t = \alpha\, x_{t-1} + \varepsilon_t\,, \qquad \text{if } x_{t-1} \text{ in "A"} \qquad \varepsilon \sim N, \text{iid}$$

$$(2.6) \qquad = b x_{t-1} + \varepsilon_t \qquad \text{otherwise}$$

The difference between the two models is that the set "A" for the TAR model is comprised of the past observations of its own data points, whereas the Markov process uses an unobservable state variable. This makes TAR models susceptible to data-snooping. Hamilton (1989), in particular, models postwar GNP and argues that its variations are more likely due to changes in the business cycle rather than rather than some type of self-induced variation.

II. B. 2. ARCH-type parametric models

It has been widely noted in the finance literature that security-return volatility is time-varying and serially correlated. That volatility changes and is possibly forecastable has implications for investors, as they desire to be compensated appropriately for fluctuating levels of risk. The models used to explain this heteroskedastic and correlated behavior are the ubiquitous ARCH/GARCH types introduced by Engle (1981) and Bollerslev (1986). The ARCH model formulates the conditional variance as a function of past squared innovations:

(2.7) $$\sigma_t^2 = \omega + \alpha(L)\eta_t^2$$

$\alpha(L)$is a backward lag operator; this equation makes it evident that the coefficients of $\alpha(L)$ must be greater than or equal to zero in order for the variance to remain positive. The generalized version of the ARCH formulation allows us to model the persistence of a shock more parsimoniously:

(2.8) $$\sigma_t^2 = \omega + B(L)\sigma_{t-1}^2 + \alpha(L)\eta_t^2$$

The above equation is a $GARCH_{(p,q)}$ model, in which the order of B(L) is *p*, and the order of $\alpha(L)$ is *q*. The $GARCH_{(1,1)}$ model dominates the empirical finance literature as a method to represent the volatility of security returns:

(2.9) $$\sigma_t^2 = \omega + B\sigma_{t-1}^2 + \alpha\eta_t^2$$

$$= \omega + (\alpha + B)\,\sigma_{t-1}^2 + \alpha\,(\eta_t^2 + \sigma_{t-1}^2\,)$$

The coefficient α measures how strongly an innovation affects the next period's shock; while the coefficient (α + B) measures the rate at which the shock dies out.

Bollerslev, Chou and Kroner (1990) provide an in-depth account of the research that has been completed with all types of ARCH/GARCH models. Since their introduction, there have been a number of enhancements to these models that incorporate other specific behavior of stock returns. As noted earlier, investors are interested not only in the volatility of a return series, but also its mean, as they are balancing the risk/return trade-off. A model that incorporates information about both moments of the series is the GARCH-M, or GARCH-in-mean, of Engle, Lilien, and Robin (1987):

(2.10) $$r_{t+1} = \mu_t + \sigma_t \varepsilon_{t+1} \quad , \text{ where}$$

(2.11) $$\mu_t = \gamma_0 + \gamma_1 \sigma_t^2$$

Another notable enhancement to these models is Nelson's (1991) exponential GARCH. This model allows for asymmetric variance behavior due to different types of news. Volatility is at a minimum for no news, changes more quickly in response to bad news (exemplified by falling prices, Black's (1976) "leverage effect"), and changes less quickly in response to good news.

More recently, Ghysels and Jasiak (1998) introduce the ACD-GARCH, which is an autoregressive conditional duration GARCH model. The innovation of this model is it does not require equally spaced time periods. It is better characterized as a bivariate model, and the time interval between each security transaction is one of the variables modeled. They use it to examine the tic-by-tic transactions of IBM during November of 1993, and suggest that volatility and trading duration are interdependent.

II. B. 3. Non-parametric models

Chaos modeling is a procedure that became very popular in the early nineties as it represents a deterministic state that is predictable in the short-term, although virtually unforecastable in the long term. Serletis and Dormaar (1996) describe it as “fluctuations and irregularities in economic time series that are endogenous and can be traced back to a strong nonlinear deterministic structure that pervades the economic system”. Chaos is characterized by sensitivity to initial conditions: one may begin two identical chaotic systems with two imperceptibly different starting states, and they will proceed very quickly to two extremely different states. Chaotic systems can be described with (numerically calculated) Lyapunov exponents. These exponents measure the trajectories of the two nearly identical systems and their measures give a precise indication of the sensitivity of the system to initial conditions.

Artificial neural networks, which originated in physiology, have also become popular over the last two decades. A large subclass of these are known as “learning networks”, and two of the most familiar models in this subclass, the binary threshold model and the multiplayer perceptron (MLP), are briefly discussed here. The binary threshold model is a very early and simple model attributable to McCulloch and Pitts (1943):

(2.12) $$Y = g\left(\sum_{j=1}^{J} B_j X_j - \mu\right)$$

Each of the input *x's* is weighted by a coefficient *B*, and then summed across all inputs. If the weighted sum of the inputs is greater than the threshold μ, then the artificial neuron is switched on by the activation function *g*,

(2.13) where $$g(\mu) = 1 \quad \text{if } \mu >= 0 \qquad \text{if the function is discrete,}$$
$$= 0 \quad \text{if } \mu < 0$$

(2.14) and $$g(\mu) = \frac{1}{1 + e^{-u}} \qquad \text{if the function is continuous.}$$

This system may be extended by the addition of any other number of activation functions, each known as a layer, giving rise to a multi-layer perceptron (MLP):

$$Y = h\left(\sum_{k=1}^{K} \alpha_k \, g\left(B'_k \mathbf{X}\right)\right) \tag{2.15}$$

All of the interim activation functions, or layers, are known as hidden units. These MLP's, as an attempt to approximately model a complex nonlinear relationship by an arbitrary number of hidden layers, have been shown to work well (Campbell *et al*, 1997) Lye and Martin's earlier comments notwithstanding.

II. C. Tests for Nonlinear Behavior

There are several ways to distinguish tests for nonlinearity; one may choose to differentiate between tests that specify an alternative nonlinear model and those that do not. Or one may differentiate between tests that examine lower-order moments (first and second), and those that examine higher-order moments. The development of higher-moment testing was partly motivated by chaos modeling in the past decade, as lower-moment tests are unable to distinguish between chaotic and stochastic systems. Although it is not as strictly subdivided as other sections of this chapter, the following discussion attempts to point out, when applicable, whether or not each test specifies an alternative model, and what moments are examined. Generally speaking the first tests discussed below, the Lagrange Multiplier types, the McLeod Li, the Bera Higgins, and the BDS, focus on lower moments, and the tests discussed after these, the Hsieh, the Hinich Bispectral, and the HP Bicovariance focus on higher moments. Underlying assumptions of all of these tests is that the data are stationary and that mixing conditions hold, that is, if two observations are far enough apart in time (some arbitrary "t", they are statistically independent).

A first group of tests have a Lagrange Multiplier (LM) interpretation, and although they were not originally intended to specify an alternative model, they have been shown to be sensitive to departures from linearity in the mean (which might indicate a type of switching, or a bilinear model). They are the Keenan (1985) test, the Ramsey (1969) RESET test, and the Tsay (1986) test. These tests employ similar procedures (based on Volterra expansions); the RESET test is a more generalized version of the Keenan test, and the Tsay test is a more complicated version of the Keenan test, in that it truncates the expansion at a higher order, and features a second stage that involves cross-products.

The McLeod Li (1983) test exploits the idea fact that if residuals follow a linear i.i.d. process, the cross-product of their squares should have the same correlation structure as the square of their cross products. McLeod and Li apply a standard portmanteau for serial correlation to the squared residuals. This test has a chi-square distribution, and although it was originally presented as a general test, it has good power against ARCH models. More recently, Pena and Rodriguez (2002) introduce a new portmanteau test, and use the sunspot series to show that the test can be up to 50% more powerful than the Box and Ljung tests, and the McLeod –Li tests. They show that the asymptotic distribution of their test statistic is a linear combination of chi-squared distributions and can be approximated by a gamma distribution.

Bera and Higgins (1997) develop a joint test statistic for a model that incorporates both GARCH and bilinear models. Since it is a joint test, however, it will not distinguish which effect is predominant, so the user must resort to simulations.

The Brock, Dechert, and Scheinkman test (BDS 1987; a later version, BDLS 1997, includes an enhancement by LeBaron) is very commonly used, and as it is based fundamentally on the work of Grassberg and Procaccia (GP, 1983) their method will be highlighted here. The GP technique was originally developed to distinguish deterministic (chaotic) systems from stochastic systems. If the process is chaotic, a line graph representing the embedding dimension versus the correlation integral will level off.[3] If the process is random, the graph will slope upwards indefinitely. The more quickly the graph levels off (the lower the dimension) the greater the probability that the system is a deterministic one. Besides being only a graphing

[3] The embedding dimension "n" is a parameter representing data organized into "n-histories" and is defined as $x_t^n = \{x_{t-n+1},\ldots.x_t\}$. The correlation integral is the limit (as the sample size, t, increases to infinity) of the percent of pairs of n-histories that are "close" defined by an arbitrary distance "k". (Alternatively, the correlation integral gives the probability that a randomly selected pair of n-histories is close.) Ceteris paribus, as this arbitrary distance k decreases, the fraction of pairs that are close to each other also decreases proportionally (n times as fast as k) and this limit is denoted ν_n. The correlation dimension is the limit (if it exists) of ν_n as n approaches infinity.

procedure, and not a statistical test, the GP algorithm has some other shortcomings. It is biased downwards for small samples, so one tend to find chaos where it doesn't exist; infinite correlation dimensions are not verifiable with finite data sets (the correlation dimension for a truly random process is infinity); and it is sometimes unable to distinguish true chaos from certain nonlinear stochastic models. The BDS statistic attempts to correct some of these pitfalls, and succeeds in addressing the problem of bias. The statistic relies on their proof that even when *k* is finite, if the data are distributed i.i.d., then:

(2.16) $$C_n(k) = C_1(k)^n$$

In other words, in calculating the correlation integral, or the fraction of pairs that are close, for a n-history set, one may begin with the fraction of pairs that are close using single point data sets. However, because the null hypothesis of the BDS statistic is distributed i.i.d., rejection of the null can imply any number of situations: 1) linear dependence, 2) nonstationarity, or 3) nonlinear dependence. To use the BDS test appropriately the data needs to be first filtered so that all linear dependence is removed, which necessitates combining the BDS with other types of (linear) tests. Even though it is arguable that this BDS test statistic can indeed detect chaotic systems, (see Creedy and Martin, 1994) it has been widely used in attempts to do so. Ashley and Patterson (1989) suggested that the BDS test could more fruitfully be put to use detecting nonlinearity in a process.

The Hinich (1982) bispectrum test is an improved version of the Subba Rao and Gabr (1980) approach, both of which are used, as the name suggests, in the frequency domain. Hinich points out that Subba Rao and Gabr's original test can be sensitive to outliers due to small values of the estimated functions at certain frequencies. He tests for systematic three-way relationships between residuals: if $E[e_t,e_{t-k},e_{t-j}]$ does not equal zero for k not equal to j, then the residuals are jointly related. He defines the skewness function in terms of the bispectrum. If the skewness function is zero then the data series is Gaussian, and if it is Gaussian then it is linear. This test is biased downwards, so the value for the skewness function will appear smaller than it actually is; thus the null will not be rejected as often as it should be. The implication is that when the test does reject, we can be sure that the series exhibits non-Gaussian behavior. Several studies (including Chan and Tong, 1986) evaluate the Hinich bispectrum test and find that it has low power against nonlinear MA models, low power against series with zero third-order cumulants (ARCH models), and that it can not distinguish between various stochastic processes that have in common symmetric distributions about the origin. However, this is one of the few statistics that tests directly for nonlinearity; pre-whitening the data is not required, and one need not be concerned picking up linear serial dependence.

Hsieh (1989) develops a test with the intention of indicating what model might work best for fitting. He categorizes two types of nonlinearity as either "additive", in which nonlinearity is articulated through the level of the series, or its mean; or "multiplicative", in which nonlinearity appears in the conditional variance, as in ARCH models. Additive nonlinearity is preferably modeled with state dependent models such as nonlinear MA's, STARs, and bilinear models. A shortcoming of Hsieh's procedure is that his test will reject only in the presence of additive nonlinearity, and not in the presence of multiplicative nonlinearity, so must be used in conjunction with a test such as Tsay's, which rejects for any and all types of nonlinearities.

The Hinich Patterson test is a generalization of the Box-Pierce portmanteau statistic, assumes that the time series is a third-order stochastic stationary process, and tests for serial independence using the sample bicovariances of the data. Recall that the autocovariance function measures the relationship between sets of two residuals; the bicovariance function measures the relationship between sets of three residuals. Using the notation in the *Toolkit* manual, pages 42-43, the (r,s) sample bicovariance is

(2.17) $$C_3(r,s) = (N-s)^{-1} \sum_{t=1}^{N-s} x_t \, x_{t+r} \, x_{t+s} \qquad 0 <= r <= s$$

If we let $G(r,s) = (N-s)^{1/2} C_3(r,s)$ and define X_3 as

(2.18) $$X_3 = \sum_{s=2}^{l} \sum_{r=1}^{s-1} [G(r,s)]^2$$

Hinich and Patterson (1995) show that X_3 is asymptotically distributed chi-square with ($l[l-1]/2$) degrees of freedom. The X_3 statistic indicates non-zero third order correlations.

II. D. Empirical Literature

The objective of many nonlinear time series articles in finance has been to either fit a nonlinear model for stock return behavior, propose a new test statistic to identify nonlinear behavior, or both. Much of the empirical literature summarized below follows the same format. The author(s) compare two or three different models to fit the return-generating process of stock price changes, generally: a form of an ARIMA model, a form of an ARCH/GARCH model, and a nonlinear model (usually their favorite). These models are judged against each other by out-of-sample forecasting, or several of the nonlinear tests mentioned earlier. Here are three other general observations about the extant literature: first, much of the early 1990's information on nonlinearity was a by-product of research that attempted to distinguish between deterministic and stochastic systems. In these articles, nonlinear behavior is often noted only briefly, as it was not of primary interest to the authors. Second, discerning readers will note that in the articles summarized below, many of the different nonlinear models have all been successfully fit to the same databases for the same time period. Third, all of the studies summarized below do find evidence of nonlinearity, with the exception of Willey (1992), who was specifically testing for nonlinearity and failed to establish it.

The studies below sample the data at a variety of frequencies: monthly, weekly, daily, and intra-day. Almost all of the authors who investigate nonlinear behavior test the time series in its entirety, and arrive at a basic yes/no response for whether or not nonlinearity exists. Occasionally they will test a large sub-period to see if there is a structural break in the mean of the series. Except for Hinich and Patterson (1993,1996), Ammermann (1999), Ammermann and Patterson (2001), and Brooks and Hinich (1999), there is no determination of the episodic nature of nonlinear behavior, which is the focus of this study. Authors of the papers summarized below will occasionally include calendar dummy variables in the models of daily returns, but one more as a rote matter, as none of the authors make a point of distinguishing whether the behavior shows up more frequently at one calendar period versus another.

The first part of this review summarizes nonlinear research on United States stock returns and exchanges, the second part outlines recent research on foreign stock exchanges, and the third part briefly mentions some studies that have been completed on other types of financial assets.

II. D. 1. U.S. Stock Returns

This section is subdivided into three parts: research that focuses on models for nonlinear behavior, research that focuses on tests for nonlinearity, or research that focuses on both.

II. D. 1. a. Empirical Research (U.S. Securities) Models of Nonlinearity

Gu (1993) constructs a model with two types of investors and a market maker, and tests to see if his model-generated distribution of returns is statistically different from the empirical distribution, which is the monthly return (1928-1989) of the S&P Composite Index. Since there is no appreciable difference, he finds evidence in favor of both a stochastic generating process and a simple nonlinear deterministic model for returns. Cao and Tsay (1992) model the monthly returns (1929-1989) of the value-weighted and equal-weighted CRPS portfolios, and the S&P Composite Index, and then the daily returns for each of these series from 1985 through 1989. They compare a GARCH, an EGARCH and a threshold autoregressive (TAR) model, using several tests that Tsay has developed, along with the BDS test. LeBaron (1992) models the weekly returns (Friday-to-Friday close) of the S&P 500 for January 1946 through May 1990. He tests a GARCH model, using the level of volatility as the conditioning information, and the “nearest neighbor” nonlinear method, using the Granger-Newbold (1986) test for forecast improvement. He discerns between quiet and more volatile market periods and finds a very small improvement in forecasting the S&P 500 during the quieter periods, which is consistent with extant trading models in which the non-trading period is the result of a deliberate strategy not to trade. Brorsen and Yang (1994) use the daily 1979-1987 closing figures for the value-weighted and equal-weighted CRSP, and the S&P500. They test three models: a diffusion-jump process (combining continuous Brownian motion with a Poisson jump process), an extended GARCH, and a combination jump/GARCH process. With their GARCH model they include day-of-the-week dummy variables and model (instead of inserting another dummy) for monthly effects. They employ the Box-Ljung test, the Kolmorgorov-Smirnov (KS) test for goodness-of-fit to check non-normality, and the BDS test. They find both linear and nonlinear dependence, although they note that the linear dependence is usually limited to a day, and so surmise that it may be related to nonsynchronous trading. Granger and Ding (1996) propose using a fractionally integrated model to capture the behavior of the returns from the daily closing prices of the S&P 500 (1928-1990). They note that the return autocorrelation damps out very quickly at first, then damps out extremely slowly over a very long period. They employ both the correlogram and the spectrum in their approach, as the "long memory" characteristic of this series can be statistically modeled so that the series has a finite spectrum at all frequencies but zero, at which it has an infinite frequency. Ghysels and Jasiak (1998) use the 1993 tic-by-tic data of IBM in order to demonstrate their ACD-GARCH model, which does not require an equally spaced sampling period. They are able to eliminate much of the temporal dependence in the series (more so than with other models), and they find causality between stock volatility and intra-trade durations. McCulloch and Tsay (2001) examine three months of transaction data of IBM stock and use as variables the price changes, and the time duration between trades. If they use a moderate trading span of five days, they find that a simple threshold model will adequately describe the time durations between trades. When they consider both price changes and time durations jointly, they use Markov chain Monte Carlo methods to estimate a hierarchical model that consists of six simple conditional models. They find this method necessary and sufficient to model the dynamics within a trading day, and between the trading days for the full sample time period.

