

**STOCK MARKET PRICES DO
NOT FOLLOW RANDOM WALKS: EVIDENCE
FROM A SIMPLE SPECIFICATION TEST**

by

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ABSTRACT

In this paper, we test the random walk hypothesis for weekly stock market returns by comparing variance estimators derived from data sampled at different frequencies. The random walk model is strongly rejected for the entire sample period (1962-1985) and for all sub-periods for a variety of aggregate returns indexes and size-sorted portfolios. Although the rejections are largely due to the behavior of small stocks, they cannot be completely attributed to the effects of infrequent trading or time-varying volatilities. Moreover, the rejection of the random walk for weekly returns does not support a mean-reverting model of asset prices.

I. INTRODUCTION.

Since Keynes' (1936, Chapter 12) now famous pronouncement that most investors' decisions "can only be taken as a result of animal spirits--of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of benefits multiplied by quantitative probabilities," a great deal of research has been devoted to examining the efficiency of stock market price formation. In Fama's (1970) survey, the vast majority of those studies were unable to reject the "efficient markets" hypothesis for common stocks. Although several seemingly anomalous departures from market efficiency have been well-documented,¹ many financial economists would agree with Jensen's (1978) belief that "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Markets Hypothesis."

Although the precise formulation of an empirically refutable efficient markets hypothesis is obviously model specific, historically the majority of such tests have focused on the forecastability of common stock returns. Within this paradigm, which has been broadly categorized as the "random walk" theory of stock prices, few studies have been able to statistically reject the random walk model. However, several recent papers have uncovered empirical evidence which suggests that stock returns contain predictable components. For example, Keim and Stambaugh (1986) find statistically significant predictability in stock prices using forecasts based upon certain predetermined variables. In addition, Fama and French (1987) show that long holding-period returns are significantly negatively serially correlated, implying that 25 to 40 percent of the variation of longer-horizon returns is predictable from past returns.

In this paper, we provide further evidence that stock prices do not follow random walks by using a simple specification test based upon variance estimators. Our empirical results indicate that the random walk model is generally not consistent with the stochastic behavior of weekly returns, especially for the smaller capitalization stocks. However, in contrast to the negative serial correlation which Fama and French (1987) find for longer horizon returns, we find significant positive serial correlation for weekly and monthly holding-period returns. For example, using 1216 weekly observations from September 6, 1962 to December 26, 1985 we compute the weekly first-order autocorrelation coefficient of the equal-weighted CRSP index to be 30 percent! The statistical significance of our results is robust to heteroscedasticity. We also develop a simple model which indicates that these large autocorrelations cannot be solely attributed to the effects of infrequent trading. This empirical puzzle becomes even more striking when we show that autocorrelations of individual securities are generally negative.

Of course, these results do not necessarily imply that the stock market is inefficient or that prices are not rational assessments of 'fundamental' values. As Leroy (1973) and Lucas (1978) have shown, rational expectations equilibrium prices need not even form a martingale sequence, of which the random walk is a special case. Therefore, without a more explicit economic model of the price-generating mechanism, a rejection of the random walk hypothesis has few implications for the efficiency of market price formation. Although our test results may be interpreted as a rejection of some economic model of efficient price formation, there may exist other plausible models which are consistent with the empirical findings. Our more modest goal in this study is to employ a test which is capable of distinguishing among an interesting set of alternative stochastic price

processes. Our test exploits the fact the variance of the increments of a random walk is linear in the sampling interval. If stock prices are generated by a random walk (possibly with drift) then, for example, the variance of monthly-sampled log-price relatives must be four times as large as the variance of a weekly sample. Comparing the (per unit time) variance estimates obtained from weekly and monthly prices may then indicate the plausibility of the random walk theory.² Such a comparison is formed quantitatively along the lines of the Hausman (1978) specification test and is particularly simple to implement.

In Section 2 we derive our specification test for both homoscedastic and heteroscedastic random walks. The main results of the paper are given in Section 3, where rejections of the random walk are extensively documented for weekly returns indexes, size-sorted portfolios, and individual securities. Section 4 contains a simple model which demonstrates that infrequent trading cannot fully account for the magnitude of the estimated autocorrelations of weekly stock returns. In Section 5 we discuss the consistency of our empirical rejections with a mean-reverting alternative to the random walk model. We summarize briefly and conclude in Section 6.