II. D. 1. b. Empirical Research (U.S. Securities) Tests for Nonlinearity

Scheinkman and LeBaron (1989) model weekly and daily returns of the value-weighted CRSP and test with the correlation dimension and the BDS statistic. Hseih (1991) examines the weekly and daily returns (1983-1989) of the S&P 500 with his 'three-moments' test and the BDS test. He finds no evidence of nonlinearity using the three-moments test, but is able to reject the null with the BDS test. Hinich and Patterson (1985a, 1985b) were the first to identify nonlinear behavior in stock returns beyond that which is modeled by the usual ARCH/GARCH models. They use the Bispectral test to analyze the daily returns (1962-1977) of 15 NYSE/AMEX stocks. In the earlier version they do not fit a model since the Bispectral test does not require a linear filter; in the later version they demonstrate that this diagnostic indicates that the returns could be appropriately characterized by a quadratic model. The interaction between the various frequencies of these returns are evidence of a nonlinear return-generating process: in the earlier version they discover peaks in similar areas of their contour plots, which are equivalent to time-clustered significant coefficients in their later version. The implication is that there may be an exogenous shock that commonly affects many of the stocks. As they develop the statistic (1987a) they also test the daily excess returns of General Electric from 1973 through 1983; this particular security nicely illustrates how the ACF function can indicate white noise, while the bispectrum test finds significant nonlinearity and non-Gaussianity. Their results are consistent with the later results of Brockett *et al* (1988). Ashley and Patterson (1986, 1989) test the daily returns for five stocks[4] and the equal-weighted and value-weighted CRSP Index from 1962-1981. Since all seven of the series are found to be non-Gaussian, they compare the empirical distributions to a simulated sampling distribution and reject linearity for all but CP&L. Patterson and Ashley (2000) use their *Toolkit* [5] approach to test the daily returns of the S&P 500 from 1962 through 1997. They find significant nonlinearity for five sub-periods (the BDS and Bispectral tests occasionally fail to reject the null). They also test each year individually and find that different tests will reject linearity in different years. Several tests reject the null for less than half the years tested, and there is a pattern: the null is rejected much more frequently in the earlier years and far less so in the later years. The McLeod –Li and the Engle-Lagrange Multiplier tests especially fail to reject linearity increasingly over the years from 1962 through 1997. These statistics are usually interpreted to mean that the series has conditional heteroskedasticity that might warrant modeling with an ARCH/GARCH model. That these tests fail reject nonlinearity is not a comment on their power or lack of it, but rather an indication that the particular series does not need ARCH modeling at that time. Kohers, Pandy and Kohers (1997) use equal-

[4] Carolina Power and Light, Holly Sugar Corp, General Public Utilities Corp., Exxon Corp., E-Systems Corp.
[5] This computer program will calculate asymptotic and bootstrapped values for these test statistics: McLeod-Li, Engle-Lagrange, BDS, Hinich Bispectral, HP Bicovariance, and Tsay.

weighted CRSP daily returns (1973-1990) to test for efficiency among the NYSE, AMEX, and OTC exchanges. They reference Berk (1995) to establish theoretically why size (market capitalization) should be taken into account for any empirical testing, and form three size-sorted portfolios for each exchange (from 60 to 150 firms per portfolio per year). Using Akaike's Information Criterion to determine an AR model, they employ the BDS statistic, plot the GP correlation integrals (and reshuffle), and use Hsieh's three-moments test to check for nonlinearity and chaos. The results from the BDS test are consistent with nonlinearity, but they are surprised to find that the large-cap NYSE portfolio (only) exhibits a degree of low-dimensional chaos. Because of the size of the large-portfolio firms, the frequency with which the firms are traded, and the amount of information publicly available on these companies, they expected that the NYSE large-cap would be the one portfolio that would *not* show any signs of forecastability. They surmise the phenomenon could be due to feedback mechanisms from factors such as institutional trading. Tauchen *et al* (1996) use the daily closing prices (1982-1988) of four individual securities: Boeing, IBM, MMM, and Coca-Cola. They include 24 calendar dummy variables; find no evidence of nonlinearity in the mean, but some evidence of nonlinearity in the variance. For three of the stocks—IBM, MMM, Coca-Cola--- the volatility resulting from price shocks appears to take from ten to twenty days to damp out. Abhyankar, Copeland and Wong (ACW 1997) measure six indices for the three months of September through November 1991. They use a one-minute sampling frequency for the FTSE-100, the DAX, and the Nikkei; a 15-second sampling frequency for the S&P 500, and transactions for the FTSE and S&P futures indices. They test with the BDS statistic and the Lee-White-Granger 1993 test (which is neural-network based). They find nonlinearity for all six series, which they surmise is partly due to volatility clustering. They also try to document that these returns follow a deterministic system and are unable to do so. They conclude that the chaotic system does not exist at all in this data, or that it is masked by an exceptionally strong stochastic process. Hinich and Patterson (1987b, 1995) sample 15 DJIA stocks every fifteen minutes over a three-year period (1978-1981) and test the returns with the bispectrum; they do not find that any particular day of the week is significantly associated with nonlinearity, but do find evidence that it appears to happen more frequently at the opening and close of the trading day.

There is a final note about the sampling frequency. Ashley and Patterson (2000) compare the *Toolkit* tests results for daily, weekly (Friday-to-Friday close), and monthly S&P 500 returns from 1962 through 1997. They also compare five-year subsets and divided the time period into two sub-periods: 1962-1980 and 1981-1997. When the length of time over which a return is computed increases, the probability that a “nonlinear-behavior-generating” event will occur also increases, simply because there is more time. So as the data begins to move from very high frequency to lower frequency, we might at first expect to see more occurrences of nonlinearity per sampling period. But if the nonlinear episode is very brief, (perhaps it just lasts for one day), then relative to a long time-period of linear behavior (if, for example, the sampling period is one month) the episode will not be noticed in the testing. When they go from daily to weekly sampling, the incidence of nonlinearity increases, but then as the length of the sampling period continues to increase, the nonlinearity disappears. For the two sub-periods (each an average of 15 years), there is very little evidence of nonlinearity in the first period, and none at all in the second period. McKenzie (2001) develops and compares the close returns test to the BDS test in evaluating the nonlinear behavior of several major national stock market indices. He finds that while the close returns test indicates that the index return data are not chaotic, the test reveals more nonlinearity than the BDS test does.

II. D. 1. c. Empirical Research (U.S. Securities) Both Models and Tests

Qi (1999) uses monthly data for nine economic and financial variables, including the S&P Composite Index. He employs a neural network approach in which the investor may choose between linear and nonlinear models for every new forecast. He tests his model with the Jarque-Bera non-normality statistic, the Box-Ljung statistic, the Tsay test, and the BDS test. Van Noorden and Schaller (1997) extend Hamilton’s Markov-switching regime to look for changes in both the mean and the variance of the (1929-1989) value-weighted CRSP monthly returns. Using the specification testing of White (1987) and Hamilton (1990), they find two extended periods of high volatility: 1929-1933 and 1937-1940; they also find isolated bursts of volatility in the 1970’s, and bursts around 1987. Mayfield and Mizrach (1992) sample the 1987 S&P 500 at 20-second intervals and test three models: the simple log difference, an ARMA model, and a

GARCH model. They include opening and closing dummy variables for the first and last hours of the day. They calculate the Grassberg and Procaccia (1983) correlation exponents, and use the shuffling diagnostic from Scheinkman and LeBaron (1989). Willey (1992) models the daily closing prices of the S&P Composite Index (1982-1988) and the OEX100 (1985-1989) using AR and ARCH models. He tests the series with the Box-Ljung statistic, the BDS statistic, and the Scheinkman/LeBaron shuffling technique to test for deterministic chaos. He is not able to stabilize the correlation exponent, so cannot claim evidence for a deterministic, chaotic system; since changes in the price level appear to be independent, he cannot claim a strong nonlinear relationship in the data, either.

II. D. 2. International Stock Returns

All of the research on foreign stock exchanges summarized here finds significant nonlinearity.

II. D. 2. a. Empirical Research (Foreign Stocks) Models of Nonlinearity

De Gooijer (1989) tests 27 individual stocks, roughly five per country, for France, Germany, the Netherlands, Japan, and USA. He tests a bilinear versus a linear AR model using daily closing prices from 1977-1978, and evaluates them with the Box-Ljung and Lagrange Multiplier statistics. Kunitomo and Sato (1999) claim that because of the asymmetry in variance changes with respect to shocks, a Gaussian ARIMA or an ARCH model is not useful. They propose a stationary and a nonstationary simultaneous switching autoregressive (SSAR) model, which are essentially nonlinear time switching models. They test the Nikkei 225 Spot Index (January 1985 to May 1986), and the Nikkei 225 Futures Index (January 1990 through August 1991). Scheicher (1999) compares a Markov-switching to a GARCH model for (1986-1992) daily data from the Vienna Stock Exchange Index. He finds relatively higher autocorrelation (but does not say compared to what) due to the lower market capitalization of this exchange. He tests his models with the Box-Ljung, the Lagrange Multiplier, and the BDS statistics. Poon and Taylor (1992) model the daily, weekly, fortnightly and monthly returns on Financial Times All-Share Index from 1965 through 1989. They employ an appropriate form of the ARIMA model, a

GARCH model, an E-ARCH model, and a GARCH-M model. They test their models with the Durbin-Watson, skewness, and kurtosis statistics. Fornari and Mele (1996) test a variety of ARCH/GARCH models in an effort to capture the asymmetry of the conditional variance of the daily returns of the S&P500, the Paris CAC40, and the Milan MIB. They test with Engle's 1982 statistic and a goodness-of-fit test. McMillan (2001) uses a nonparametric regression technique to see if there is a nonlinear relationship between stock market returns and macroeconomic variables. He finds that a smooth-transition threshold type model improves both in-sample and out-of-sample results. Brooks and Garrett (2002) use a self-exciting threshold autoregressive (SETAR) model on UK FTSE 100 stock and stock index futures. They show that the basis can fluctuate in between an upper and lower threshold (representing transactions costs) without triggering arbitrage behavior. When the basis moves outside of the threshold, the nonlinearity disappears.

II. D. 2. b. Empirical Research (Foreign Stocks) Tests for Nonlinearity

Panunzi *et al* (1993) use the BDS statistic and a version of the Hinich Bispectral (1982) test on a random walk model of daily prices from ten firms on the stock exchange of Milan. They examine the 1985-1989 period, which was especially notable because it was just after the exchange opened to small investors in 1985. Ahmed *et al* (1999) examine the daily returns (1986–1996) for the exchanges of ten Pacific Rim countries[6]. Although the economies are significantly different from each other, the countries have relatively free, liquid, and open markets. They use ARCH models to remove lower moment correlations and test with the BDS (1987) and the BDLS (1996) statistics. Ammermann and Patterson (2001) use the Hinich bispectrum and the Hinich Patterson statistics to test the daily returns of six international indices, plus the daily returns of 258 individual Taiwanese securities (from roughly 1982-1993). They find episodes of nonlinearity for essentially all of the indices and the stocks. Most notable about their contribution is that Taiwan's stock market has certain fundamental characteristics that are different from the NYSE. The Taiex prohibits short selling, has no other derivative markets, matches trades electronically rather than through open outcry, allows a very small amount of

[6] Australia, Hong Kong, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan, Thailand.

foreign investment (through mutual funds only), and during this period enforced daily price limit changes of 3-7%. The Taiex is also among the most heavily traded markets in the world. The implication of these results is that nonlinearity may be associated with high trading volume, but not with certain idiosyncratic characteristics of U.S. markets.

II. D. 2. c. Empirical Research (Foreign Stocks) Both Models and Tests

Chyi (1997) tests an adaptive fuzzy system against a GARCH-M model, using the BDS test and the correlation dimension technique of Grassberg and Procaccia (1983). He models the daily stock returns of five firms (1976-1993) from Taiwan's stock exchange. Silvapull and Choi (1999) test the value-weighted index of all common stocks listed on the Korean Stock Exchange from 1980 through 1994. Because this period was characterized by severely different economic conditions, they are careful to partition their tests into three sub-periods. They use dummy variables for calendar effects, and test a GARCH and an EGARCH model, with the Lagrange Multiplier statistic.

Kosfeld and Robe (2001) examine the nonlinearity in German bank stock returns using the McLeod-Li and BDS tests. They then apply the Hsieh test to show that the multiplicative dependencies in the returns can be usefully modeled by a lower-order GARCH model.

II. D. 3. Other financial assets and economic time series

II. D. 3. a. Empirical Research (Other Assets) Models of Nonlinearity

Guarda and Salmon (1996) test GARCH residuals of the U.S. Dollar/British pound exchange rates (weekly and monthly) from 1973-1990. They find more evidence of nonlinearity in the weekly rather than the monthly series; for both series the nonlinearity is intermittent, and they caution that models may not be able to detect it when it is weak in this manner. For the weeks in which nonlinearity measures were the highest, they check back issues of *The Economist* for news relevant to exchange rates. They find that these weeks coincide with changes in Presidents Carter's and Reagan's (non) interventionist policies with respect to rate changes. Mizrach (1996) tests four models: a random walk, an AR_3, a 5-nearest neighbor, and a Markov Switching process with probit transitions, for the French franc/German mark exchange rates. The latter model is useful to anticipate the chance of devaluation; there are six of these episodes in his time series, where two percent of the observations explain 61 percent of the variance of the sample. He establishes a rule of thumb "not to predict" if the probit risk measure is more than two standard deviations above the mean (in other words, get out of the market) and improves his forecasting ability by 300 percent. Koop and Potter (2001) use a Bayesain approach to compare models that address whether nonlinearities in macroeconomic data are endogenous (and thus may be captured by a threshold autoregressive model) or are due to structural instabilities over time. They find that structural instability may be more likely than endogenous shocks. Enders and Hurn (2002) use a threshold autoregressive model to model the nonlinearity in the Phillips curve (using recent Australian data) caused by asymmetric price adjustment. Skalin and Terasvirta (2002) further address asymmetries, by modeling several OECD countries' unemployment data. They use a simple univariate model, based on a logistic smooth transition autoregression, that includes a lagged term. The model allows for asymmetric behavior by permitting local nonstationarity in a globally stable model.

II. D. 3. b. Empirical Research (Other Assets) Tests for Nonlinearity

Hsieh (1989) examines the daily closing bid prices of five foreign currencies (in terms of U.S. dollars): the British pound, the Canadian dollar, the German mark, the Japanese yen and the Swiss franc, from 1974-1983. He uses the BDS and the McLeod-Li tests, and shows evidence of nonlinearity from ARCH effects. Cao and Soofi (1999) repeat this experiment ten years later, and test the daily returns of the U.S. dollar exchange rate with the Canadian dollar, the British pound, the German mark, the Japanese yen, and the French franc. They use the Grassberg and Procaccia (1983) correlation dimension and discover that the series has a very high embedding dimension, perhaps due to the fact (they surmise) that exchange rates are determined by a large number of variables. Brockett *et al* (1988) find evidence of nonlinearity in the spot and forward dollar/yen exchange rates (sampled from 1981-1983) using the Hinich Bispectral test. Brooks and Hinich (1999) propose two bi-correlation and cross-correlation tests between two time series (second and third-order dependence), which are modified forms of Hinich's (1996) univariate work. They test the log differences of 5192 UK-pound denominated daily mid-price exchange rates of seven currencies,[7] from 1974 through 1994. They test 148 non-overlapping periods of roughly seven weeks each, and find short-lived episodic occurrences of nonlinearity. Ashley and Patterson (1989) apply the Bispectral test to monthly changes in the industrial production index (1947-1985); this work is followed up with the study by Altug *et al* (1998), in which they apply three tests, the BDS, the McLeod-Li, and the Hinich Patterson, to GNP growth and the labor input series. All three series exhibit strong nonlinearity. Gilmore (2001) adapts a topological method from the hard sciences that uses a qualitative test for chaos and that can be adapted to financial data. She applies it to exchange-rate data, and finds no evidence of chaos, but does find nonlinear dependence. Lobato (2003) uses a bootstrap method, and applies the Cramer-von Mises and Kolmogorov-Smirnov test to five U.S. monthly economic time series. He finds evidence of nonlinearity for the personal income and unemployment rate, but none for the U.S. dollar/ Japanese yen exchange rate, the three-month T-bill rate, or the M2 money stock.

II. D. 3. c. Empirical Research (Other Assets) Both Models and Tests

Yang and Brorsen (1993) test a GARCH model against deterministic chaos for the daily closing prices of 15 actively traded futures contracts (1979-1989). They test with the BDS statistic and the Brock residuals test, and find linear independence, but nonlinear dependence, and that the variance of the contracts is much greater on Mondays and after holidays. Vaidyanathan and Krehbiel (1992) test an ARCH model of the S&P 500 futures contract mis-pricing series with the BDS statistic, the correlation dimension and the reshuffling technique, and find evidence of low-order determinism and nonlinear dependence. Psaradakis and Spagnolo (2002) evaluate and compare a variety of tests
(including the Keenan, Tsay, McLeod-Li, BDS, and neural networks) on time series data that is generated by Markov switching autoregressive models.

[7] Austrian schilling, Danish krone, French franc, German mark, Italian lira, Japanese yen, U.S. dollar.

CHAPTER III: DATA AND METHODOLOGY

III. A. Data

The sample consists of 60 New York Stock Exchange (NYSE) securities, sorted into three size-portfolios (large-cap, mid-cap, and small-cap) of 20 stocks each. To insure that the stocks have wide dispersion of ownership and trade frequently enough for the experiment to be meaningful, the stocks are randomly chosen from a sample of securities that belong to one of the Standard and Poor (S&P) indices: the *S&P 500 Index*, the *S&P Midcap 400 Index*, and the *S&P SmallCap 600 Index*. The S&P criteria used for admitting a security to any of these indices are listed in Appendix A. The chosen securities are listed in Appendix B.

The intra-day returns for these securities are computed from TAQ data, for the years 1993, 1995, 1997, 1999, and 2001. As any chosen security was 'de-listed' from its index, it was replaced in the portfolio, to the extent possible, with the actual firm that replaced it on the index itself. If this was not possible (if, for example, the firm was replaced with a NASDAQ stock) then the replacement firm was chosen from NYSE companies that were newly listed on the index at about the time the original firm departed. The TAQ data also provided information about trading volume. Additional data was obtained from the Center for Research on Security Prices (CRSP) to adjust the price-return data for stocks splits and dividends. The put/call ratio (from October 1995 through December 2001) was obtained from the Chicago Board of Exchange (CBOE) and used to test a fourth hypothesis about nonlinearity occurring more often on days of negative surprises in the market.

The TAQ data are filtered so that only transactions which occur on the NYSE are considered; transactions which occur on other regional exchanges are deleted. Also deleted are transactions that occur after 4 p.m., errors and their corrections, and trades that qualify as "G", Rule 127, or stopped stock trades. The final sample of data is that which are unremarkable in any way. The data for each security are sampled at ten-minute intervals. The first interval of the day runs from 9:30 a.m. to 9:40 a.m., and the last interval of the day runs from 3:50 p.m. to 4:00 p.m. The last actual trade (the trade closest to the end of each ten-minute interval) is used as the "closing price" of that interval. If the security did not trade during any particular ten-minute interval, then the closing price of the previous interval is substituted. If the security does not trade during the first ten minutes of the day, then the price from the closing interval of the day before is used as price of the first interval. Fifteen out of the 1258 days were deleted from the sample because the market was closed for some time period during those days.[8] The return to a ten-minute interval is calculated as the log difference of the closing price of two consecutive intervals. The returns are also adjusted for stock splits and dividends. The number of days each security exhibited significant nonlinear behavior at an alpha level equal to 0.05 is listed in the tables of Appendix C.

Two additional small issues that are sometimes raised regarding the use and testing of the data are: the use of transaction prices to generate returns, and the validity of the test statistic. Researchers often choose to use the quote average to generate returns (rather than the transaction price) to avoid spurious correlation problems associated with bid-ask bounce. During the 1990's, microstructure investigation on the differences and similarities between prices and quotes revealed that researchers often trade off one problem for another when choosing to use either quotes or prices. Also, depending on what effect one is measuring, it often makes no difference to the final results if prices or quotes are used.[9] To check to see whether using prices or quotes might give different results in this study, a small sub-sample of securities was tested both ways, and the results are listed in Appendix D. There are six stocks per year tested, over a five-year period, for a total of thirty observations. In general, when the bid/ask average is used instead of price generated returns, the incidence of significant (at alpha = 0.05) nonlinearity increases for 16 of the observations, decreases for 12 of the observations, and does not change at all for 2 of the observations. Half of the decreases (6 of the 12) occur in the small-cap stocks. There are only two instances of large-cap stocks decreasing, and for these instances the decrease

[8] There are fifteen days over the five-year period in which the market is only open for part of the day, either because of holidays or temporary closures due to computer tribulations. Because the filtering and sampling method force fits a 39-observation window for each day, on these particular days there is a relatively large number of intervals with returns equal to zero, resulting in an abnormally low variance, and an abnormally high nonlinear statistic, especially for large-cap stocks. These fifteen days are dropped from the sample. The deleted (partially closed) days are: 11/26/93, 7/3/95, 11/24/95, 12/18/95, 7/3/97, 10/27/97, 11/28/97, 12/24/97, 12/26/97, 11/26/99, 12/31/99, 6/8/01, 7/3/01,11/23/01,12/24/01.

[9] Lee (1993) cautions that trade time series and the quote time series can not necessarily proxy for each other since trades are often executed inside of quotes, and that trades are often reported with delays (Lee and Ready 1991). Hasbrouck (1995), Harris *et. al.* (1995), and Tse (2000) document that price discovery between regional exchanges and the NYSE depends on whether one uses prices or quotes. Bloomfield and O'Hara (1999) note that trade disclosure will increase information dissemination but that quote disclosure will not, perhaps because, as Easley and O'Hara (1992) note that quotes may change even though there is not trading and presumably no new information.

is only by one day. The rational for this small experiment was that spurious *linear* correlation has been observed more frequently in price-generated returns rather than quote-generated returns, and the results for the C-05 indicator statistic bear this out. It is the linear correlation that decreases 16 out of the 30 times when the bid/ask average is used instead of the price.

As statistics are developed they evolve through a rigorous testing method in which their attributes are compared to more established test statistics using data purposefully generated from a known distribution. As the Bicovariance statistic is relatively new, a small sub-sample of its results are compared to other nonlinear test statistics in Appendix E. Although several of these tests focus on different moments, it is not unreasonable to expect to see some overlap among their results. The returns for days on which the H Indicator statistic surpassed an alpha level of 0.001 were also tested for linear correlation (the C statistic), and for other types of nonlinearity using the McLeod-Li, the BDS, the Lagrange Multiplier, and the Tsay tests. For these other tests the alpha level was set at 0.05. Out of 13 instances of a significant h-001 indicator statistic, there were five instances each for the McLeod-Li, the Lagrange Multiplier, and the C-Statistic (not completely overlapping days), eight instances of the BDS test, and two instances for the Tsay test.

III. B. Methodology

The Hinich Patterson test results are computed with the aid of the *T23* software program.[10] The program estimates coefficients for an AR model for a given window of observations in a set of data. Several criteria are employed to arrive at an appropriate lag: a relatively short lag (up to an AR_2), a minimization of the Schwartz Bayesian Criterion (SBC),[11] and the lowest chi-squared statistics for the null hypothesis that the residuals from the fitted model are not autocorrelated. The SBC for the unfitted, the AR1, and the AR2 models for returns are compared to each other: in order to fit a model, the SBC is required to improve by more than 0.1% over an unfitted model. In Appendix C, the securities that required a fitted

[10] The T23 software program is written by Melvin Hinich. Given a non-overlapping window of 39 in a set of 9900+ observations per security per year, the program estimates and re-estimates 250+ sets of AR coefficients, (all 250+ sets for a security have the same lag).
[11] The Schwartz Bayesian Criterion is computed as: $-2\ln(L) + \ln(n)k$, where L is the likelihood function, k is the number of free parameters, and n is the number of residuals.

model are noted with asterisks. The *T23* program outputs a number of descriptive statistics for each window (in this case, the window is a trading day), including an H statistic that indicates nonlinear autocorrelation in residuals, and a C statistic that indicates linear autocorrelation in the residuals. To designate the results of both the H and the C test, the *T23* program produces a number for each that equals one minus the p-value for the statistic; henceforth in this paper the terms “H statistic” and “C statistic” will mean this (1-p) term. The closer this number is to ‘1’, (clearly, the smaller the p-value of the test) the greater the degree of nonlinear or linear autocorrelation in the security’s return behavior for that day. An H or C statistic with a value greater than 0.95 indicates (a one-tailed test) significance with a p-value less than 0.05.

Several authors of previous studies have cautioned that one can not proceed from the general to the specific: finding or not finding evidence of nonlinearity on an index return does not give any indication that one might find the same result on the individual securities that make up the index. Granger (1992) warns that while combining stocks into portfolios may wash out unwanted noise and thus reveal overarching patterns, it may also eliminate our ability to detect phenomena that affect securities individually. Atchison and White (1996) simulate a portfolio in which every individual security follows a deterministic pattern[12], but as each deterministic security is added to the portfolio, the portfolio returns appear more and more random. Ashley and Patterson (1986) also note that when comparing a set of actual individual securities to two indices, the individual securities exhibit nonlinear dependence, but the indices do not. It is important to remember that this study tests the nonlinearity of each security individually; the “portfolio results” listed in the tables are not a test of an average return on a portfolio, but rather it is the average of the test statistics for each individual security return.

[12] They point out on page 22: “Nonlinearity is a necessary, but not sufficient, condition for chaotic behavior” (a deterministic system).

CHAPTER IV: RESULTS

IV. A. Descriptive Statistics

. The return observations for each security are tested with the *T23* Software program: the coefficients of each security's AR model are re-estimated daily; an H and a C statistic from the HP test are computed for the security's return pattern for each of the trading days. A statistic greater than 0.95 is considered significant at a test power of five percent ($\alpha = 0.05$); a statistic greater than 0.99 is considered significant at a test power of one percent ($\alpha = 0.01$), etc. These results are used to calculate an "indicator statistic" which equals zero if the H or C statistic is not significant (at whatever alpha level chosen) and equals one if the statistic is significant. The indicator statistics will always be noted as such. The C statistic for each security is computed using only an unfitted (AR_0) model, whereas the H statistic is computed first with unfitted models, and then, if appropriate, with fitted models (up to a lag of 2). This is to guard against the masking of nonlinear behavior by over-fitting the model.

Tables 1 through 3 present descriptive statistics for the HP results of the H and C tests, for the large, mid, and small-cap portfolios respectively. The H statistics for each individual security are averaged (or cumulated, in the case of the indicator form) across the stocks in each portfolio for each day, and then over the number of trading days in the year, to give an indication of how the group (large, mid, small) in general behaves. For the H (C) statistic, the table represents the average level of nonlinear (linear) correlation in any security's intra-day returns in that portfolio for any day of the year. For the indicator form of the H (C) statistic, the table represents the number of stocks (in terms of percent) in each portfolio that exhibit nonlinearity (linear correlation) at a particular significance level for any day of the year. The average H statistic for each portfolio (large, mid, small) increases monotonically as capitalization increases, that is, the average level of the nonlinear statistic is larger for larger-cap stocks. From 1993 to 2001 the average daily level of the H statistic (H mean, unfitted models) increases markedly. It rises from 0.3101 (1993) to 0.4327 (2001) for the large-cap portfolio, from 0.2300 (1993) to 0.4110 (2002) for the mid-cap, and 0.1265 (1993) to 0.3344 (2001) for the small-cap. The number of stocks that, on any given day, exhibit nonlinear behavior at each level of significance also increases. At an alpha level of 5%, the percentage of each portfolio that exhibits significant nonlinearity nearly doubles across the decade: 6.53% to 12.03% for the large-cap, 6.79% to 11.91% for the mid-cap, and 4.72% to 9.86$ for the small-cap. At $\alpha = 0.05$, five percent of each portfolio should, on average, exhibit significant indicator statistics; at $\alpha = 0.01$, one percent of each portfolio should, on average, exhibit significant indicator statistics; at $\alpha = 0.001$, one-tenth of a percent of each portfolio should, on average, exhibit significant indicator statistics. With the exception of the small-cap portfolio in 1993 and 1995, the incidence of measured nonlinearity is higher than expected for any given alpha level. What is especially notable is that for $\alpha = 0.001$, the percentage of stocks that exhibit significant nonlinearity (for both fitted and unfitted models) is 15 to 30 times what we would expect. The implication is that when a stock does exhibit significant nonlinearity, it is at an intense level. Note that the portfolios that include H statistics derived from returns filtered with an ARIMA model appear to have nearly identical descriptive statistics as the portfolios that contain only unfitted returns. Accordingly, the remaining tests in this paper are performed only on the portfolios of unfitted returns. Note also that the level and incidence of linear correlation (as measured by the forms of the C statistic) are decreasing over the decade, and is much more in accordance with the alpha levels. The annual averages are compared to each other using two common ANOVA tests: the Waller-Duncan k-ratio t-test, which minimizes the Bayes risk under additive loss, and the Duncan's Multiple range test, which controls for the Type 1 comparison error rate. (In this particular instance, the two tests' results are identical.) The letters "A", "B", "BC", etc. that are printed next to the averages in the cells of these tables are the results of these ANOVA tests, in which the same letters are assigned to means that are not significantly different from each other, and different letters are assigned to means that are significantly different. The letter "A" is always assigned to the highest mean in the grouping, and the letters proceed downwards to the lowest mean. For the mean of the H statistic, the each portfolio average differs significantly from year-to-year. The differences between years are not quite so marked for indicator forms of the H statisitic or all forms of the C statistic.

Table 4 (H statistic) Table 5 (C Statistic) record the results of an ANOVA test (again using Duncan/Waller groupings) between the descriptive statistics of the large, mid, and small-cap portfolios to determine if they are indeed significantly different from each other. The average daily level of the H and C statistic (H mean, C mean) are examined, as well as the indicator forms of the statistics. The p-values from the corresponding F-tests are listed in the table, the letters “L”, “M”, “S” indicate the size-portfolio, and the letters “A”, “B”, “C” indicate whether or not there is a measurable difference in the portfolios. The letter “A” represents a value that is essentially equal to the point “AB” (“A” in common); the point “AB” is essentially equal to the point “BC” (“B” is common); but the point “A” is significantly different than the point “BC” (no letter in common). For each of the five years, the average daily level of both the H statistic and the C statistic is largest for the large-cap stocks and smallest for the small-cap stocks. This pattern is also replicated for the first indicator form of these statistics, that is, what percent of the portfolio is, on any given day, exhibiting significant linear or nonlinear correlation at an alpha level of 0.05. In this case, the large-cap and the mid-cap portfolios have an indistinguishable percentage of stocks exhibiting significant nonlinear behavior, and the small-cap portfolio has considerably fewer. This relationship, for both the linear and nonlinear test statistic, is somewhat mitigated at higher alpha levels (of 0.01 and 0.001).

The results from Tables 1-3 indicate that there is a large degree of “trending” among all forms of the H (especially) and C statistics over the decade, and suggest that any tests involving these statistics may need to employ forms of the variables that have been scaled to adjust for this strong trending behavior. Tables 6, 7, and 8 (for indicator levels of 0.05, 0.01, and 0.001, respectively) exhibit the results of a test to resolve whether or not there is some overarching characteristic that persistently drives the nonlinear behavior of all stock returns. This conjectured property may be thought of as similar to market risk, in that we would expect to see a contemporaneous correlation between the nonlinear percentages of the size-sorted portfolios. Because of the earlier determined substantial trending, the indicator forms of the H and C statistics are scaled by their annual (or bi-annual or tri-annual) averages, if necessary, and then a simple Pearson correlation coefficient is obtained for any contemporaneous or lead/lag relationship between the large, mid, and small-cap portfolios, for both the H and C statistics. Only if the p-value is less than or equal to 0.1000, the Pearson correlation coefficient is listed in the top row of the cell, and its p-value is listed directly beneath it. Insignificant correlations are represented by a dashed line. In these tables, the correlations are calculated across all years (n equal to 1243). There does not appear to be any lead/lag relationship of either statistic between these portfolios (of interest due to the lead/lag relationship between the *returns* of larger and smaller cap portfolios); nor does there appear to be any consistent contemporaneous relationship either. The most consistent relationship appears to be between the H and C statistics themselves, within the portfolios. For example, the large-Cap H-05 is highly correlated with the large-cap C-05, and this correlation holds for both the mid- and small-cap portfolios, and for most of the other forms of the indicator variables. Even so, the correlation is not what one might term "strong". The correlation for the indicator forms H05/C05 and H01/C01 is about 10% for the large-cap, 22% and 14% for the mid-cap, and 26% for the small-cap.

For the indicator forms H001/C001, there is no significant correlation for the large-cap, and the mid-cap is about 10% and the small-cap is about 16%. Even though there does not seem to be a recurring, day-to-day, systematic phenomenon that is equally affecting the Bicovariance test for the stocks in these portfolios, there may be occasional market-wide or macroeconomic events that cause a large percentage of stocks to exhibit nonlinearity. This would be consistent with previous studies that have found only episodic nonlinearity in security return behavior.

IV. B. Calendar Effects

The portfolios were tested across all years and each year for calendar effects relating to month-of-the-year, quarter-of-the-year, and day-of-the-week patterns. The results are listed in Tables 9, 10, and 11. In the tables, 'M' stands for 'month', 'Q' for 'quarter', and 'D' for 'day-of-the-week'; the months are numbered as January equals "1" and December equals "12"; the days of the week are numbered as Monday equals "1", and Friday equals "5". For tidiness, if there is no significant relationship, a dashed line '------' is put in place of a p-value. If the p-value from the F-test indicates significance (or close) it is listed next to the time period, and underneath, the time periods are listed in order from the largest to smallest mean. For the monthly tests, only the five months with the highest measure of the statistics are listed. For example, in Table 9, for the large-cap portfolio across all years, the average level of the H statistic (H mean) is significantly different in various months. The month with the highest mean level is December (12), followed by August (8), then February (2), and so on. The large-cap portfolio exhibits similar results for the average level of the C statistic, which is also highest in December. The results are strongest for the test across all years, and are not well supported by the test for each year, so may be driven simply by a large sample size (the full sample was scaled annually to eliminate trending). If and when any particular day of the week turns up significant for the large-cap portfolio, it tends to be Friday.

For the mid-cap portfolio (Table 10) there are sporadic occurrences of significance--- the year 1997 in particular---but these occurrences do not follow any perceivable pattern in calendar time or type of statistic. It is only for the small-cap portfolio (Table 11) that a well-defined pattern occurs for the mean level of the H statistic. It is significantly higher in December across all years and for the years 1995 and 2001. In 1999, December is still the month with the highest mean level of the statistic, but it is not differentially higher than the other months. For 1993 and 1997, the level of the p-value indicates that fitting a model that differentiates months is useful, and December is among the highest. These results for December are further supported by the fact that the fourth quarter of the year, across all years, and in particular the years 1997 and 2001, are also significantly higher than the other quarters. Figure 1 is a graph of the mean level of the H statistic for the months (January equals 1, December equals 12) across all years for the small-cap portfolio.

IV. C. Relation to Trading Volume

The relationship between trading volume and the H statistic, and trading volume and the C statistic, is examined in Tables 12-17. The regression tests are for each portfolio, across all years and for each year, and for various forms of both the H and C statistic. Again for tidiness, if there is no significance, a dashed line '-----' is used instead of the actual p-value. An OLS regression was run for the relationship between several forms and variations of the H statistic (or C statistic) and several variations of trading volume, and these various forms are delineated as "Model (1)", "Model (2)", and "Model (3)". Model (1) is daily average H (or C) statistic for the portfolio (or the daily sum of the indicator form at alpha equals 0.05, 0.01, 0.001) and the total trading volume for the twenty stocks in each portfolio for each day. Because these statistics have exhibited trending and some seasonality, and because as time series data they are

prone to autocorrelation and nonstationarity, models (2) and (3) attempt to adjust for these problems with the data. Model (2) is the daily H (or C) statistic (either mean or indicator) scaled by its annual average, and the daily trading volume scaled by its monthly average.
Trading volume was examined at some length for all of the portfolios and was found to vary a lot during the year, which is why monthly scaling is used. (The noted variability in these portfolios is consistent with the findings of extant research on volume.) Model (3) uses the log difference of both the daily H (or C) and trading volume variables. Additionally, for each regression the Durbin-Watson statistic is computed to check autocorrelation of residuals, and is significant in only one instance for all six of the H (or C) vs. volume tables: Table 14, small-cap H statistic for all years, the Durbin Watson computed critical value is 1.55, which is borderline, or inconclusive.

A Chi-square test to check for first and second moment misspecification is also calculated (to indicate heteroskedasticity) and does indicate sporadic occurrences throughout the years, and strong occurrences across all years, again due to the trending.

In Table 12, for the large-cap portfolio we can see that across all years, the unadulterated forms of the H-average and the indicators H-05, H-01, H-001, appear to be significantly related to trading volume (Model 1); but that the chi-square test indicates misspecification, and the scaled and log differences versions of the variables (Models 2 and 3) do not indicate a significant relationship. As Models 2 and 3 appear to be correctly specified (or at least, not obviously mis-specified) it is reasonable to conclude that the apparent correlation between the forms of the H-statistic of and trading volume of the large-cap portfolio across all years is spurious, and due to model misspecification. There is some sporadic correlation: in 1995 and 1997, a significant relation between the log difference of the H-average and the log difference of trading volume (model 3); and again model (3) for H-05 and trading volume in 1997 and 2001, although for 1997 the relationship is negative.

In Table 13 we see that the for the mid-cap portfolio Model (1) cross all years suffers the same mis-specification problem as in Table 12 above. However, for every individual year there is some relationship between some form of the H-statistic and trading volume. In 1993, all three models for the H-average are significant, as are models (1) and (2) for H-05, models (1) and (3) for H-001. In 1995, 1999, and 2001, model (3) for the H-average is significant, although the relationship is negative in 1999. In 1997, Model (1) is again significant for the H-average and H-05, as it is in 2001 for H-001, (although again in 2001 it is negative).

In Table 14 we see the strongest relationship out of all of these tests, between the various forms of the H-statistic for the small-cap portfolio and trading volume. Although again the unadulterated versions of the statistics (Model 1) across all years indicate misspecification, the scaled or log difference versions maintain a significant relationship. Model (2) and Model (3) indicate a significant relationship between the H-average and trading volume across all years, with no misspecification, and this is supported by significant relationships in the years 1993 through 1999. It is only in the year 2001 that the relationship begins to dissipate. Also Model (3) for the log-difference form of the H-05 and H-01 statistic across all years indicate significance. (Model 1 for these two forms looks spurious, due to the p-value on the chi-square test). In addition, there is significance for H-05 Model (3) in 1993, H-01 Model (2) in 1997, H-01 and H-001, Models (1), (2), and/or (3) in 1999. In 2001 the relationships are still significant but they have become negative.

For the C-statistic, there is overall less instances of significant correlation between it and trading volume. In Table 15 there is a negative relationship, between the C-average and the C-05 and trading volume across all years, that does not appear to be mis-specified. Although most of the C-correlations in the large-cap portfolio appear to be negative, there are some strong positive correlations in the year 1999. In Table 16 there is sporadic correlation for the mid-cap portfolio, in 1997, 1999, and 2001, again, most of it is negative. In Table 17 there is consistent positive correlation between the C-average and trading volume.