2. THE SPECIFICATION TEST.

Denote by P_t the stock price at time t and define $X_t \equiv \ln P_t$ as the log-price process. Our maintained hypothesis is given by the recursive relation:

$$X_t = \mu + X_{t-1} + \varepsilon_t . \quad (1)$$

We assume throughout that for all t , $E[\varepsilon_t] = 0$. Although the traditional random walk hypothesis restricts the ε_t 's to be independently and identically distributed Gaussian random variables, there is mounting evidence that financial time series often possess time-varying volatilities and deviate from

normality. Since it is the unforecastability or uncorrelatedness of price changes that is of interest, a rejection of the i.i.d. Gaussian random walk due to heteroscedasticity or non-normality would be of less import than a rejection which is robust to these two aspects of the data. In Section 2.2 we develop a test statistic which is sensitive to correlated price changes but is otherwise robust to many forms of heteroscedasticity and non-normality.

Although our empirical results rely solely on this statistic, for expositional purposes we also present in Section 2.1 the sampling theory for the more

restrictive i.i.d. Gaussian random walk.

2.1 HOMOSCEDASTIC INCREMENTS.

We begin with the null hypothesis that the disturbances ϵ_t are independently and identically distributed normal random variables with variance σ_0^2 , thus:

$$H: \epsilon_t \text{ i.i.d. } N(0, \sigma_0^2) . \quad (2)$$

In addition to homoscedasticity, we have made the assumption of independent Gaussian increments. An example of such a specification is the exact discrete-time process X_t obtained by sampling the following well-known continuous-time process at equally spaced intervals:

$$dX(t) = \mu dt + \sigma_0 dW(t) . \quad (3)$$

This Itô process corresponds to the popular lognormal diffusion price process.

One important property of the random walk X_t is that the variance of its increments is linear in the observation interval. That is, the variance of $X_t - X_{t-2}$ is twice the variance of $X_t - X_{t-1}$. Therefore, the plausibility of the random walk model may be checked by comparing the variance estimate of

essence of our specification test; the remainder of this section is devoted to developing the sampling theory required to compare the variances quantitatively.

Suppose we obtain $2n+1$ observations X_0, X_1, \dots, X_{2n} of X_t at equally spaced intervals and consider the following estimators for the unknown parameters μ and σ_0^2 :

$$\hat{\mu} \equiv \frac{1}{2n} \sum_{k=1}^{2n} (X_k - X_{k-1}) = \frac{1}{2n} (X_{2n} - X_0) \quad (4a)$$

$$\hat{\sigma}_a^2 \equiv \frac{1}{2n} \sum_{k=1}^{2n} [X_k - X_{k-1} - \hat{\mu}]^2 \quad (4b)$$

$$\hat{\sigma}_b^2 \equiv \frac{1}{2n} \sum_{k=1}^n [X_{2k} - X_{2k-2} - 2\hat{\mu}]^2 . \quad (4c)$$

The estimators $\hat{\mu}$ and $\hat{\sigma}_a^2$ correspond to the maximum-likelihood estimators of the μ and σ_0^2 parameters; $\hat{\sigma}_b^2$ is also an estimator of σ_0^2 but uses only the subset of $n+1$ observations $X_0, X_2, X_4, \dots, X_{2n}$ and corresponds formally to one-half times the variance estimator for increments of even-numbered observations. Under standard asymptotic theory, all three estimators are strongly consistent. That is, holding all other parameters constant, as the total number of observations $2n$ increases without bound the estimators converge almost surely to their population values. In addition, it is well-known that both $\hat{\sigma}_a^2$ and $\hat{\sigma}_b^2$ possess the following Gaussian limiting distributions:

$$\sqrt{2n} (\hat{\sigma}_a^2 - \sigma_0^2) \stackrel{a}{\approx} N(0, 2\sigma_0^4) \quad (5a)$$

$$\sqrt{2n} (\hat{\sigma}_b^2 - \sigma_0^2) \stackrel{a}{\approx} N(0, 4\sigma_0^4) . \quad (5b)$$