To summarize these results: it appears that only the small-cap portfolio exhibits a consistent relationship between some form of either the H or C statistic and some measure of trading volume. A possible explanation for this more consistent behavior is that (earlier in the decade, especially) small-cap stocks trade less often, and with less noise traders, so that relatively high trading volume signals an important event.

CHAPTER V: CONCLUSION AND FURTHER STUDY

V. A. Summary of Results

There is a notable difference in the average level (and other measures of central location, the median and the mode) and significant incidence of nonlinearity between portfolios of large-cap, mid-cap, and small-cap stocks. Even though all three portfolios show a marked increase in both the level and incidence of nonlinearity across the time period measured, this difference persists throughout the decade. There is also the same notable difference in the measurement of linear correlation in returns for securities in the three size-sorted portfolios, and measures of linear correlation decrease throughout the decade.

Calendar effects for month, quarter, and day-of-the-week are examined, and although there are some sporadic instances of these calendar periods associated with each portfolio, it is only the small-cap portfolio that indicates a persistent relationship with a monthly calendar effect. The average level of the H statistic for the small-cap stocks tends to be higher in December, measured across all years and most of the individual years (with the exception of 1999). This pattern is emphasized by the fact that the average level of the H statistic is also higher in the fourth quarter of the year for the small-cap portfolio. There is also faint evidence that Friday is an important day for large-cap securities, in both the level of the H statistic and the incidence of significant nonlinearity are greater on Fridays than other days of the week, measured across all years.

The relationship between trading volume and the H and C statistics is somewhat more tenuous. A regression of the mean daily level of the H and C statistics on trading volume for each portfolio indicates the most consistent relationship is that for the trading volume of the small-cap portfolio and the mean level of its H statistic. Although in the year 2001 this relationship (with the mean level of H) begins to dissipate, the indicator form of the H statistic (especially H at $\alpha = 0.001$) becomes significantly correlated with trading volume, although these relationships are negative. Generally speaking, the ANOVA results for calendar effects, trading volume, and portfolio correlation are weaker for tests regarding association with the C statistic (linear correlation) than for tests regarding association with the H statistic (nonlinear correlation).

V. B. Further Study

This study attempts to determine whether nonlinear behavior exists more often for securities at times in which returns do not appear to be identically distributed, i.e., the calendar effects, and the size effect for the small-cap portfolio. Another potential avenue for research focuses on times in which returns do not appear to be independently distributed, that is, periods of price overreactions and reversals. The graphs in Figures 2 and 3 indicate the number of stocks (out of 60) that achieve a significant level of the H and C statistics on the trading days examined. More stocks more frequently achieve a significantly high level of nonlinear correlation than linear correlation. There are approximately 30 instances over the five-year time period in which nine or more stocks (out of 60, approximately 15%) achieve an H statistic greater than 0.95. There are only three instances where ten or more stocks achieve a C statistic of greater than 0.95.

Granger (1992) points out how just a handful of extreme values or outliers can mask simple patterns in a time series, making it appear more complex than it actually is. The question that naturally arises out of this observation is that perhaps there are macro-economic or market-wide events that are correlated with these particular days. Black (1976) notes what is called the "leverage effect": volatility tends to increase more after a "bad news" surprise, than a "good news" surprise, due to the fact that the value of a levered firm falls with bad news. An examination of 1992 results (not reported here) suggests that nonlinearity also may increase as the market receives "bad news". This hypothesis is testable by regressing changes in measurements of nonlinearity on changes in the put/call ratio, to proxy for investor sentiment:

> H_{1D}: *Nonlinearity will tend to be associated with episodes of a "negative surprise" in the market.*

Tables 18 and 19 exhibit the results of the test of this hypothesis. OLS regressions, similar to the ones used to test the trading volume hypothesis were run. Again, the daily averages of the H and C statistics along with the indicator forms of these variables were used. The Chicago Board of Exchange's daily put/call ratio (as reported on its web page) from October 1995 through December 2001 was used to proxy for investor sentiment. As the put/call ratio exhibits the autocorrelation and stationarity problems associated with many economic time series, all three versions of the Models (1), (2), and (3), employed in the trading volume regressions, were used. In this case instead of trading volume the monthly scaled "relative put/call ratio" and the log difference of the daily put/call ratio was used. The Durbin Watson statistic was used to check residual correlation, and the Chi-square test was used to check model misspecification, and only the models that exhibited significant correlations and had no residual correlation or first and second moment misspecification are listed in Tables 18 and 19. Unexpectedly, the relation between nonlinearity in the large-cap portfolio and the put/call ratio is negative. As the put/call ratio is expected to increase when the market is digesting bad news, as is the incidence of nonlinearity (according to this hypothesis), we would expect this relationship between the two variables to be positive. The small-cap portfolio does have a strong positive relation with the put/call ratio in 2001, as does the mid-cap portfolio exhibit a strong positive relation between the C-statistic and the put/call ratio in 1997. Table 20, with comments from the Wall Street Journal regarding the highest nonlinear 31 days over this period, sheds some light on these results. There are 18 days in which the market closed "down" (as measured by the Dow Jones Industrial Average) and 13 days when the market closed "up". If we would expect the Dow to close "down" on days of negative surprises, this is a preliminary indication that the relation between nonlinearity and bad news in the market may not be robust over time. There are two days with record movements in the Dow (9/2/97 and 3/14/01) and two days where virtually nothing happened (4/16/99 and 12/15/99). There are days of unusually high volume and low volatility (3/17/95), and days of unusually low volume and high volatility (8/27/99). There are twenty instances where macro-economic data, especially interest rates, are mentioned. It may be difficult to establish a relationship between days of high nonlinearity and other market behavior as these are outlier days, associated with outlier events, and it seems presumptuous to make nay distributional assumptions.

It was noted in the introduction to this dissertation that there has been only a very little work done to differentiate episodes of nonlinearity from linearity in security prices. It appears that there is much research that remains to be completed in this area.

Table 1. Large Cap Portfolio (20 securities) Descriptive Statistics					
	1993 252 days	1995 249 days	1997 248 days	1999 250 days	2001 244 days
H unfitted					
H-mean	0.3101 E	0.3379 D	0.3638 C	0.3840 B	0.4327 A
H-median	0.1850	0.2235	0.2625	0.2905	0.3650
H-mode	0.0000	0.0000	0.0000	1.0000	1.0000
Variance	0.1054	0.1066	0.1090	0.1121	0.1220
Skewness	0.8480	0.6954	0.6096	0.5295	0.3169
Kurtosis	(.6426)	(.8755)	(1.0260)	(1.1313)	(1.3760)
H—05	6.53 % C	6.67 % C	7.38 % BC	8.40 % B	12.03 % A
H—01	3.27 % C	3.53 % C	3.41 % BC	4.32 % B	6.13 % A
H—001	1.19 % C	1.39 %BC	1.11 % BC	1.68 % B	2.58 % A
H fitted					
H-mean	0.3177	0.3350	0.3678	0.3840	0.4307
H-median	0.1990	0.2270	0.2690	0.2905	0.3610
H-mode	0.0000	0.0000	0.0000	1.0000	1.0000
Variance	0.1046	0.1031	0.1086	0.1121	0.1217
Skewness	0.8052	0.7107	0.5802	0.5295	0.3306
Kurtosis	(.7105)	(.8226)	(1.0630)	(1.1313)	(1.3646)
H—05	6.01 %	6.06 %	7.12 %	8.40 %	11.99 %
H—01	3.00 %	2.93 %	3.13 %	4.32 %	6.09 %
H—001	1.29 %	1.24 %	1.05 %	1.68 %	2.56 %
C unfitted					
C-mean	0.5337 A	0.5269 A	0.5123 B	0.5034 B	0.5129 B
C-median	0.5480	0.5393	0.5052	0.5003	0.5147
C-mode	0.0000	0.0000	1.0000	0.0353	0.1151
Variance	0.0888	0.0867	0.0862	0.0850	0.0842
Skewness	(.1295)	(.0916)	(.0127)	0.0071	(.0320)
Kurtosis	(1.1839)	(1.1919)	(1.1976)	(1.2020)	(1.1744)
C—05	8.75 % A	7.81 % A	6.67 % B	6.14 % B	6.62 % B
C—01	2.40 %AB	2.61 % A	2.06 %AB	1.82 % B	1.84 % B
C—001	0.60 % A	0.54 % A	0.52 % A	0.36 % A	0.33 % A

The letters "A", "B", "C", etc., next to the measures for the H and C statistics are results of ANOVA testing and Waller groupings for significant differences. Completely differing letter patterns indicate a significant difference between the measures: The H-mean for 1993 "0.3101 E" is significantly different from the one for 1995 "0.3379 D". For H-001, the years 1993-1997 are not significantly different ("C", "BC", "BC"), and the years 1995-1999 are not significantly different ("BC", "BC", "B"), leaving a significant difference between 1993 "C", and 1999 "B", only. The letter "A" is assigned to the highest number in the grouping, "B" assigned to the next highest. etc.

Table 2. Mid Cap Portfolio (20 securities) Descriptive Statistics					
	1993 252 days	1995 249 days	1997 248 days	1999 250 days	2001 244 days
H unfitted					
H-mean	0.2300 E	0.2487 D	0.2866 C	0.3505 B	0.4110 A
H-median	0.0260	0.0550	0.1390	0.2280	0.3075
H-mode	0.0000	0.0000	0.0000	0.0000	1.0000
Variance	0.1118	0.1116	0.1114	0.1166	0.1226
Skewness	1.2222	1.1161	0.9037	0.6545	0.4243
Kurtosis	(.0066)	(.2263)	(.6141)	(1.0247)	(1.3221)
H—05	6.79 % C	6.71 % C	6.83 % C	8.68 % B	11.91 %A
H—01	4.15 % C	4.16 % C	3.75 % BC	4.74 % B	7.21 % A
H—001	2.16 % C	1.85 % BC	1.47 % BC	1.76 % B	3.26 % A
H fitted					
H-mean	0.2384	0.2530	0.2926	0.3528	0.3975
H-median	0.0320	0.0610	0.1430	0.2305	0.2995
H-mode	0.0000	0.0000	0.0000	0.0000	1.0000
Variance	0.1123	0.1105	0.1097	0.1153	0.1250
Skewness	1.2080	1.1077	0.9162	0.6448	0.4563
Kurtosis	(.0331)	(.2317)	(.5757)	(1.0274)	(1.2860)
H—05	7.00 %	6.57 %	6.69 %	8.26 %	11.39 %
H—01	4.19 %	3.86 %	3.65 %	4.54 %	6.74 %
H—001	2.14 %	1.91 %	1.41 %	1.64 %	3.24 %
C unfitted					
C-mean	0.4572 D	0.4878 C	0.4803 C	0.4971 B	0.5083 A
C-median	0.4545	0.5000	0.4705	0.4929	0.5087
C-mode	0.0000	0.0000	0.0000	1.0000	0.0000
Variance	0.1036	0.0998	0.0886	0.0851	0.0866
Skewness	0.0697	(.0473)	0.0617	0.0291	(.0252)
Kurtosis	(1.2979)	(1.2550)	(1.1940)	(1.1841)	(1.2177)
C—05	6.59 %AB	7.59 % A	5.73 % B	5.78 % B	6.31 % B
C—01	1.65 % A	1.97 % A	1.65 % A	1.92 % A	1.91 % A
C—001	0.50 % A	0.46 % A	0.30 % A	0.32 % A	0.33 % A

The letters “A”, “B”, “C”, etc., next to the measures for the H and C statistics are results of ANOVA testing and Waller groupings for significant differences. Completely differing letter patterns indicate a significant difference between the measures: The H-mean for 1993 “0.2300 E” is significantly different from the one for 1995 “0.2487 D”. For H-001, the years 1993-1997 are not significantly different (“C”, “BC”, “BC”), and the years 1995-1999 are not significantly different (“BC”, “BC”, “B”), leaving a significant difference between 1993 “C”, and 1999 “B”, only. The letter “A” is assigned to the highest number in the grouping, “B” assigned to the next highest. etc.

Table 3. Small Cap Portfolio (20 securities) Descriptive Statistics					
	1993 252 days	1995 249 days	1997 248 days	1999 250 days	2001 244 days
H unfitted					
H-mean	0.1265 E	0.1436 D	0.2179 C	0.2533 B	0.3344 A
H-median	0.0000	0.0000	0.0140	0.0660	0.1770
H-mode	0.0000	0.0000	0.0000	0.0000	0.0000
Variance	0.0794	0.0882	0.1094	0.1107	0.1257
Skewness	2.2289	1.9738	1.3483	1.1344	0.7123
Kurtosis	3.5119	2.3789	0.2963	(.1797)	(1.0157)
H—05	4.72 % C	4.92 % C	6.88 % B	7.20 % B	9.86 % A
H—01	3.45 % B	3.31 % B	3.79 % B	3.84 % B	5.55 % A
H—001	1.63 % B	1.55 % B	1.92 % B	1.84 % B	2.52 % A
H fitted					
H-mean	0.1303	0.1463	0.2190	0.2541	0.3336
H-median	0.0000	0.0000	0.0160	0.0680	0.1780
H-mode	0.0000	0.0000	0.0000	0.0000	0.0000
Variance	0.0812	0.0879	0.1096	0.1097	0.1250
Skewness	2.1805	1.9456	1.3474	1.1271	0.7147
Kurtosis	3.2846	2.2876	0.2922	(.1831)	(1.0063)
H—05	4.88 %	4.88 %	6.90 %	7.02 %	9.67 %
H—01	3.59 %	3.37 %	3.93 %	3.86 %	5.49 %
H—001	1.87 %	1.45 %	1.96 %	1.84 %	2.46 %
C unfitted					
C-mean	0.3389 D	0.3483 D	0.4196 C	0.4481 B	0.4662 A
C-median	0.2614	0.2940	0.3802	0.4386	0.4521
C-mode	0.0000	0.0000	0.0000	0.0000	0.0000
Variance	0.1075	0.1116	0.0958	0.0943	0.0925
Skewness	0.5106	0.4532	0.2327	0.1323	0.1022
Kurtosis	(1.1404)	(1.2096)	(1.1928)	(1.2392)	(1.2397)
C—05	4.46 % A	5.18 % A	4.48 % A	4.88 % A	5.08 % A
C—01	0.89 % B	1.08 %AB	1.21 % B	1.46 % A	1.50 % A
C—001	0.22 % A	0.22 % A	0.28 % A	0.20 % A	0.31 % A

The letters “A”, “B”, “C”, etc., next to the measures for the H and C statistics are results of ANOVA testing and Waller groupings for significant differences. Completely differing letter patterns indicate a significant difference between the measures: The H-mean for 1993 “0.1265 E” is significantly different from the one for 1995 “0.1436 D”. For C-01, the years 1993-1995 are not significantly different (“B”, “AB”, “AB”), and the years 1995-2001 are not significantly different (“AB”, “AB”, “A”, “A”), leaving a significant difference between 1993 “B”, and 2001 “A”, only. The letter “A” is assigned to the highest number in the grouping, “B” assigned to the next highest. etc.

Table 4. ANOVA tests for significantly different levels of the H statistic between the large, mid, and small-cap portfolios

H mean	1993 n=252 **p-value .0001**			1995 n=249 **p-value .0001**			1997 n=248 **p-value .0001**			1999 n=250 **p-value .0001**			2001 n=244 **p-value .0001**		
	L	M	S	L	M	S	L	M	S	L	M	S	L	M	S
	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
	.310	.230	.127	.338	.249	.144	.364	.287	.218	.384	.351	.253	.433	.411	.334
H-05	**p-value .0002**			**p-value .0006**			p-value .4085			**p-value .0193**			**p-value .0003**		
	M	L	S	M	L	S	L	S	M	M	L	S	L	M	S
	A	A	B	A	A	B	A	A	A	A	A	B	A	A	B
	6.79	6.53	4.72	6.71	6.67	4.92	7.38	6.88	6.83	8.68	8.40	7.20	12.03	11.91	9.86
H-01	p-value .1906			p-value .0876			p-value .6024			p-value .1100			**p-value .0002**		
	M	S	L	M	L	S	S	M	L	M	L	S	M	L	S
	A	A	A	A	A	A	A	A	A	A	A	A	A	B	B
	4.15	4.72	3.27	4.16	3.53	3.31	3.79	3.75	3.41	4.74	4.32	3.84	7.21	6.13	5.55
H-001	**p-value .0055**			p-value .1981			**p-value .0042**			p-value .8320			**p-value .0034**		
	M	S	L	M	S	L	S	M	L	S	M	L	M	L	S
	A	AB	B	A	A	A	A	B	B	A	A	A	A	B	B
	2.16	1.63	1.19	1.85	1.55	1.39	1.91	1.47	1.11	1.84	1.76	1.68	3.26	2.58	2.52

The portfolios are arranged in order of highest to lowest annual mean of the H statistic. The p-value represents the F-test; significant p-values are in **bold** print. The letters "A", "B", "C", etc., underneath the portfolio notation, are results of ANOVA testing and Waller groupings for significant differences. Completely differing letter patterns indicate a significant difference between the measures: The H-mean for 1993 Large-cap portfolio, "0.310 A" is significantly different from the one for the Mid-cap portfolio, "0.230 B". Same letters, (H-05 Mid-cap = .679 = A) and (H-05 Large-Cap = 6.53 = A) indicate no significant difference. The letter "A" is assigned to the highest number in the grouping, "B" assigned to the next highest, etc.

Table 5. ANOVA tests for significantly different levels of the C statistic between the large, mid, and small-cap portfolios

C - mean	1993 n=252 **p-value .0001**			1995 n=249 **p-value .0001**			1997 n=248 **p-value .0001**			1999 n=250 **p-value .0001**			2001 n=244 **p-value .0001**		
	L	M	S	L	M	S	L	M	S	L	M	S	L	M	S
	A	B	C	A	B	C	A	B	C	A	A	B	A	A	B
	.534	.457	.339	.527	.488	.348	..512	.480	.420	.503	.497	.448	.513	.508	.466
C-05	**p-value .0001**			**p-value .0001**			**p-value .0009**			**p-value .0202**			**p-value .0039**		
	L	M	S	L	M	S	L	M	S	L	M	S	L	M	S
	A	B	C	A	A	B	A	B	A	A	A	B	A	A	B
	8.75	6.59	4.46	7.81	7.59	5.18	6.67	5.73	4.48	6.14	5.78	4.88	6.62	6.31	5.08
C-01	**p-value .0001**			**p-value .0001**			**p-value .0046**			p-value .2744			p-value .1188		
	L	M	S	L	M	S	L	M	S	M	L	S	M	L	S
	A	B	C	A	A	B	A	AB	B	A	A	A	A	A	A
	2.40	1.65	0.89	2.61	1.97	1.08	2.06	1.65	1.21	1.92	1.82	1.46	1.91	1.84	1.50
C-001	**p-value .0131**			p-value .0502			p-value .1270			p-value .3167			p-value .9776		
	L	M	S	L	M	S	L	M	S	L	M	S	L	M	S
	A	AB	B	A	AB	A	A	A	A	A	A	A	A	A	A
	0.60	0.50	0.22	0.54	0.46	0.22	0.52	0.30	0.28	0.36	0.32	0.20	0.33	0.33	0.31

The portfolios are arranged in order of highest to lowest annual mean of the C statistic. The p-value represents the F-test; significant p-values are in **bold** print. The letters "A", "B", "C", etc., underneath the portfolio notation, are results of ANOVA testing and Waller groupings for significant differences. Completely differing letter patterns indicate a significant difference between the measures: The C-mean for 1993 Large-cap portfolio, "0.534 A" is significantly different from the one for the Mid-cap portfolio, "0.457 B". Same letters, (C-001 Large-cap = 0.60 = A) and (C-001 Mid-Cap = 0.50 = AB) indicate no significant difference. The letter "A" is assigned to the highest number in the grouping, "B" assigned to the next highest, etc.