Of course, it is the limiting distribution of the difference of the variances which interests us. Although it may readily be shown that such a difference

is also asymptotically Gaussian with zero mean, the variance of the limiting distribution is not apparent since the two variance estimators are clearly not asymptotically uncorrelated. However, since the estimator $\hat{\sigma}_a^2$ is asymptotically efficient under the null hypothesis H, we may apply Hausman's (1978) result which shows that the asymptotic variance of the difference is simply the difference of the asymptotic variances.³ If we define

$J_d \equiv \hat{\sigma}_b^2 - \hat{\sigma}_a^2$, then we have the result:

$$\sqrt{2n} J_d \stackrel{a}{\approx} N(0, 2\sigma_0^4) . \quad (6)$$

Using any consistent estimator of the asymptotic variance of J_d , a standard significance test may then be performed. A more convenient alternative test statistic is given by the ratio of the variances J_r :⁴

$$J_r \equiv \frac{\hat{\sigma}_b^2}{\hat{\sigma}_a^2} - 1, \quad \sqrt{2n} J_r \stackrel{a}{\approx} N(0, 2) . \quad (7)$$

Although the variance estimator $\hat{\sigma}_b^2$ is based upon differences of every other observation, alternative variance estimators may be obtained by using differences of every q-th observation. Suppose that we obtain $nq+1$ observations X_0, X_1, \dots, X_{nq} where q is any integer greater than 1. Define the estimators:

$$\hat{\mu} \equiv \frac{1}{nq} \sum_{k=1}^{nq} (X_k - X_{k-1}) = \frac{1}{nq} (X_{nq} - X_0) \quad (8a)$$

$$\hat{\sigma}_a^2 \equiv \frac{1}{nq} \sum_{k=1}^{nq} [X_k - X_{k-1} - \hat{\mu}]^2 \quad (8b)$$

$$\hat{\sigma}_b^2(q) \equiv \frac{1}{nq} \sum_{k=1}^n [X_{qk} - X_{qk-q} - q\hat{\mu}]^2 \quad (8c)$$

$$J_d(q) \equiv \hat{\sigma}_b^2(q) - \hat{\sigma}_a^2 \quad J_r(q) \equiv \frac{\hat{\sigma}_b^2(q)}{\hat{\sigma}_a^2} - 1 . \quad (8d)$$

The specification test may then be performed using:⁵

Theorem 1: Under the null hypothesis H, the asymptotic distributions of $J_d(q)$ and $J_r(q)$ are given by:

$$\sqrt{nq} J_d(q) \stackrel{a}{\approx} N(0, 2(q-1)\sigma_0^4) \quad (9a)$$

$$\sqrt{nq} J_r(q) \stackrel{a}{\approx} N(0, 2(q-1)) . \quad (9b)$$

Two further refinements of the statistics J_d and J_r result in more desirable finite sample properties. The first is to use overlapping q-th differences of X_t in estimating the variances by defining the following estimator of σ_0^2 :

$$\hat{\sigma}_c^2(q) = \frac{1}{nq^2} \sum_{k=q}^{nq} [X_k - X_{k-q} - q\hat{\mu}]^2 . \quad (10)$$

This differs from the estimator $\hat{\sigma}_b^2(q)$ since this sum contains $nq - q + 1$ terms whereas the estimator $\hat{\sigma}_b^2(q)$ contains only n terms. By using overlapping q-th increments, we obtain a more efficient estimator and hence a more powerful test. Using $\hat{\sigma}_c^2(q)$ in our variance ratio test, we define the corresponding difference and ratio test statistics as:

$$M_d(q) \equiv \hat{\sigma}_c^2(q) - \hat{\sigma}_a^2 \quad M_r(q) \equiv \frac{\hat{\sigma}_c^2(q)}{\hat{\sigma}_a^2} - 1 . \quad (11)$$

The second refinement involves using unbiased variance estimators in the calculation of the M statistics. Denote the unbiased estimators as $\bar{\sigma}_a^2$ and

$\sigma_c^{-2}(q)$ where

$$\sigma_a^{-2} = \frac{1}{nq - 1} \sum_{k=1}^{nq} [X_k - X_{k-1} - \hat{\mu}]^2 \quad (12a)$$

$$\sigma_c^{-2}(q) = \frac{1}{m} \sum_{k=1}^{nq} [X_k - X_{k-q} - q\hat{\mu}]^2 \quad m = q(nq - q + 1) \cdot \left(1 - \frac{q}{nq}\right) \quad (12b)$$

and define the statistics:

$$\bar{M}_d(q) \equiv \sigma_c^{-2}(q) - \sigma_a^{-2} \quad \bar{M}_r(q) \equiv \frac{\sigma_c^{-2}(q)}{\sigma_a^{-2}} - 1 \quad (13)$$

Although this does not yield an unbiased variance ratio, simulation experiments show that the finite-sample properties of the test statistics are closer to their asymptotic counterparts when this bias adjustment is made.⁶ Inference for the overlapping variance differences and ratios may then be performed using:

Theorem 2: Under the null hypothesis H, the asymptotic distributions of the statistics $M_d(q)$, $M_r(q)$, $\bar{M}_d(q)$, and $\bar{M}_r(q)$ are given by:

$$\sqrt{nq} M_d(q) \stackrel{d}{\approx} \sqrt{nq} \bar{M}_d(q) \stackrel{d}{\approx} N\left(0, \frac{2(2q-1)(q-1)}{3q} \sigma_o^4\right) \quad (14a)$$

$$\sqrt{nq} M_r(q) \stackrel{d}{\approx} \sqrt{nq} \bar{M}_r(q) \stackrel{d}{\approx} N\left(0, \frac{2(2q-1)(q-1)}{3q}\right) \quad (14b)$$

In practice, the statistics in (14) may be standardized in the usual manner [e.g., $z(q) \equiv \sqrt{nq} \bar{M}_r(q) \cdot \left(\frac{2(2q-1)(q-1)}{3q}\right)^{-\frac{1}{2}} \stackrel{d}{\approx} N(0, 1)$].

To develop some intuition for these variance ratios, observe that for an aggregation value q of 2, the $M_r(q)$ statistic may be re-expressed as:

$$M_r(2) = \hat{\rho}(1) - \frac{1}{nq} [(X_1 - X_0 - \hat{\mu})^2 + (X_2 - X_1 - \hat{\mu})^2] \equiv \hat{\rho}(1) \quad (15)$$

hence for $q = 2$ the $M_r(q)$ statistic is approximately the first-order autocorrelation coefficient estimator $\hat{\rho}(1)$ of the differences. More generally, it may be shown that:

$$M_r(q) \approx \frac{2(q-1)}{q} \hat{\rho}(1) + \frac{2(q-2)}{q} \hat{\rho}(2) + \dots + \frac{2}{q} \hat{\rho}(q-1) \quad (16)$$

where $\hat{\rho}(k)$ denotes the k -th order autocorrelation coefficient estimator of the first-differences of X_t .⁷ Equation (16) provides a simple interpretation for the variance ratios computed with an aggregation value q : they are (approximately) linear combinations of the first $q-1$ autocorrelation coefficients estimators of the first differences with arithmetically declining weights.⁸

2.2 HETEROSCEDASTIC INCREMENTS.

Since there is already a growing consensus among financial economists that volatilities do change over time,⁹ a rejection of the random walk hypothesis due to heteroscedasticity would not be of much interest. We therefore wish to derive a version of our specification test of the random walk model which is robust to changing variances. As long as the increments are uncorrelated, even in the presence of heteroscedasticity the variance ratio must still approach unity as the number of observations increase without bound since the variance of the sum of uncorrelated increments must still equal the sum of the variances. However, the asymptotic variance of the variance ratios will clearly depend upon the type and degree of heteroscedasticity present. One possible approach is to assume some specific form of heteroscedasticity, and then calculate the asymptotic variance of $\bar{M}_r(q)$ under this null hypothesis. However, to allow for more general forms of heteroscedasticity, we employ an approach due to White (1980) and White and Domowitz (1984). This approach also allows us to relax the requirement of

returns' well-documented empirical departures from normality.¹⁰ Specifically, we assume:¹¹

H*: (i) For all t , $E[\varepsilon_t] = 0$, $E[\varepsilon_t \varepsilon_{t-\tau}] = 0$ for any $\tau \neq 0$.