Table 6. H and C statistics at $\alpha = 0.05$: Contemporaneous and serial correlations of portfolios n=1242, 1243

	LH05$_{t-1}$	MH05$_t$	MH05$_{t-1}$	SH05$_t$	SH05$_{t-1}$	LC05$_t$	LC05$_{t-1}$	MC05$_t$	MC05$_{t-1}$	SC05$_t$	SC05$_{t-1}$
LH05$_t$	(------)	------	(.0477) (.0929)	------	(------)	.0981 .0005	(------)	------	.0493 (.0828)	------	(------)
LH05$_{t-1}$		------	------	------	------	(------)	.0980 .0005	(------)	------	(------)	------
MH05$_t$			(------)	(------)	(------)	(------)	.0462 .1039	.2172 .0001	(------)	(------)	------
MH05$_{t-1}$				(------)	(------)	(------)	(------)	(------)	.2175 .0001	(------)	(------)
SH05$_t$					(------)	.0551 .0521	(------)	(.0531) (.0611)	------	.2650 .0001	------
SH05$_{t-1}$						(------)	.0541 .0567	(------)	(.0518) (.0678)	(------)	.2651 .0001
LC05$_t$							------	(------)	------	(------)	------
LC05$_{t-1}$								------	(------)	------	(------)
MC05$_t$									------	(------)	------
MC05$_{t-1}$										(------)	(------)
SC05$_t$											.0705 .0129

For computation of correlation coefficients, the H and C statistics were scaled by annual averages (if required) to eliminate trending.
The Pearson Correlation Coefficients and corresponding p-values (H0: Correlation = 0) are listed above only if the p-value <=0.1000. The notation '----' indicates non-significance, and if it is in parentheses, the correlation coefficient for that relationship is negative.

Table 7. H and C statistics at $\alpha = 0.01$: Contemporaneous and serial correlations of portfolios
n = 1242, 1243

	$LH01_{t-1}$	$MH01_t$	$MH01_{t-1}$	$SH01_t$	$SH01_{t-1}$	$LC01_t$	$LC01_{t-1}$	$MC01_t$	$MC01_{t-1}$	$SC01_t$	$SC01_{t-1}$
$LH01_t$	(------)	------	(------)	(------)	(.0568) (.0455)	.1036 .0003	(------)	(------)	------	------	------
$LH01_{t-1}$		------	------	(------)	(------)	------	.1032 .0003	(------)	(------)	(------)	------
$MH01_t$			(------)	(------)	(.0594) (.0363)	(------)	------	.1377 .0001	------	(------)	(------)
$MH01_{t-1}$				------	(------)	(------)	(------)	(------)	.1381 .0001	------	(------)
$SH01_t$					(------)	------	(------)	(------)	.0528 .0630	.2657 .0001	------
$SH01_{t-1}$						(------)	------	(------)	(------)	(------)	.2655 .0001
$LC01_t$							(------)	------	------	(------)	(------)
$LC01_{t-1}$								(------)	------	(------)	(------)
$MC01_t$									(------)	(------)	------
$MC01_{t-1}$										------	(------)
$SC01_t$											(------)

For computation of correlation coefficients, the H and C statistics were scaled by annual averages (if required) to eliminate trending.
The Pearson Correlation Coefficients and corresponding p-values (H0: Correlation = 0) are listed above only if the p-value <=0.1000.
The notation '----' indicates non-significance, and if it is in parentheses, the correlation coefficient for that relationship is negative.

Table 8. H and C indicator statistics at $\alpha = 0.001$: Contemporaneous and serial correlations of portfolios
n = 1242, 1243

	$LH001_{t-1}$	$MH001_t$	$MH001_{t-1}$	$SH001_t$	$SH001_{t-1}$	$LC001_t$	$LC001_{t-1}$	$MC001_t$	$MC001_{t-1}$	$SC001_t$	$SC001_{t-1}$
$LH001_t$	------	------	(.0722) (.0109)	------	(------)	------	.0495 .0814	------	------	.0728 .0103	(------)
$LH001_{t-1}$		(------)	-------	(------)	------	------	------	.0523 (.0656)	------	(------)	.0727 .0104
$MH001_t$			(------)	------	(------)	(------)	------	.1007 .0004	------	(------)	(------)
$MH001_{t-1}$				------	------	(------)	(------)	------	.1006 .0004	------	(------)
$SH001_t$					------	(------)	(------)	------	------	.1571 .0001	------
$SH001_{t-1}$						(------)	(------)	------	------	(------)	.1570 .0001
$LC001_t$							(------)	(------)	(.0540) (.0573)	------	------
$LC001_{t-1}$								------	(------)	------	------
$MC001_t$									------	(------)	------
$MC001_{t-1}$										(------)	(------)
$SC001_t$											------

For computation of correlation coefficients, the H and C statistics were scaled by annual averages (if required) to eliminate trending.
The Pearson Correlation Coefficients and corresponding p-values (H0: Correlation = 0) are listed above only if the p-value <=0.1000.
The notation '----' indicates non-significance, and if it is in parentheses, the correlation coefficient for that relationship is negative.

Table 9. Large-Cap Portfolio : ANOVA results for Calendar Effects						
	All Years	1993	1995	1997	1999	2001
	n=1243	n=251	n=248	n=247	n=249	n=243
H-mean	M: 0.0323 12,8,2,3,6 Q: ------- D: 0.0529 5,2,3,4,1	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------ D: ------	M: ------ Q: ------- D: -------	M: 0.0244 8,12,3,6 Q: ------- D: -------
H – 05	M: ------- Q: -------- D: 0.0556 5,3,4,1,2	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0025 5,3,4,2,1	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
H –01	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0308 7,10,5,3,1 Q: ------- D: -------	M: ------ Q: 0.0444 3,1,4,2 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
H—001	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C-mean	M: 0.0048 12,2,8,6 Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0001 5,4,2,1,3	M: 0.0001 2,1,3,6,12 Q: 0.0001 1,2,4,3 D: -------	M: 0.0063 12,5,11,4,8 Q: ------- D: -------	M: ------ Q: ------- D: -------
C—05	M: 0.0468 12,8,1,3 Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0026 5,4,2,1,3	M: 0.0045 2,3,11,2,6 Q: 0.0018 1,3,2,4 D: -------	M: 0.0052 7,8,11,12,5 Q: ------- D: -------	M: ------ Q: ------- D: -------
C—01	M: 0.0585 7,12,8,2 Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0520 5,2,4,3,1	M: 0.0368 2,1,12,7,6,5 Q: 0.0246 1,3,4,2 D: -------	M: 0.0186 11,8,7,2,3,4 Q: ------- D: -------	M: ------ Q: ------- D: -------
C-001	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0301 2,3,4,5,1	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------

This table exhibits the results of ANOVA testing for monthly (M), quarterly (Q), and day-of-the-week (D) seasonality. The p-values represent the F-test, and they are listed only if p<= 0.0600. A p-value <= 0.05 indicates there is a significant difference between at least two means for the measured calendar period. The p-value is listed beside the notation for the calendar period, i.e.,M: 0.0323. If there is significance, then underneath, in order of largest to smallest mean, are listed the actual calendar periods in question. For Day-of-the-week, ‘1’ = Monday, ‘5’ = Friday. For months, ‘1’ = January, ‘12’ = December. The notation ‘----’ indicates non-significance.

Table 10. Mid-Cap Portfolio : ANOVA results for Calendar Effects

	All Years	1993	1995	1997	1999	2001
	n=1243	n=251	n=248	n=247	n=249	n=243
H-mean	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0056 11,12,9,5,6 Q: 0.0060 4,3,2,1 D: 0.0481 3,4,2,1,5	M: ------ Q: ------- D: -------	M: ------ Q: 0.0321 2,4,1,3 D: -------
H – 05	M: ------ Q: ------- D: -------	M: ------ Q: .0444 3,4,1,2 D: -------	M: ------ Q: ------- D: 0.0455 1,5,4,3,2	M: ------ Q: 0.0363 4,3,2,1 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
H –01	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
H—001	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C-mean	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0058 6,1,2,5,8,9 Q: 0.0053 1,2,3,4 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0283 4,5,8,1,7,12 Q: ------- D: -------
C—05	M: 0.0016 5,1,6,7,3,4 Q: 0.0021 2,1,3,4 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0217 6,5,1,10,2,3 Q: 0.0028 2,1,4,3 D: -------	M: ------ Q: ------- D: 0.0095 5,1,3,4,2	M: ------ Q: 0.0206 2,1,3,4 D: -------
C—01	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: 0.0418 1,2,4,3 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C-001	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------

This table exhibits the results of ANOVA testing for monthly (M), quarterly (Q), and day-of-the-week (D) seasonality. The p-values represent the F-test, and they are listed only if p<= 0.0600. A p-value <= 0.05 indicates there is a significant difference between at least two means for the measured calendar period. The p-value is listed beside the notation for the calendar period, i.e., M: 0.0323. If there is significance, then underneath, in order of largest to smallest mean, are listed the actual calendar periods in question. For Day-of-the-week, '1' = Monday, '5' = Friday. For months, '1' = January, '12' = December. The notation '----' indicates non-significance.

Table 11. Small-Cap Portfolio : ANOVA results for Calendar Effects

	All Years	1993	1995	1997	1999	2001
	n=1243	n=251	n=248	n=247	n=249	n=243
H-mean	M: .0021 12 * 10,11,1,6 Q: .0011 4 * 3,1,2 D: -------	M: 0.0494 2,10,12,7,1,4,8 Q: ------- D: -------	M: 0.0277 12,6,3,11,9,2,1 Q: ------- D: -------	M: 0.0527 9,11,8,12,10,7 Q: 0.0035 3,4,2,1 D: ------	M: 0.4328 12,6,4,3,1,11 Q: ------- D: -------	M: 0.0009 12,6,1,7,10,9 Q: 00013 4,2,3,1 D: -------
H – 05	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
H – 01	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: 0.0263 3,2,5,1 / 4	M: ------ Q: ------- D: -------
H—001	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0355 3,8,2,9,12,11 Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C-mean	M: ------ Q: ------- D: .0340 2 * 5,2,4,1	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: 0.0129 11,3,1,12,4,6 Q: 0.0257 1,4,2,3 D: -------	M: 0.0002 12,6,1,7,10,9 Q: ------- D: -------
C—05	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------- Q: 0.0434 1,2,3,4 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C—01	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------
C-001	M: ------ Q: ------- D: -------	M: 0.0136 8,9,2,10,12,3,5 Q: 0.0234 3,1,4,2 D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------	M: ------ Q: ------- D: -------

This table exhibits the results of ANOVA testing for monthly (M), quarterly (Q), and day-of-the-week (D) seasonality. The p-values represent the F-test, and they are listed only if p<= 0.0600. A p-value <= 0.05 indicates there is a significant difference between at least two means for the measured calendar period. The p-value is listed beside the notation for the calendar period, i.e., M: 0.0323. If there is significance, then underneath, in order of largest to smallest mean, are listed the actual calendar periods in question. For Day-of-the-week, ‘1’ = Monday, ‘5’ = Friday. For months, ‘1’ = January, ‘12’ = December. The notation ‘----’ indicates non-significance.

* The December and Last Quarter H-mean for the Smallcap portfolio, across all years, are highly significantly different from the other months/quarters of the year.

Table 12. LargeCap Portfolio: Regression of H-statistic on Trading Volume

	All Years *df*=1242			1993 *df*=251			1995 *df*=248			1997 *df* =247			1999 *df* = 249			2001 *df*= 243		
Regression Model:	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-tat p-al	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Hm=trades																		
Model (1)	.000	**17.80** **.0001**	---- .0984	.000	**1.96** **.051**	---- ----	.000	1.81 .072	---- ----	.000	**2.04** **.043**	---- .015	.000	**2.09** **.038**	---- ----	.000	(0.74) .459	---- ----
Model (2)	.000	.1023	----	.000	.114	----	.000	.216	----	.000	.686	.054	.000	.084	----	.000	(.137)	----
Model (3)	(---)	**.0020**	----	(---)	.095	----	----	**.016**	----	(---)	(.983)	---	----	**.038**	----	(---)	.648	----
H05=trades																		
Model (1)	.000	**11.12** **.000**	---- .008	.097	0.86 .388	---- ----	.008	0.31 .753	---- ----	.002	-0.04 .965	---- ----	.083	0.96 .338	---- ----	.001	-0.10 .922	---- ----
Model (2)	.000	(.513)	---	.059	.573	----	.001	(.651)	----	.000	(.166)	----	.012	.966	----	.000	(.864)	.067
Model (3)	----	.972	.063	----	.549	----	(---)	.713	----	(---)	**(.001)**	----	----	.127	----	(---)	**.023**	----
H01=trades																		
Model (1)	.000	**8.28** **.000**	---- .000	----	1.01 .313	---- ----	.108	0.58 .562	---- ----	.061	0.10 .923	---- ----	----	1.76 .080	---- ----	----	1.66 .098	---- .002
Model (2)	.000	.905	---	----	.321	----	.009	(.559)	----	.006	(.253)	----	----	.609	----	----	.324	----
Model (3)	----	.299	.081	----	.221	----	(---)	.567	----	----	(.214)	----	----	.281	----	(---)	.561	----
H001=trades																		
Model (1)	.000	**6.13** **.000**	---- .005	(---)	1.42 .1565	---- ----	----	-0.22 .828	---- ----	----	0.43 .667	---- ----	----	0.94 .350	---- ----	.081	-0.26 .794	---- ----
Model (2)	.020	.788	----	(---)	.191	----	.036	.365	----	----	(.677)	----	----	.384	----	----	.924	----
Model (3)	(---)	.104	----	----	**.032**	----	(---)	(.516)	.089	(---)	**.059**	----	----	.660	----	(---)	(----)	----

Model (1): Unaltered variables: H statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled H statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily H statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 13. MidCap Portfolio: Regression of H-statistic on Trading Volume

	All Years *df*=1242			1993 *df*=251			1995 *df*=248			1997 *df* =247			1999 *df* = 249			2001 *df*= 243		
Regression Model: Hm=trades	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-sat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Model (1)	.00	**25.86** **.0001**	---- .014	.00	**2.69** **00**	---- ----	.00	1.27 .207	---- ----	.000	**2.89** **.004**	---- ----	.000	(.50) .618	---- ----	.000	(.78) .438	---- ----
Model (2)	.00	**.050**	.057	.000	**.002**	----	.000	.185	----	.000	.817	.045	.000	(.337)	----	.000	(.081)	----
Model (3)	----	.157	.092	----	**.037**	----	----	**.030**	----	----	(.550	---	----	**(.040)**	----	----	**.041**	----
H05=trades																		
Model (1)	.000	**11.33** **.000**	---- .000	----	**2.61** **.010**	---- ----	.003	0.51 .618	---- ----	.002	**2.09** **.038**	---- ----	.000	(0.31) .757	---- ----	.000	-0.97 .335	---- .035
Model (2)	.000	.263	---	----	**.017**	----	.004	.574	----	.002	(.570)	----	.001	(.599)	----	.000	(.619)	----
Model (3)	----	.513	----	----	.126	----	----	(.899)	----	----	(.704)	----	----	.848	----	----	(.732)	.074
H01=trades																		
Model (1)	.000	**8.60** **.000**	---- .001	.066	0.70 .482	---- ----	.003	(0.23) .820	---- ----	.009	1.00 .318	---- ----	.002	(0.57) .570	---- ----	.000	1.75 .081	---- ----
Model (2)	.000	(.699)	.083	.038	.660	----	.002	(.694)	----	.085	.921	----	.003	(.331)	----	.004	(.840)	----
Model (3)	----	.655	----	----	**.059**	----	----	(.802)	----	(---)	.795	----	----	(.311)	----	----	(.634)	----
H001=trades																		
Model (1)	.000	**5.46** **.000**	---- .001	(---)	**1.89** **.060**	---- ---	.011	(0.75) .456	---- ----	----	1.23 .219	---- ----	055	(0.17) .865	---- ----	.000	(2.69) .008	---- .089
Model (2)	.001	(.969)	----	----	.103	----	.018	(.568)	----	(---)	.212	.022	013	(.244)	.032	.001	(.101)	.023
Model (3)	(---)	.740	----	----	**.015**	----	----	(.871)	.060	(---)	.558	----	----	(.372)	----	(---)	**(.052)**	----

Model (1): Unaltered variables: H statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled H statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily H statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 14. Small Cap Portfolio: Regression of H-statistic on Trading Volume

	All Years df=1242			1993 df=251			1995 df=248			1997 df =247			1999 df = 249			2001 df= 243		
Regression Model:	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-tat p-al	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Havg = trades																		
Model (1)	.000	**29.92** **.0001**	1.55 .048	.034	**3.84** **.000**	---- ----	.000	**3.35** **.001**	---- ----	.000	**4.17** **.000**	---- ----	.000	**3.270** **.001**	---- ----	.000	1.36 .174	---- ----
Model (2)	.000	**.000**	----	.042	**.005**	----	.000	**.048**	----	.000	**.005**	----	.000	**.013**	----	.000	(.703)	----
Model (3)	(---)	(.000)	.091	----	**.006**	----	----	**.045**	----	(--)	**.001**	---	(---)	**.003**	----	----	.519	----
H05 = trades																		
Model (1)	.000	**10.01** **.000**	---- .003	----	1.51 .134	---- ----	.021	0.89 .372	---- ----	.000	0.97 .331	---- .007	.013	0.96 .337	---- .095	.000	(1.61) .109	---- ----
Model (2)	.000	.531	----	----	.404	----	.017	.596	----	.028	.157	.012	.004	.741	----	.000	**(.008)**	----
Model (3)	(---)	**.031**	----	----	**.035**	----	----	.729	----	(--)	.164	----	(---)	.309	----	----	(.639)	----
H01=trades																		
Model (1)	.000	**5.86** **.000**	---- .082	----	1.20 .231	---- ----	.002	(0.51) .608	---- ----	.002	0.55 584	---- ----	----	**2.02** **.044**	---- ----	.000	(1.92) .056	---- ----
Model (2)	.000	.470	----	----	.404	----	.002	(.459)	----	----	106	----	----	.168	----	000	**(.035)**	----
Model (3)	(---)	**.028**	----	(---)	.094	----	----	(.881)	----	(---)	405	----	(---)	**.037**	----	(---)	.948	----
H001=trades																		
Model (1)	.000	**3.30** **.001**	---- .031	.015	(.75) .453	---- ----	.061	0.11 .909	---- ----	.061	0.85 .397	---- ----	----	**2.20** **.029**	---- ----	.000	**(2.65)** **.011**	---- ----
Model (2)	.002	.383	----	----	(.980)	----	.050	(.875)	----	(---)	**.043**	.063	(---)	**.031**	----	.001	**(.002)**	.031
Model (3)	(---)	.088	----	----	.409	----	----	(.780)	----	(---)	.076	.053	(---)	.109	----	----	(.899)	----

Model (1): Unaltered variables: H statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled H statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily H statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 15. Large-Cap Portfolio: Regression of C-statistic on Trading Volume

	All Years df=1242			1993 df=251			1995 df=248			1997 df =247			1999 df = 249			2001 df= 243		
Regression Model:	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Cm = trades																		
Model (1)	.000	**(3.53)** **.000**	---- ----	.000	(1.40) .164	---- ----	.000	(0.86) .391	---- ----	.000	**(3.36)** **.001**	---- ----	.000	0.22 .823	---- ----	.000	(0.70) .487	---- ----
Model (2)	.000	(.504)	----	.000	(.504)	----	.000	.297	----	.000	.444	----	.000	(.383)	----	.000	.752	----
Model (3)	(---)	(.245)	----	(---)	(.286)	----	----	.895	----	(---)	.435	---	----	.636	----	(---)	(.076)	----
C05= trades																		
Model (1)	.000	**(3.98)** **.000**	---- ----	.000	(1.80) .073	---- ----	.000	(1.35) .177	---- ----	.000	**(3.16)** **.002**	---- .013	.004	(0.81) .418	---- ----	.000	(1.25) .211	---- ----
Model (2)	.000	**(.014)**	---	.000	(.267)	----	.000	(.200)	----	.000	(.060)	----	.028	(.820)	----	.001	(.351)	----
Model (3)	(---)	.831	----	(---)	.609	----	----	.850	.010	(---)	.432	----	(----)	(.523)	----	(---)	(.487)	.080
C01=trades																		
Model (1)	.000	**(2.65)** **.008**	---- .035	.003	(1.62) .107	---- ----	.008	(0.79) .433	---- ----	.001	(.179) .074	---- ----	----	2.01 .045	---- ----	.016	(1.21) .227	---- ----
Model (2)	.000	(.091)	---	032	(.413)	----	.002	(.196)	----	.063	(.640)	----	(----)	.038	----	.000	(.022)	.010
Model (3)	(---)	.887	.068	----	.268	----	----	.470	.024	----	(.164)	----	(----)	.126	----	----	(.837)	----
C001=trades																		
Model (1)	.000	**(2.24)** **.026**	---- .019	----	(0.22) .823	---- ----	----	(0.10) .921	---- ----	----	(0.64) .523	---- ----	(.007)	3.28 .001	---- .044	.028	(1.68) .095	---- .032
Model (2)	.087	(.846)	----	----	.689	----	.071	(.312)	----	----	(.533)	.086	(.005)	.001	.056	.042	(.138)	.002
Model (3)	(---)	.203	----	----	.109	----	(---)	.977	----	----	(.496)	----	(----)	.020	----	----	(.361)	----

Model (1): Unaltered variables: C statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled C statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily C statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 16. MidCap Portfolio: Regression of C-statistic on Trading Volume

	All Years *df*=1242			1993 *df*=251			1995 *df*=248			1997 *df* =247			1999 *df* = 249			2001 *df*= 243		
Regression Model:	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Cm = trades																		
Model (1)	.000	**6.61** **.000**	---- ----	.000	(1.00) .319	---- ----	.000	(0.50) .620	---- ----	.000	**(2.35)** **.020**	---- ----	.000	(0.86) .390	---- ----	.000	(0.94) .348	---- ----
Model (2)	.000	(.151)	.108	.000	(.449)	----	.000	(.923)	----	.000	(.911)	----	.000	(.349)	----	.000	(.123)	----
Model (3)	----	.688	.073	(---)	(.796)	----	(---)	.339	----	(----)	(.783)	---	----	(.868)	----	(---)	.488	----
C05 = trades																		
Model (1)	.000	(1.63) .103	---- ----	.000	(0.78) .434	---- .108	.000	(0.90) .367	---- ----	.000	(0.90) .369	---- ----	.000	(1.21) .227	---- ----	.000	**(2.54)** **.012**	---- ---
Model (2)	.000	(.135)	---	.000	(.552)	----	.000	(.604)	----	.076	.612	----	.001	(.404)	----	.000	(.079)	.078
Model (3)	----	(.259)	----	(---)	.919	----	(---)	.845	----	----	(.269)	----	----	(.406)	----	----	(.144)	.031
C01 = trades																		
Model (1)	.000	0.65 .516	---- ----	----	0.41 .681	---- ----	.006	(1.56) .121	---- ----	.058	0.44 .658	---- ----	.000	**(2.21)** **.028**	---- ----	.014	(0.83) .406	---- ----
Model (2)	.001	.924	----	----	.803	----	.028	(.757)	----	(----)	**.008**	.081	.050	(.521)	----	007	(.177)	----
Model (3)	(---)	.795	----	----	.949	----	(---)	(.308)	----	----	.101	----	(---)	.937	----	(---)	.883	----
C001=trades																		
Model (1)	.000	(1.04) .299	---- ----	----	0.08 .940	---- ----	----	0.68 .495	---- ----	----	0.93 .352	---- ----	.101	(0.96) .340	---- ----	----	(0.12) .906	---- ----
Model (2)	(---)	(.087)	----	----	(.950)	----	(---)	.384	----	(.026)	**.006**	.088	----	(.462)	----	(---)	.194	----
Model (3)	(---)	**.048**	----	----	.216	----	(---)	.759	----	(----)	.223	----	----	.465	----	(---)	.318	----

Model (1): Unaltered variables: C statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled C statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily C statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 17. Small Cap Portfolio: Regression of C-statistic on Trading Volume

	All Years *df*=1242			1993 *df*=251			1995 *df*=248			1997 *df* =247			1999 *df* = 249			2001 *df*= 243		
Regression Model: Cm= trades	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val	B_0 p-val	B_1 t-stat p-val	DW* Ψ^2 ** p-val
Model (1)	.000	**17.19** **.000**	---- .015	.000	**3.16** **.002**	---- ----	.000	**4.33** **.000**	---- ----	.000	0.96 .337	---- .005	.000	**.2.20** **.029**	---- .072	.000	**2.27** **.024**	---- ----
Model (2)	.000	**.000**	----	.000	**.003**	----	.000	**.000**	----	.000	**.037**	.016	.000	**.072**	----	.000	.483	----
Model (3)	(---)	(.000)	----	----	**.001**	----	(---)	**.071**	----	----	**.001**	----	----	.228	----	----	.440	.003
C05=trades																		
Model (1)	.000	0.61 .539	---- .003	.000	(1.31) .193	---- ----	.000	(0.11) .909	---- ----	.000	(1.94) .054	---- ----	.132	1.37 .171	---- ----	.002	(0.26) .795	---- .010
Model (2)	.000	(.732)	----	.001	(.288)	----	.000	(.708)	----	.000	(.280)	----	.196	.137	.087	.006	.939	.032
Model (3)	----	.645	----	----	(.137)	----	(---)	(.022)	.016	(---)	.881	----	(---)	.002	----	----	.134	----
C01=trades																		
Model (1)	.002	.08 .935	---- ----	.000	2.22 .026	---- .036	----	0.88 .379	---- ----	----	(0.17) .866	---- ----	.016	(0.51) .612	---- ----	057	(0.40) .691	---- ----
Model (2)	----	.986	----	(---)	.274	----	.019	(.380)	.081	----	.693	----	----	.628	----	010	(.256)	.069
Model (3)	(---)	(.143)	.023	(---)	.312	.018	----	.605	----	----	(.455)	----	(---)	.189	.052	----	.817	----
C001=trades																		
Model (1)	.000	0.31 .759	---- ----	----	(.72) .474	---- ----	----	(0.88) .379	---- .052	----	(0.45) .652	---- ----	----	0.35 .727	---- ----	.005	**(2.15)** **.032**	---- ----
Model (2)	.032	(.453)	----	----	(.264)	----	----	(.429)	.062	(---)	.417	----	(---)	.321	----	.020	(.093)	.098
Model (3)	----	(.523)	----	(---)	(.542)	----	----	(.171)	.092	(---)	.749	----	(---)	.346	----	----	(.447)	----

Model (1): Unaltered variables: C statistics vs. number of trades in portfolio per day. Both the t-statistic and the p-value of the t-statistic are printed for B_1 (trading volume). Significant p-values for B_1 are highlighted in **bold** print.

Model (2): Annually scaled C statistics vs. monthly scaled relative trading volume. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

Model (3): Log difference of daily C statistics vs. log difference of number of trades in portfolio per day. Only the p-value for the t-statistic is printed for B_1. P-values in parentheses indicate the t-statistic is negative. Significant p-values for B_1 are highlighted in **bold** print.

DW*: Because the data are time series, the Durbin Watson statistic for each regression was calculated to check for autocorrelation of residuals. The critical value for these sample sizes is 1.56. As virtually none of the above regressions exhibited residual serial correlation, no DW statistics are printed.

**The p-value for the Ψ^2 test (and the B_0 for each model) is printed only if p <= 0.100, otherwise the notation '---' indicates a non-significant value. The Ψ^2 test is a test of first and second moment misspecification (heteroskedasticity).

Table 18. Regression of H Statistics on Put/Call Ratio

	All Years n=802	1995 Oct-Dec n=60	1997 n=247	1999 n=249	2001 n=243
Large-Cap	H-01 Model (3) B_1 p-value: (.0302)			H-05 Model (3) B_1 p-value: (.0286) H-01 Model (1) B_1 p-value: (.0122) H-0001 Model (2) B_1 p-value: (.0134)	
Mid-Cap			H-Avg Model (2) B_1 p-value: .0264		H-01 Model (1) B_1 p-value: (.0447)
Small-Cap	H-01 Model (3) B_1 p-value: .0243		H-Avg Model (1) B_1 p-value: (.0138)	H-Avg Model (1) B_1 p-value: (.0385) H-05 Model (1) B_1 p-value: (.0482)	H-05 Model (3) B_1 p-value: .0229 H-01 Model (1) B_1 p-value: .0069 H-01 Model (2) B_1 p-value: .0062 H-01 Model (3) B_1 p-value: .0019

Model (1): Unaltered variables: H statistics vs. daily put/call ratio
Model (2): Annually scaled H statistics vs. monthly scaled put/call ratio
Model (3): Log difference of daily H statistics vs. log difference of daily put/call ratio

Table 19. Regression of C Statistics on Put/Call Ratio					
	All Years n=802	1995 Oct-Dec n=60	1997 n=247	1999 n=249	2001 n=243
Large-Cap		C-Avg Model (1) B_1 p-value: (.0037) C-Avg Model (2) B_1 p-value: (.0036)	C-Avg Model (1) B_1 p-value: .0323	C-Avg Model (1) B_1 p-value: (.0147)	C-Avg Model (3) B_1 p-value: (.0252)
Mid-Cap		C-Avg Model (2) B_1 p-value: .0318	C-05 Model (2) B_1 p-value: .0152 C-05 Model (3) B_1 p-value: .0015 C-01 Model (2) B_1 p-value: .0028 C-01 Model (3) B_1 p-value: .0099 C-001 Model (1) B_1 p-value: .0061 C-001 Model (2) B_1 p-value: .0472 C-001 Model (3) B_1 p-value: .0078	C-Avg Model (1) B_1 p-value: (.0442)	C-Avg Model (1) B_1 p-value: (.0128)

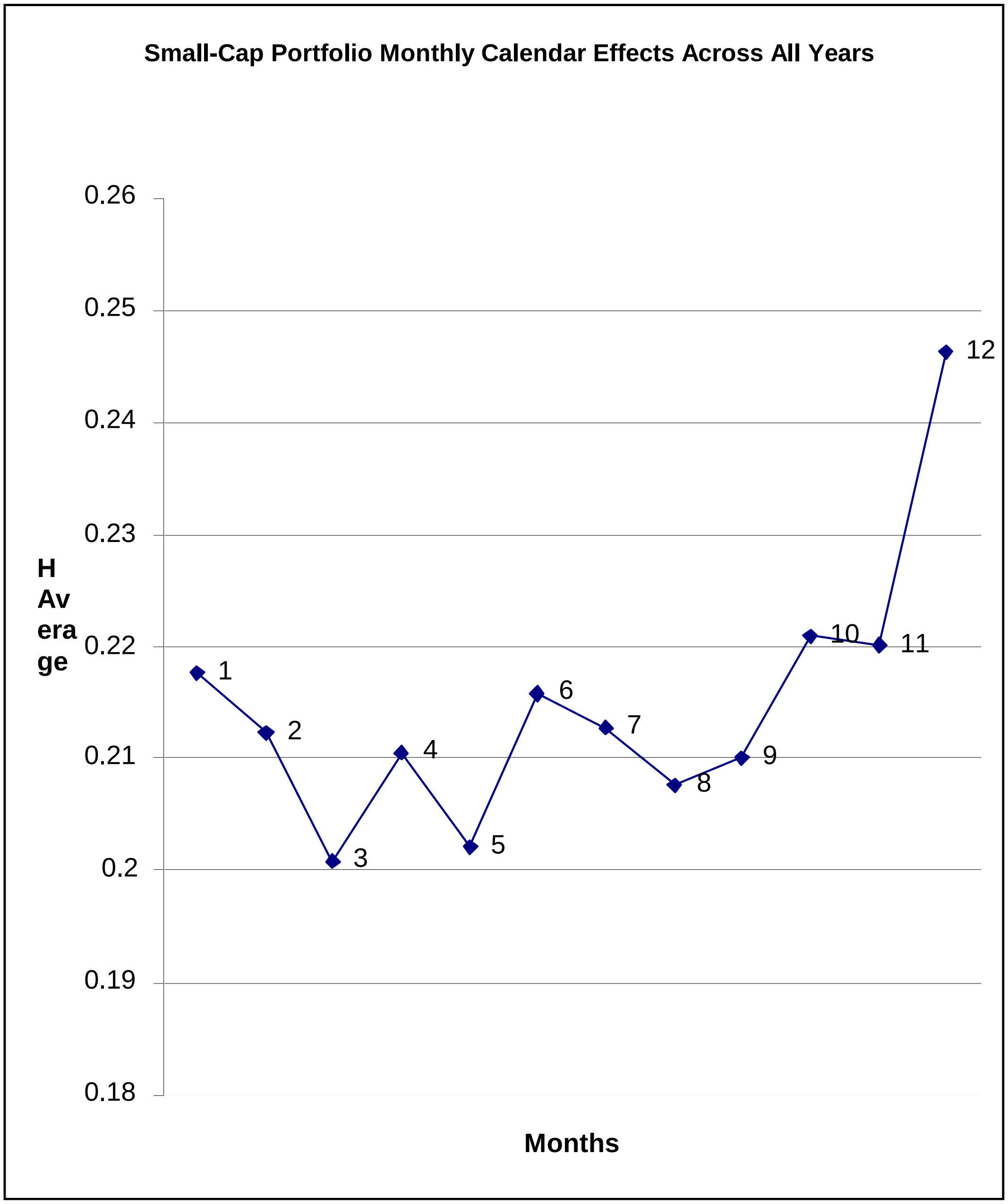
Table 19. cont., Regression of C Statistics on Put/Call Ratio					
	All Years n=802	1995 Oct-Dec n=60	1997 n=247	1999 n=249	2001 n=243
Small-Cap	C-Avg Model (2) B_1 p-value: (.0029) C-Avg Model (3) B_1 p-value: (.0282)			C-Avg Model (1) B_1 p-value: (.0003) C-05 Model (1) B_1 p-value: (.0400) C-05 Model (2) B_1 p-value: (.0177)	C-Avg Model (1) B_1 p-value: (.0479) C-05 Model (3) B_1 p-value: (.0391) C-01 Model (3) B_1 p-value: (.0700)

Model (1): Unaltered variables: H statistics vs. daily put/call ratio
Model (2): Annually scaled H statistics vs. monthly scaled put/call ratio
Model (3): Log difference of daily H statistics vs. log difference of daily put/call ratio

Table 20. Days of Many Stocks Exhibiting Nonlinearity at $\alpha = 0.05$			
Date	H05	DJIA	Market Review Comments from *The Wall Street Journal*
02/16/93	9	d	"Stocks Slump as Clinton's Plan Sparks Fears": frightened by the prospect of higher taxes (Clinton's prep speech to his State-of-the-Union address) that could choke off the budding economic recovery, investors sent the stock market tumbling in a broad-based sell-off.
03/10/93	9	u	"Industrials Rise 6.22 to a Record on Positive Deficit Cutting News": prices turned in the late afternoon on a report that the White House may be willing to consider deferring spending for parts of its stimulus plan; health care and drug stocks gained after a report that a federal judge yesterday put some brakes on Clinton's [health care plans]; bank stocks advanced after Clinton unveiled plans to ease lending rules
08/27/93	9	d	"Nervous Investors Vacillate Between Growth, Cyclical Stocks": investors took profits after the market's recent run-ups.
09/09/93	11	u	"Sell-Off Sweeps Bond Market—Stocks rise 0.56": investors dumped U.S. bonds overnight on rumors that Congress plans to consider re-imposing a 30% withholding tax on foreign investments in U.S. Treasurys.
11/05/93	9	u	"Economy's Upturn Sends Analysts to the Barometers": Friday's report on October employment showed healthy job growth…but comes on the heels of earlier reports that [are] lackluster.
03/09/95	9	u	"Stocks Edge Up and Bonds Firm As the Dollar Appears to Stabilize": analysts mentioned a slight rise in unemployment insurance as giving investors hope that the economy is slowing and the Fed won't raise rates…a couple of market rumors had an effect on stocks.
03/17/95	10	u	Stocks posted slight gains as the 'triple-witching' quarterly expiration [day] inflated volume but failed to deliver the usual volatility. The session also featured the NYSE's ninth-highest one-day total.
05/02/95	9	u	Analysts said the report of a modest pickup in sales of new homes in March contributed to the feeling that the economy is slowing.
07/28/95	9	d	In the session's key release, the Commerce Department said the nations GDP expanded at a 0.5% annual rate in the 2nd quarter. The reading matched forecasts, and investors who had hoped for a more dramatic reading began to panic, fearing that the Fed won't cut rates next month.
01/02/97	9	d	"Bonds Drop, Stocks Gyrate on Economic Data": a plunging bond market routed stocks …following the release of a stronger-than-expected purchasing manager's report, implying stronger economic growth and the risk of higher interest rates.
08/01/97	11	d	Even Friday's bond market sell-off, triggered by signs economic growth may have re-ignited in the third quarter, didn't damp investor's enthusiasm for stocks very long; a rekindling of economic growth – suggested by the plethora of employment and manufacturing activity data Friday – could change that outlook…for now, many are digesting the unexpectedly strong second-quarter results.
09/02/97	12	u	"Blue Chips Soar 257.36 on Buying Binge": The DJIA smashes the previous record for a one-day point gain (Oct 21, 1987); though far from a record in percentage terms, it was still the biggest percentage gain in the average since January 1991; the catalyst was the release of the NAPM index report which indicated that while the manufacturing economy is still expanding, it was a lower reading than economists expected and relieved fear that the Fed would have to tighten credit to control inflation pressure.
12/02/97	9	u	A flurry of earnings warnings from high-profile technology companies held down stocks…