(ii) $\{\varepsilon_t\}$ is ϕ -mixing with coefficients $\phi(m)$ of size $r/(2r-1)$ or is α -mixing with coefficients $\alpha(m)$ of size $r/(r-1)$, $r > 1$ such that for all t and for any $\tau \geq 0$, there exists some δ for which:

$$E|\varepsilon_t \varepsilon_{t-\tau}|^{2(r+\delta)} < \Delta < \infty . \quad (17)$$

(iii) $\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T E[\varepsilon_t^2] = \sigma_0^2 < \infty$.

(iv) For all t , $E[\varepsilon_t \varepsilon_{t-j} \varepsilon_t \varepsilon_{t-k}] = 0$ for any non-zero j, k where $j \neq k$.

This null hypothesis assumes that X_t possesses uncorrelated increments but allows for quite general forms of heteroscedasticity, including deterministic changes in the variance (due, for example, to seasonal factors) and Engle's [1982] ARCH processes (in which the conditional variance depends upon past information).

Since $\bar{M}_r(q)$ still approaches 0 under H*, we need only compute its asymptotic variance [call it $\theta(q)$] to perform the standard inferences. We do this in two steps. First, recall that the following equality obtains asymptotically:

$$\bar{M}_r(q) \cong \sum_{j=1}^{q-1} \frac{2(q-j)}{q} \hat{\rho}(j) . \quad (18)$$

Second, note that under H* [Condition (iv)] the autocorrelation coefficient estimators $\hat{\rho}(j)$ are asymptotically uncorrelated.¹² If we can obtain asymptotic variances $\delta(j)$ for each of the $\hat{\rho}(j)$ under H*, we may readily

calculate the asymptotic variance $\theta(q)$ of $\bar{M}_r(q)$ as the weighted sum of the $\delta(j)$ where the weights are simply the weights in (18) squared. More formally, we have:

Theorem 3: Denote by $\delta(j)$ and $\theta(q)$ the asymptotic variances of $\hat{\rho}(j)$ and $\bar{M}_r(q)$ respectively. Then under the null hypothesis H^* :

- (a) The statistics $J_d(q)$, $J_r(q)$, $M_d(q)$, $M_r(q)$, $\bar{M}_d(q)$, $\bar{M}_r(q)$ all converge almost surely to 0 for all q as n increases without bound.
- (b) The following is a heteroscedasticity-consistent estimator of $\delta(j)$:

$$\hat{\delta}(j) = \frac{\sum_{k=j+1}^{nq} (X_k - X_{k-1} - \hat{\mu})^2 \cdot (X_{k-j} - X_{k-j-1} - \hat{\mu})^2}{\left[\sum_{k=1}^{nq} (X_k - X_{k-1} - \hat{\mu})^2 \right]^2} . \quad (19)$$

- (c) The following is a heteroscedasticity-consistent estimator of $\theta(q)$:

$$\hat{\theta}(q) \equiv \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q} \right]^2 \cdot \hat{\delta}(j) . \quad (20)$$

Despite the presence of general heteroscedasticity, the standardized test statistic $z^*(q) \equiv \bar{M}_r(q)/\sqrt{\hat{\theta}}$ is still asymptotically standard normal. In Section 3 we use the $z^*(q)$ statistic to empirically test for random walks in weekly stock returns data.

3. THE RANDOM WALK HYPOTHESIS FOR WEEKLY RETURNS.

To test for random walks in stock market prices, we focus on the 1216-week time span from September 6, 1962 to December 26, 1985. Our choice of a weekly observation interval was determined by several considerations. Since our sampling theory is wholly based upon asymptotic approximations, a large

number of observations is appropriate. While daily sampling yields many observations, the biases associated with non-trading, the bid-ask spread, asynchronous prices, etc. are troublesome. Weekly sampling is the ideal compromise, yielding a large number of observations while minimizing the biases inherent in daily data.

The weekly stock returns are derived from the CRSP daily returns file. The weekly return of each security is computed as the return from Wednesday's closing price to the following Wednesday's close. If the following Wednesday's price is missing, then Thursday's price (or Tuesday's if Thursday's is missing) is used. If both Tuesday's and Thursday's prices are also missing, the return for that week is reported as missing.¹³

In Section 3.1 we perform our test on both equal and value-weighted CRSP indexes for the entire 1216-week period as well as for 608-week sub-periods using aggregation values q ranging from 2 to 16.¹⁴ Section 3.2 reports corresponding test results for size-sorted portfolios and Section 3.3 presents results for individual securities.