Table 20. (cont.) Days of Many Stocks Exhibiting Nonlinearity at $\alpha = 0.05$			
Date	H05	DJIA	Market Review Comments from *The Wall Street Journal*
03/22/99	10	d	Large-capitalization stocks gave in to growing worries about first quarter earnings in the technology sector. AT&T launched the largest corporate bond issue ever; investors fret that AT&T is issuing now because it fears rates could move higher later; "They are making a statement that now is a good time to come to market…you would expect other companies to mimic them, which could push rates up."
04/16/99	10	u	
08/05/99	11	u	Even by the stock market's recent volatility, yesterday's trading was enough to give investors whiplash. Stocks were all the more volatile because of a nervous bond market, which was roiled by rumors that originated in Europe before U.S. markets opened. The turnaround was even more startling because it came despite more bad economic news.
08/27/99	10	d	Alan Greenspan worried aloud about the market's stratospheric level and indicated he would pay closer attention to the impact of rising stock market wealth on economic growth. Investors, who saw that as a sign that Tuesday's rate increase may not be the last this year, sent the DJIA down after hitting a record high on Wednesday. What exacerbated the weakness was low volume…Friday was the quietest trading day of the year on the NYSE.
11/09/99	10	d	Stocks fell due to profit taking and uncertainty around the October PPI, due to be announced this morning, which is one of the last [of recent] announcements that could influence the Fed's decision on whether to raise rates.
12/07/99	10	d	Yahoo! joined the S&P 500 after the close of trading last night; because it is so much bigger than the firm it replaced, index fund managers did much rebalancing of their portfolios during the last hour of trading.
12/15/99	12	u	
01/26/01	12	d	High-tech stocks showed surprising fortitude in the face of gloomy earnings prospects.
02/27/01	12	d	News that Greenspan was revising today's congressional testimony had ratcheted up expectations for a rate cut, as early as yesterday afternoon. Disappointed that the Fed didn't "surprise" the market with a rate cut, investors slammed NASDAQ; analysts said profit warnings that have ravaged the tech sector recently probably haven't yet fully accounted for how weak profits will be this year. Goldman Sachs cut profit goals for some 40 tech firms. The session featured a piece of data that consumer confidence fell more in February than economists had anticipated, dropping to its lowest since June 1996.
03/14/01	12	d	With selling frantic from the start, the Dow Industrials sank more than 300 points within minutes of the opening bell (its 10th-worst one-day point loss in history); an added element of uncertainty was tomorrow's 'triple-witching day'.
05/07/01	16	d	"We're in something of an information vacuum…we're waiting on Fed meetings, earnings confessions…and people are turning their boredom into profit-taking.
05/11/01	13	d	"Summer's Outlook Remains Weak Despite Anticipation of Rate Cuts"
06/06/01	13	d	"[Stocks] Decline Amid Downbeat Earnings News"
06/14/01	13	d	"Investors Scramble to Limit Pain From Trades Tied to GE-Honeywell"
07/20/01	12	d	"Amid Earnings Gloom, Investor's Still Hope That a Turnaround is Around the Corner"
11/05/01	13	u	Stocks rallied as investor's placed bets ahead of today's interest rate announcement by the Fed. The economic readings last week were so disastrous that …many...who were anticipating a quarter-point reduction in rates expect a half-point cut at today's meeting.
11/27/01	12	d	An unexpectedly weak reading on consumer sentiment parked questions about the imminence and strength of any economic recovery…sending stock prices lower.
12/12/01	14	u	The day's big gainers were bonds. The Fed's comment that economic growth remains tentative and that inflation is still falling made some investors conclude that the Fed doesn't plan to raise rates soon.

Figure 1.



Small-Cap Portfolio Monthly Calendar Effects Across All Years
0.26
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0.22
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Months

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Figure 2.

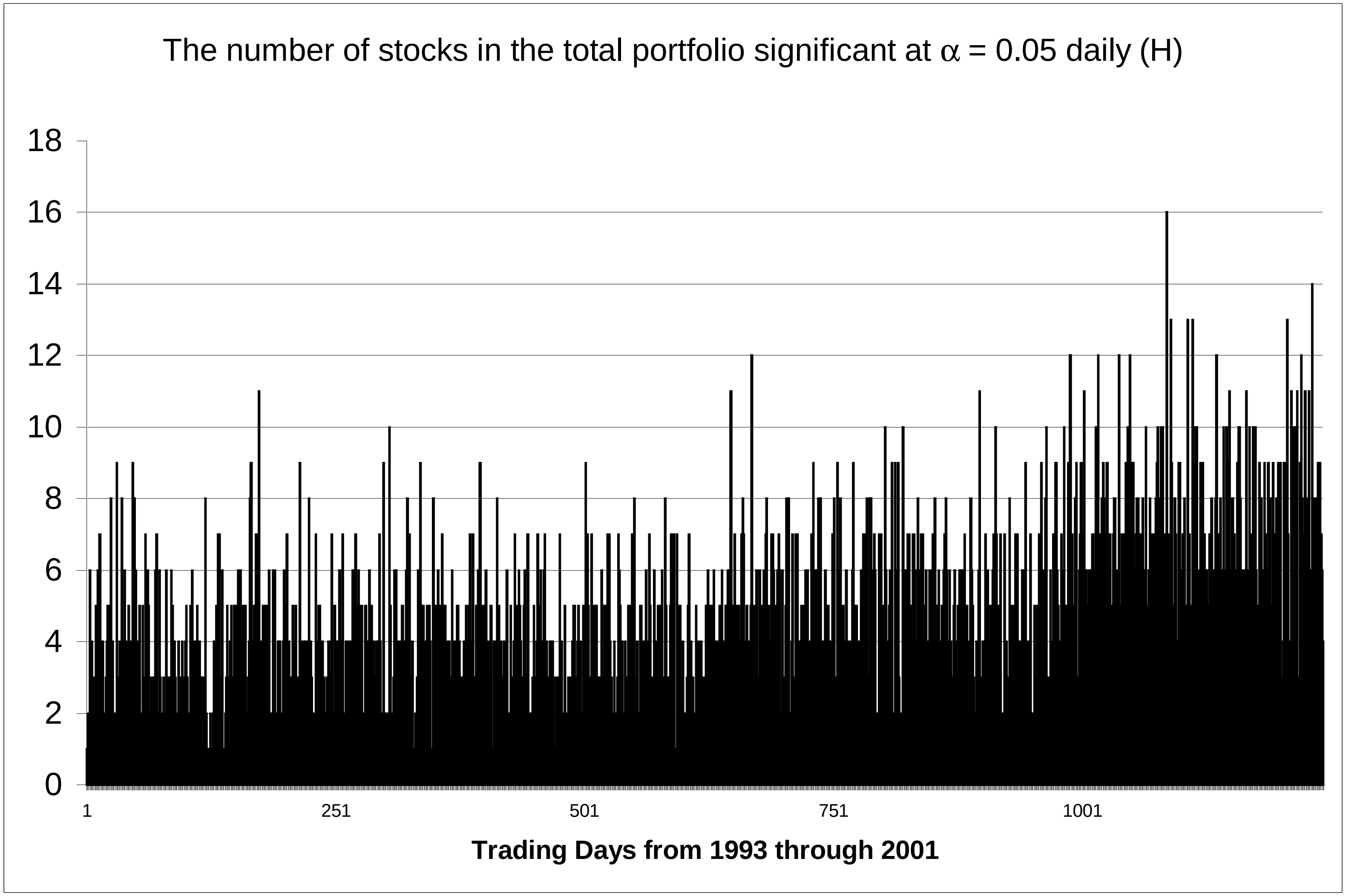
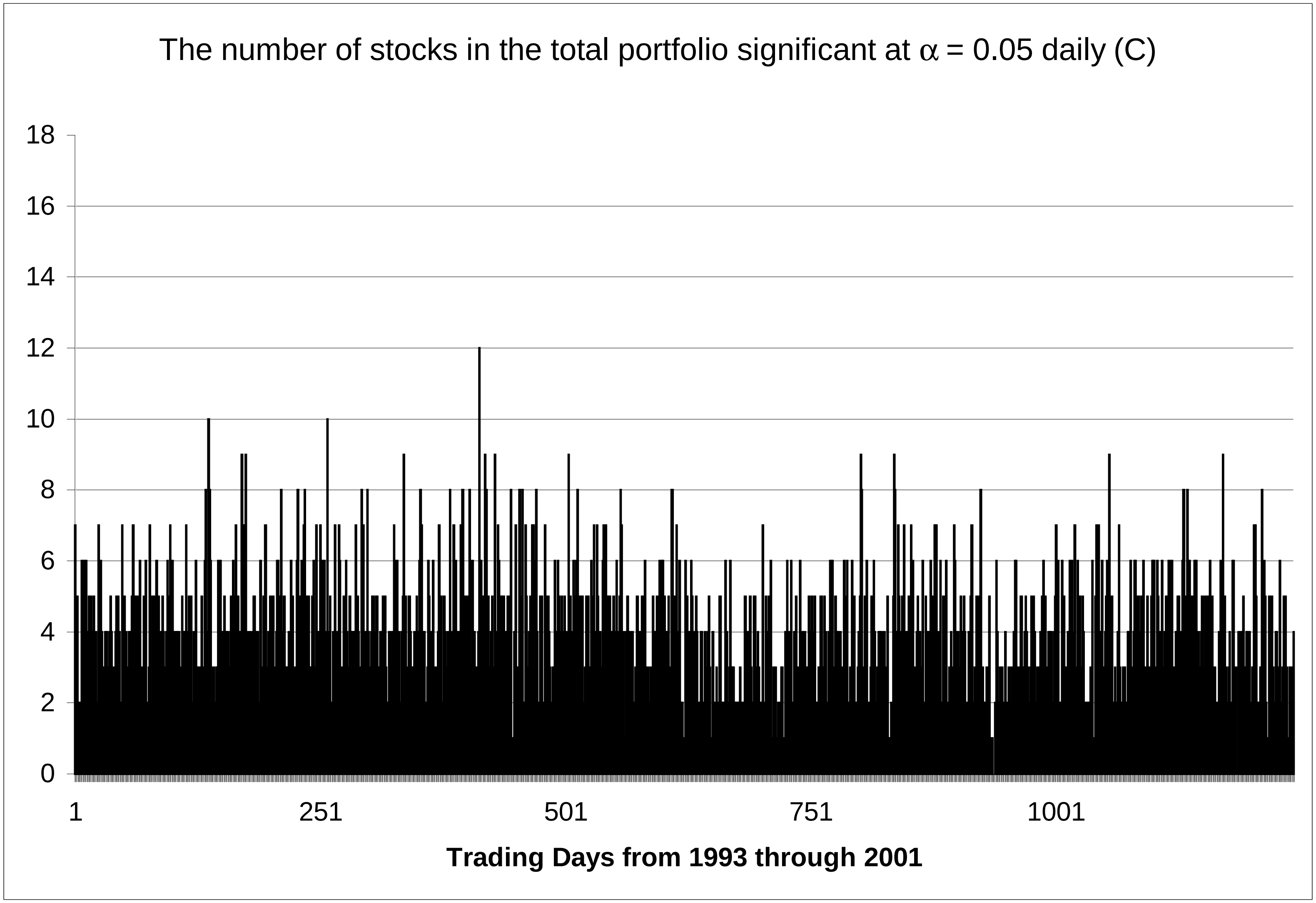

The number of stocks in the total portfolio significant at α = 0.05 daily (H)
18
16
14
12
10
8
6
4
2
0
1
251
501
751
1001
Trading Days from 1993 through 2001

Figure 3.


The number of stocks in the total portfolio significant at α = 0.05 daily (C)
18
16
14
12
10
8
6
4
2
0
1
251
501
751
1001
Trading Days from 1993 through 2001

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APPENDIX A. STANDARD AND POOR'S INDEX CRITERIA

1) Trading Analysis:	-Review of price history to minimize inclusion of stocks with single digit prices (below $1 not considered) -Must be at least six months after an IPO for a small or mid-cap firm; 12 months after an IPO for a large-cap firm -Will not be included if did not trade on any three business days during a 12-month period, or during the shorter time it has traded as a public firm
2) Liquidity:	-Share Turnover, defined as monthly average volume divided by shares outstanding, must be at least 0.3 for NYSE/AMEX stocks and 0.6 for NASDAQ stocks (At mid-cap inception in 1991, and small-cap inception in 1993, turnover was calculated as an annual average and was required to be at least 0.20)
3) Ownership:	-No single entity may hold more than 50% of shares outstanding -Multiple entities may not hold more than 60% of shares outstanding -Does not include open or closed-end mutual funds
4) Fundamental Analysis	-For initial inclusion, must have 4 quarters of positive net income on operating basis, although will make an occasional exception for a loss due to an M&A.
5) Market Capitalization	-Small-cap: at time of inception (93) Average $400 mm -Small-cap recent: $300-400 mm to $1 billion ($1.5 for higher cap sectors such as technology) -Mid-cap: at time of inception (91) $300 mm to $5.2 bill -Mid-cap recent: $1 billion to $5 billion -Large-cap: no restrictions, generally over $4 billion

NO: Stocks headquartered in foreign countries (although less than a dozen are grandfathered in, and exceptions are made for those firms organized offshore solely for tax purposes), ADRs, ADSs, REITs, closed-end funds, equity derivatives, tracking stocks.

APPENDIX B1. FIRMS IN THE LARGE-CAP PORTFOLIO

				Begin Date	Through Date
1.		AHC	Amerada Hess	01/01/93	12/31/01
2.		BFI	Browning Ferris	01/01/93	07/30/99
		AW	Allied Waste Industries	08/02/00	12/31/01
3.		BUD	Budweiser	01/01/93	12/31/01
4.		CMY	Community Psychiatric Ctrs	01/01/93	12/31/95
		UPR	Union Pacific Resources Grp	01/01/97	12/31/99
		CIT	CIT Group Inc.	01/01/01	05/13/01
		PBG	Pepsi Bottling	5/14/01	12/31/01
5.		DD	Dupont	01/01/93	12/31/01
6.		DNB	Dun & Bradstreet	01/01/93	12/31/99
		MCO	Moody's Corp.	01/01/01	12/31/01
7.		FMC	FMC Corporation	01/01/93	12/31/01
8.		GDW	Golden West Financial Corp.	01/01/93	12/31/01
9.		HOU	Houston Industries	01/01/93	02/03/99
		REI	Reliant Energy (name change)	02/04/99	12/31/01
10.		HPC	Hercules Inc.	01/01/93	12/31/01
11.		HSY	Hershey Foods	01/01/93	12/31/01
12.		IPG	Interpublic Group of Companies	01/01/93	12/31/01
13.		LDG	Longs Drug Store	01/01/93	06/29/01
		COL	Rockwell Collins	07/02/01	12/31/01
14.		MCL	Moore Corp Ltd	01/01/93	05/28/99
		DPH	Delphi Auto Systems	06/01/99	12/31/01
15.		MHP	McGraw Hill	01/01/93	12/31/01
16.		NUE	Nucor Corp.	01/01/93	12/31/01
17.		PBI	Pitney Bowes Inc.	01/01/93	01/01/93
18.		RAD	Rite Aid Corp.	01/01/93	12/31/99
		SV	Stilwell Financial	01/01/01	12/21/01
19.		TA	Transamerica Corp.	01/01/93	07/21/99
		CNC	Conseco	07/22/99	12/31/01
20.		WFC	Wells Fargo & Co.	01/01/93	12/31/01

APPENDIX B2. FIRMS IN THE MID-CAP PORTFOLIO						
				Begin Date		Through Date
1.		ABF	Airborne Freight Group	01/01/93		12/31/01
2.		ABX	American Barrick Resources	01/01/93		11/15/93
		YRK	York International Corp.	11/16/93		12/31/01
3.		BEC	Beckman Instruments	01/01/93		12/31/01
4.		BID	Sotheby's Holdings	01/01/93		12/31/01
5.		BLC	Belo Corp.	01/01/93		12/31/01
6.		CDO	Comdisco Inc.	01/01/93		04/17/01
		WGR	Western Gas Resources.	04/18/01		12/31/01
7.		CZM	Calmat Co.	01/01/93		01/04/99
		RE	Everest Reinsurance	01/05/99		12/31/01
8.		EN	Enterra Corp.	01/01/93		08/01/95
		FMY	Fred Meyer	08/02/95		12/31/97
		IBC	Interstate Bakeries.	01/01/99		12/31/01
9.		FBS	First Bank System, Inc.	01/01/93		08/01/95
		HIB	Hibernia Corp.	08/02/95		12/31/01
10.		FDO	Family Dollar Stores	01/01/93		08/06/01
		ETS	Enterasys Networks	08/07/01		12/31/01
11.		FOE	Ferro Chemicals	01/01/93		12/31/01
12.		HSN	Home Shopping Network	01/01/93		12/20/96
		AEH	Alliance Banc Corp.	12/21/96		02/01/99
		HMN	Horace Mann Educators	02/02/99		12/31/01
13.		KEM	Kemper (Financial) Corp.	01/01/93		12/31/95
		ESV	ENSCO International Inc.	01/01/97		12/31/01
14.		LUC	Lukens, Inc	01/01/93		12/31/97
		HHS	Harte Hanks, Inc.	01/01/99		12/31/01
15.		MGR	Merry Go Round Enterprises	01/01/93		12/31/93
		EMC	EMC Corp	01/01/95		12/31/95
		MTX	Mineral Technologies	01/01/97		12/31/01
16.		STX	Sterling Chemicals	01/01/93		12/31/95
		ARG	Airgas Chemical	01/01/97		12/31/01
17.		OSG	Overseas Shipping Group	01/01/93		12/31/01
18.		USR	U.S. Shoe Corp.	01/01/93		05/11/95
		NIN	Nine West Co.	05/12/95		06/15/99
		RJR	RJ Reynolds Tobacco	06/16/99		12/31/01
19.		WGL	Washington Gas Light Co.	01/01/93		12/31/01
20.		WPH	WPL Holdings Inc.	01/01/93		12/31/97
		CVD	Covance	01/01/99		12/31/01

APPENDIX B3. FIRMS IN THE SMALL-CAP PORTFOLIO

					Begin Date		Through Date
1.		ATO	Atmos Energy Corp.		01/01/93		12/31/01
2.		KZ	Kysor Industrial Corp.		01/01/93		12/31/95
		HMX	Hartmarx Corp.		01/01/97		08/07/01
		TKR	Timken Corp.		08/08/01		12/31/01
3.		BMC	BMC Industries Inc.		01/01/93		12/31/01
4.		CNU	Continuum Corp.		01/01/93		12/31/95
		NRL	Norrell Corp.		01/01/97		07/06/99
		DBT	DBT Online		07/07/99		12/31/99
		PME	Penton Media		01/01/01		12/31/01
5.		COG	Cabot Oil and Gas		01/01/93		12/31/01
6.		DRV	Dravo Corp.		01/01/93		12/31/97
		CKP	Checkpoint Systems		01/01/99		12/31/01
7.		HNH	Handy and Harman, Inc.		01/01/93		12/31/97
		DLP	Delta Pine and Land		01/01/99		12/31/01
8.		IPW	Interstate Power Corp.		01/01/93		12/31/97
		UWR	United Water Resources		01/01/99		12/31/99
		AVA	Avista Corp.		01/01/01		12/31/01
9.		BEZ	Baldor Electric Corp.		01/01/93		12/31/93
		TFS	Three Five Systems Inc.		01/01/95		12/31/01
10.		KRE	Capital Re Corp.		01/01/93		12/10/99
		CHP	C & D Technologies		12/11/99		12/31/01
11.		KAS	Kasler Holding Corp.		01/01/93		12/31/95
		AGL	Angelica Corp.		01/01/97		12/31/01
12.		LCA	Living Ctrs of America		01/01/93		05/30/97
		SOL	Sola International		05/31/97		12/31/01
13.		NSS	NS Group Inc.		01/01/93		12/31/95
		RI	Ruby Tuesday		01/01/97		12/31/01
14.		OXM	Oxford Industries		01/01/93		12/31/01
15.		PLP	Plains Petroleum Co.		01/01/93		12/31/93
		GOG	Garity Oil and Gas		01/01/95		12/31/95
		GCX	GC Companies		01/01/97		12/31/99
		BCF	Burlington Coat Factory		01/01/01		12/31/01
16.		PSC	Philadelphia Suburban Corp.		01/01/93		12/31/01
17.		GRB	Gerber Scientific		01/01/93		12/31/01
18.		UHS	Universal Health Services Inc.		01/01/93		11/20/01
		VAS	Viasys Healthcare		11/21/01		12/31/01
19.		WGO	Winnebago Industries		01/01/93		12/31/01
20.		WNT	Washington National Corp.		01/01/93		12/31/95
		AXE	Anixter International		01/01/97		12/31/01