3.1 RESULTS FOR MARKET INDEXES.

Tables 1a and 1b report the variance ratios and test statistic $z^*(q)$ for CRSP NYSE-AMEX market return indexes. Table 1a presents the results for a one-week base observation period and Table 1b reports similar results for a four-week base observation period. The values reported in the main rows are the actual variance ratios $(\bar{M}_r(q) + 1)$ and entries enclosed in parentheses are the $z^*(q)$.¹⁵

Panel A of Table 1a displays the results for the CRSP equal-weighted index. The first row presents the variance ratios and test statistics for the entire 1216 week sample period and the next two give the results for the two 608 week sub-periods. The random walk null hypothesis may be rejected at all

the usual significance levels for the entire time period and all sub-periods. Moreover, the rejections are not due to changing variances since the $z^*(q)$ statistics are robust to heteroscedasticity. The estimates of the variance ratio are larger than 1.0 for all cases. For example, the entries in the first column of Panel A correspond to variance ratios with an aggregation value q of 2 which, in view of equation (15), are approximately equal to one plus the first-order autocorrelation coefficient estimator of weekly returns. The entry in the first row, 1.30, implies that the first-order autocorrelation for weekly returns is approximately 30 percent. The random walk hypothesis is

easily rejected at common levels of significance. The variance ratios increase with q , but the magnitudes of the $z^*(q)$ statistics do not. Indeed, the test statistics seem to decline with q hence the significance of the rejections becomes weaker as coarser-sample variances are compared to weekly variances. Our findings of positive autocorrelation for weekly holding-period returns differs from Fama and French's (1987) finding of negative serial correlation for long holding-period returns. This positive correlation is significant not only for our entire sample period but for all sub-periods as well.

The rejection of the random walk hypothesis is much weaker for the value-weighted index as Panel B indicates, nevertheless the general patterns persist. The variance ratios exceed 1.0, and the $z^*(q)$ statistics decline as q increases. The rejections for the value-weighted index are primarily due to the first 608 weeks of the sample period.

Table 1b presents the variance ratios using a base observation period of four weeks hence the first entry of the first row, 1.15, is the variance ratio of eight-week returns to four-week returns.

weighted index. This is consistent with the relatively weak evidence against the random walk which previous studies have found using monthly data.

Although the test statistics in Tables 1a and 1b are based on nominal stock returns, it is apparent that virtually the same results would obtain with real or excess returns. Since the volatility of weekly nominal returns is so much larger than that of the inflation and T-bill rates, the use of nominal, real, or excess returns in a volatility-based test will yield practically identical inferences.

3.2 RESULTS FOR SIZE BASED PORTFOLIOS.

An implication of the work of Keim and Stambaugh (1986) is that, conditional on stock and bond market variables, the logarithm of wealth relatives of portfolios of smaller stocks do not follow random walks. For portfolios of larger stocks their results are less conclusive. Consequently, it is of interest to explore what evidence our tests provide for the random walk hypothesis for the logarithm of size based portfolio wealth relatives.

We compute weekly returns for five size based portfolios from the NYSE-AMEX universe on the CRSP daily return file. Stocks with returns for any given week are assigned to portfolios based on which quintile their market value of equity is in. The portfolios are equal-weighted and have a continually changing composition.¹⁶ The number of stocks included in the portfolios varies from 2036 to 2720.

Table 2 reports the $\bar{M}_r(q)$ test results for the size-based portfolios using a base observation period of one week. Panel A reports the results for the portfolio of small firms (first quintile), Panel B reports the results for the portfolios of medium-sized firms (third quintile), and Panel C reports the results for the portfolio of large firms (fifth quintile). Evidence against the random walk hypothesis for small firms is strong for all time periods

considered. In Panel A all the $z^*(q)$ statistics are well above 2.0, ranging from 3.52 to 11.92. As we proceed through the panels to the results for the portfolio of large firms the $z^*(q)$ statistics become smaller, but even for the large firms portfolio the evidence against the null hypothesis is strong. As in the case of the returns indexes, we may obtain estimates of the first-order autocorrelation coefficient for returns on these size-sorted portfolios simply by subtracting 1.0 from entries in the $q = 2$ column. The values in Table 2 indicate that portfolio returns for the smallest quintile have a 42 percent weekly autocorrelation over the entire sample period! Moreover, this autocorrelation reaches 49 percent in sub-period 2 (May 2, 1974 to December 26, 1985). Although the serial correlation for the portfolio returns of the largest quintile is much smaller (14 percent for the entire sample period), it is statistically significant.