APPENDIX C1 LARGE-CAP PORTFOLIO DAYS PER YEAR EACH SECURITY EXHIBITS SIGNIFICANT NONLINEARITY

	1993 252 days α =				1995 249 days α =				1997 248 days α =				1999 250 days α =				2001 244 days α =			
	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001
1	AHC	16	9	02	AHC	25	11	4	AHC	18	11	3	AHC	40	28	14	AHC	38	29	10
2	BFI	12 13	6 5	2 1	BFI	12 9	7 4	3 2	BFI	19	7	2	BFI/ AW	20	9	2	AW	23	10	6
3	BUD	19 18	10 6	2 3	BUD	11 15	8 5	1 1	BUD	20 14	8 2	1 1	BUD	21	12	6	BUD	31	13	9
4	CMY	17 12	8 9	5 4	CMY	23 17	10 9	4 5	UPR	11 10	7 3	1 1	UPR	14	6	1	CIT/ PBG	18	7	3
5	DD	17 15	5 1	1 1	DD	20 9	9 1	3 1	DD	19	11	4	DD	25	16	6	DD	31	12	6
6	DNB	13 6	5 1	0 0	DNB	14 21	7 6	4 2	DNB	17 15	7 5	4 1	DNB	18	6	3	MCO	31	18	4
7	FMC	16	6	4	FMC	16	10	5	FMC	12	3	0	FMC	17	5	3	FMC	44	23	6
8	GDW	12	8	4	GDW	20	11	7	GDW	15	6	2	GDW	23	9	5	GDW	30	12	6
9	HOU	17 14	10 10	3 4	HOU	20 15	10 6	3 3	HOU	24 20	12 10	4 4	HOU/ REI	15	6	2	REI	31	16	9
10	HPC	21	11	5	HPC	14	6	4	HPC	23	9	4	HPC	19	14	5	HPC	26	15	10
11	HSY	20 13	10 8	1 2	HSY	12 09	5 3	3 1	HSY	13	5	1	HSY	26	9	4	HSY	26	16	10
12	IPG	18 17	8 8	4 4	IPG	17 12	10 7	4 5	IPG	13	7	3	IPG	25	17	8	IPG	27	18	7
13	LDG	11	8	3	LDG	12	8	3	LDG	11	9	2	LDG	18	10	3	LDG/ COL	29	15	4
14	MCL	12 13	6 9	3 7	MCL	17 11	13 7	3 3	MCL	25	17	7	MCL/ DPH	18	6	1	DPH	29	20	10
15	MHP	17	10	5	MHP	13	10	4	MHP	16	5	3	MHP	17	10	3	MHP	29	10	5
16	NUE	24	15	7	NUE	14	6	2	NUE	24	10	3	NUE	14	8	1	NUE	28	17	5
17	PBI	11 9	5 2	2 0	PBI	12	6	3	PBI	17	6	3	PBI	16	6	2	PBI	25	7	1
18	RAD	17 14	10 8	1 2	RAD	11 9	4 5	3 1	RAD	23	7	1	RAD	27	15	5	SV	30	12	5
19	TA	10 13	2 4	0 1	TA	22	12	3	TA	23	13	4	TA/ CNC	29	17	7	CNC	36	17	7
20	WFC	29	13	3	WFC	27	13	3	WFC	23	9	3	WFC	18	7	3	WFC *	25 23	12 10	3 2
	All securities run in T23 with unfitted models / *Also run with AR(1) / **Also run with AR(2)																			

APPENDIX C2 MID-CAP PORTFOLIO DAYS PER YEAR EACH SECURITY EXHIBITS SIGNIFICANT NONLINEARITY

	1993 252 days α =				1995 249 days α =				1997 248 days α =				1999 250 days α =				2001 244 days α =			
	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001
1	ABF	21	17	7	ABF	22	12	5	ABF *	32 29	18 16	7 6	ABF	26	11	3	ABF *	22 11	17 6	4 3
2	ABX/ YRK	16	7	3	YRK	20	9	5	YRK	13	7	3	YRK	27	14	5	YRK	38	23	6
3	BEC	20	11	4	BEC	13	8	3	BEC	21	12	4	BEC	19	9	6	BEC	38	24	11
4	BID	18	11	5	BID	24	13	5	BID	17	9	5	BID	29	19	8	BID	29	19	8
5	BLC	10	4	2	BLC	22	15	6	BLC	14	9	3	BLC *	19 11	12 8	3 4	BLC *	23 20	11 11	6 8
6	CDO	8	3	1	CDO	20	11	3	CDO	10	4	3	CDO	33	15	5	CDO/WGR	34	25	13
7	CZM	13	10	6	CZM	12	11	4	CZM	15	10	3	CZM/ RE	19	9	3	RE	39	30	20
8	EN	28	19	12	EN/ FMY	16	11	4	FMY	21	14	5	IBC	16	10	2	IBC	21	8	3
9	FBS	21	11	7	FBS/ HIB	11	5	3	HIB *	16 16	5 2	3 2	HIB *	17 11	7 4	4 0	HIB *	26 18	14 9	4 3
10	FDO *	19 15	7 6	2 3	FDO *	15 19	7 8	5 2	FDO	20	8	5	FDO *	18 16	10 8	4 2	FDO/ ETS	32	19	9
11	FOE	14	7	3	FOE	12	9	6	FOE	11	8	1	FOE	25	17	6	FOE	20	13	7
12	HSN *	8 11	5 8	2 4	HSN *	22 19	19 14	8 10	AEH	21	13	5	AEH/ HMN	21	12	2	HMN	33	16	6
13	KEM	34	17	2	KEM *	17 22	11 13	5 10	ESV	20	12	5	ESV	31	17	6	ESV	36	21	7
14	LUC	21	12	6	LUC	21	14	6	LUC	16	6	2	HHS	24	13	5	HHS	25	17	8
15	MGR *	22 24	16 17	8 6	EMC *	13 8	3 3	1 1	MTX	16	6	2	MTX	30	20	7	MTX	42	22	18
16	STX **	15 25	13 15	11 10	STX **	27 10	19 7	6 4	ARG	13	9	1	ARG	18	11	2	ARG	21	12	6
17	OSG	12	11	7	OSG	9	7	6	OSG	7	4	1	OSG	12	6	3	OSG	30	17	9
18	USR	20	14	4	USR/ NIN	21	12	6	NIN *	18 15	12 10	7 5	NIN/ RJR	15	6	3	RJR	27	14	3
19	WGL *	12 13	7 5	2 4	WGL *	10 13	7 5	4 4	WGL *	18 16	11 8	5 5	WGL *	17 12	7 6	4 3	WGL *	23 20	15 8	6 5
20	WPH *	10 9	7 6	5 2	WPH *	7 13	4 5	1 2	WPH *	20 21	9 14	3 4	CVD	18	12	7	CVD	22	15	10
	All securities run in T23 with unfitted models / *Also run with AR(1) / **Also run with AR(2)																			

APPENDIX C3. SMALL-CAP PORTFOLIO DAYS PER YEAR EACH SECURITY EXHIBITS SIGNIFICANT NONLINEAR ITY

	1993 252 days α =				1995 249 days α =				1997 248 days α =				1999 250 days α =				2001 244 days α =			
	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001	TIC	.05	.01	.001
1	ATO **	16 16	13 15	9 8	ATO *	11 16	8 12	3 1	ATO *	22 22	9 16	4 8	ATO	17	8	6	ATO	21	12	4
2	KZ	16	13	6	KZ	7	5	2	HMX	13	6	2	HMX *	20	11	8	HMX/ TKR	14	10	1
3	BMC *	14 20	12 16	5 12	BMC	22	13	6	BMC	20	13	4	BMC *	8	6	2	BMC/ BMM	20	8	5
4	CNU	12	10	5	CNU	13	7	3	NRL	17	7	3	NRL/ DBT	28	10	4	PME	21	13	8
5	COG	11	6	4	COG	17	12	9	COG	21	13	5	COG	15	11	5	COG	26	10	3
6	DRV	7	5	3	DRV	10	8	4	DRV	23	12	6	CKP *	20	10	3	CKP	26	14	9
7	HNH	6	6	3	HNH *	20 17	12 12	6 3	HNH	22	14	7	DLP	21	11	8	DLP	23	14	6
8	IPW	7	6	5	IPW	8	7	3	IPW	11	6	4	UWR	33	16	7	AVA	18	9	2
9	BEZ	13	9	3	TFS	20	15	5	TFS	21	13	8	TFS	17	9	4	TFS	30	23	15
10	KRE	8	7	2	KRE	2	2	1	KRE	24	13	8	KRE/ CHP	21	9	2	CHP	31	16	6
11	KAS *	12 11	8 8	2 8	KAS	9	8	4	AGL *	21 18	10 8	7 4	AGL *	20	12	5	AGL	9	4	2
12	LCA	21	17	7	LCA	15	9	5	LCA/ SOL	22	10	3	SOL	12	6	3	SOL	29	20	7
13	NSS	11	9	5	NSS	9	6	4	RI	13	8	4	RI	15	10	5	RI	32	20	8
14	OXM	14	8	6	OXM	12	10	3	OXM	13	10	7	OXM	14	9	6	OXM	12	8	6
15	PLP	13	6	4	GOG *	11 10	9 8	3 2	GCX	8	6	3	GCX	7	5	2	BCF	28	16	7
16	PSC	14	8	1	PSC	7	7	3	PSC	13	6	3	PSC	18	6	3	PSC	22	10	4
17	GRB	8	6	2	GRB	10	7	4	GRB	14	9	4	GRB	16	9	4	GRB	14	7	3
18	UHS	14	9	2	UHS	17	10	6	UHS	20	8	1	UHS	20	14	8	UHS/ VAS	48	24	11
19	WGO *	7 10	5 6	2 2	WGO **	9 6	5 5	2 3	WGO *	11 15	8 10	7 8	WGO	23	12	4	WGO	28	16	7
20	WNT	14	11	6	WNT	16	5	1	AXE	12	7	5	AXE	15	8	3	AXE *	29 20	17 14	9 6
	All securities run in T23 with unfitted models / *Also run with AR(1) / **Also run with AR(2)																			

APPENDIX D. COMPARISON OF H-05 AND C-05 USING TRANSACTION PRICE VS. BID/ASK AVERAGE															
	1993			1995			1997			1999			2001		
LargeCap		H	C		H	C		H	C		H	C		H	C
	NUE p	24	12	AHC p	25	22	HOU p	24	69	AHC p	40	16	AHC p	**38**	15
	b/a	31	17	b/a	29	12	b/a	32	25	b/a	42	21	b/a	**37**	15
	WFC p	**29**	13	WFC p	27	11	MCL p	25	17	RAD p	27	21	FMC p	44	17
	b/a	**28**	12	b/a	29	8	b/a	30	25	b/a	36	20	b/a	45	13
MidCap															
	EN p	**28**	14	BID p	**24**	9	ABF p	32	7	CDO p	**33**	13	MTX p	42	14
	b/a	**23**	7	b/a	**20**	21	b/a	36	14	b/a	**28**	11	b/a	46	14
	KEM p	**34**	15	STX p	27	36	BLC p	21	11	ESV p	31	22	RE p	39	20
	b/a	**31**	8	b/a	31	20	b/a	30	14	b/a	37	15	b/a	50	20
SmallCap															
	BMC p	14	19	HNH p	**20**	16	DRV p	**23**	15	UWR p	**21**	9	CHP p	31	11
	b/a	14	6	b/a	**19**	22	b/a	**12**	12	b/a	**19**	15	b/a	35	13
	LCA p	**21**	12	UHS p	17	5	KRE p	**24**	14	WGO p	23	8	RI p	**32**	20
	b/a	**11**	9	b/a	17	12	b/a	**13**	7	b/a	29	18	b/a	**27**	15

Moving from using transaction price to bid/ask average:
C-05 increases in 11 instances, decreases in 16 instances, no change in 2 instances.
H-05 increases in 16 instances, decreases in 12 instances, no change in 2 instances.
For the H05 statistic and 12 instances of decreases:
Decrease of 1-3 days: WFC93, KEM93, HNH95, UWR99, AHC01
Decrease of 4-5 days: EN93, BID95, CDO99, RI01
Decrease of > 5 days: LCA93, DRV97, KRE97

APPENDIX E.

COMPARISON OF H-001 DAYS WITH OTHER TESTS OF NON-LINEARITY

	McLeod-Li, lag 8	m=2	m=3	m=4	Lagrange Multiplier, lag 5	Tsay	C-statistic
1993							
BLC xx/xx	0.305	**0.097**	0.122	**0.022**	**0.003**	**0.019**	**0.9671**
GDW	0.264	**0.032**	0.090	0.135	0.291	0.313	0.6230
1995							
AHC	0.238	0.225	0.363	0.238	0.229	0.014	0.4769
FOE	0.383	**0.006**	**0.004**	**0.004**	0.951	0.915	**0.9890**
1997							
ESV	0.354	**0.017**	**0.020**	**0.031**	**0.001**	0.753	0.5775
HPC	0.075	0.088	0.055	0.098	0.097	0.430	**0.9598**
KRE	0.134	0.353	0.274	0.324	0.091	0.082	0.4052
1999							
IBC	**0.007**	0.574	0.648	0.674	**0.006**	0.109	0.7605
CNC	**0.000**	**0.006**	**0.019**	**0.019**	0.189	0.529	0.6923
UWR	0.110	0.211	0.323	0.149	0.091	**0.006**	0.2773
2001							
ARG	**0.027**	**0.003**	**0.002**	**0.000**	**0.002**	0.467	0.7143
DD	**0.022**	**0.018**	**0.011**	**0.022**	**0.013**	0.388	**0.9986**
DLP	**0.004**	0.199	0.093	0.074	0.829	0.599	**0.9991**

The numbers printed above are p-values from the Toolkit program, with the exception of the C-statistic, which is from the T23 program. Values > 0.95 for the C-statistic are significant at the 0.05 level or lower.

Debra Ann Skaradzinski

P.O. Box 1631
Kingston, RI 02881
home (401) 783-9420
work (617) 287-7713

Dept. of Accounting & Finance
U-Mass Boston
Boston, MA 02125-3393
Debra.Skaradzinski@umb.edu

EDUCATION

Virginia Polytechnic Institute and State University
R. B. Pamplin College of Business, Ph.D. in Finance
Dissertation: "The Nonlinear Behavior of Stock Prices: The Impact of Firm Size, Seasonality, and Trading Frequency", final defense completed July 23, 2003

Wake Forest University Babcock Graduate School of Management
M.B.A. Degree, May 1990, Concentration in Finance

University of North Carolina at Chapel Hill
B.A. Degree in French, May 1980, Minor in Chemistry

RESEARCH

"The Nonlinear Behavior of Stock Prices: The Impact of Firm Size, Seasonality, and Trading Frequency", working-paper version, co-authored with Douglas Patterson, presented at the MFA Spring 2002 meeting, and at the EFA Spring 2003 meeting.

"The Intra-day Relationship between Transaction Price, Trading Frequency, and Quotes", to be presented at the MFA Spring 2004 meeting.

COURSES TAUGHT

Managerial (Corporate) Finance, both Undergraduate and MBA level; Intermediate Finance; Topics in Corporate Finance; Business Statistics, Banking, Business Finance (for non-business majors), Principles of Macroeconomics, Senior Seminar (Case Study and Discussion), Independent Study Advisor.

EXPERIENCE

Lecturer in Finance (Sept 2002-Present) U-Mass Boston, Boston MA.

Lecturer in Economics (Sept 1996-Dec 1999) Hollins University, Roanoke, VA

Lecturer in Business (Aug 1994-May 1995) Radford University, Radford, VA.

Corporate Credit Analyst (1990-91) Qualex Inc., Durham NC. Evaluated financial and general business information on largest corporate customers for photofinishing firm with annual sales of $900 MM. Analyzed impact of economic conditions on discount retailing, grocery and drugstore industries; reported expected customer performance to upper management. Provided detailed reporting on accounts receivable performance. Identified major delinquent accounts to set priorities for corporate, regional, and divisional collection activity; directed and monitored activities of third party collection agencies and attorneys. Co-edited monthly newsletter (staff of 7) for the finance department (100 employees).

EXPERIENCE

General Assistant (Summers 1989/90) Great Guides Inc., Durham, NC. Spouse-owned business that produced *The Insider's Guide to the Triangle* and *The Insider's Guide to Charlotte* (annual publications supported by advertising sales). Compiled advertiser list for nurse-recruitment publication.

Asst.V.P., Commercial Loans (1986-88) Great Atlantic Savings Bank, Manteo, NC. Analyzed loan requests. Administered $40-60 MM portfolio. Wrote loan documentation policy manual. Automated loan accounting system, cutting labor time by 25%.

Head of Operations (1984-86) Great Atlantic Savings Bank, Manteo, NC. Hired, trained, and managed two customer service reps, five tellers, and one branch manager. Headed four-month project to convert bank account records from one data-service provider to another. Purchased computer hardware system and coordinated data services between bank, software supplier, and FHLB of Atlanta. Wrote teller operations manual.

Teller/Head Teller (1983-84) Great Atlantic Savings Bank, Manteo, NC. Supervised tellers. Balanced vault. Forecasted cash requirements and planned currency shipments.

Reading Room Supervisor (1980-82) UNC-Chapel Hill Rare Book Collection, NC. Hired, trained, and supervised student assistants. Served as Assistant Editor of *The Hanes Lecture* and *The Bookmark*. Developed public relations and tour program that doubled lecture attendance and increased Collection use by 30%.

SERVICE AND CONTINUING EDUCATION

Presenter at Eastern Finance Association Meeting Spring 2003.
Discussant & Presenter at Midwest Finance Association Meeting Spring 2002.
Faculty Advisor for all economics majors short-term internships, January 2000.
Attended conference on Classroom Experiments in Economics, William and Mary University, 1998.
Hollins Scholarship Committee, 1998-99. Awarded merit-based tuition waivers, Leadership scholarship, and NYSE internship.
Faculty Advisor for continuing education students and business majors, 1997-99.
Attended "Writing Across the Curriculum" Workshops, 1995, 1997.
Paper Discussant and Session Chair at SFA Meeting, Fall 1994, Charleston, SC.
Participant in Seminar on College Teaching, Summer/Fall 1994.

HONORS AND AWARDS

1st year tuition waiver at Virginian Tech (Fall 1991-Spring 1992).
Dean's Scholarship at Wake Forest University MBA Program (1988-1990)