Using a base observation interval of four weeks, much of the evidence against the random walk for size-sorted portfolios disappears. Although the smallest quintile portfolio still exhibits a serial correlation of 23 percent with a $z^*(2)$ statistic of 3.09, none of the variance ratios for the largest quintile portfolio are significantly different from one. In the interest of brevity, we do not report those results here and refer interested readers to Lo and MacKinlay (1987a).

The results for size-based portfolios are generally consistent with those for the market indexes. The patterns of variance ratios increasing in q and significance of rejections decreasing in q which we observed for the indexes also obtain for these portfolios. The evidence against the random walk hypothesis for the logarithm of wealth relatives of small-firms portfolios is strong in all cases considered. For larger firms and a one-week base observation interval, the evidence is also inconsistent with the random

walk. However, as the base observation interval is increased to four weeks, our test does not reject the random walk model for larger firms.

3.3 RESULTS FOR INDIVIDUAL SECURITIES.

For completeness, we perform the variance ratio test on all individual stocks which have complete return histories in the CRSP database for our entire 1216-week sample period, yielding a sample of 625 securities. Due to space limitations, we report only a brief summary of these results in Table 3. Panel A contains the cross-sectional means of variance ratios for the entire sample as well as for the 100 smallest, 100 intermediate, and 100 largest stocks. Cross-sectional standard deviations are given in parentheses below the main rows. Since the variance ratios are clearly not cross-sectionally independent, these standard deviations cannot be used to form the usual tests of significance; they are reported only to provide some indication of the cross-sectional dispersion of the variance ratios.

The average variance ratio for individual securities is less than unity when $q = 2$, implying that there is negative serial correlation on average. For all stocks, the average serial correlation is -3 percent, and -6 percent for the smallest 100 stocks. However, the serial correlation is both statistically and economically insignificant and provides little evidence against the random walk hypothesis. For example, the largest average $z^*(q)$ statistic over all stocks occurs for $q = 4$ and is -0.90 (with a cross-sectional standard deviation of 1.19); the largest average $z^*(q)$ for the 100 smallest stocks is -1.67 ($q = 2$, cross-sectional standard deviation of 1.75). These results complement French and Roll's (1986) finding that daily returns of individual securities are slightly negatively autocorrelated.

For comparison, Panel B reports the variance ratios of equal and value weighted portfolios of the 625 securities. The results are consistent with

those in Tables 1 and 2; significant positive autocorrelation for the equal-weighted portfolio, and less significant positive autocorrelation for the value-weighted.

That the returns of individual securities have statistically insignificant autocorrelation is not surprising. Individual returns contain much company-specific or "idiosyncratic" noise which makes it difficult to detect the presence of predictable components. Since the idiosyncratic noise is largely attenuated by forming portfolios, we would expect to uncover the predictable "systematic" component more readily when securities are combined. Nevertheless the negativity of the individual securities' autocorrelations is an interesting contrast to the positive autocorrelation of portfolio returns. Since this is a well-known symptom of infrequent trading, we consider such an explanation in the next section.

4. SPURIOUS AUTOCORRELATION INDUCED BY NON-TRADING.

Although we have based our empirical results on weekly data to minimize the biases associated with market micro-structure issues, this alone does not insure against their possibly substantial influences. In this section, we consider explicitly the conjecture that infrequent or non-synchronous trading may induce significant spurious correlation in stock returns.¹⁷ The common intuition for the source of such artificial serial correlation is that small capitalization stocks trade less frequently than larger stocks. Therefore, new information is impounded first into large-capitalization stock prices and then into smaller-stock prices with a lag. This lag induces a positive serial correlation in, for example, an equally-weighted index of stock returns. Of course, this induced positive serial correlation would be less pronounced in a value-weighted index. Since our rejections of the random walk hypothesis are most resounding for the equal-weighted index, they may very well be the result

of this non-trading phenomenon. To investigate this possibility, we consider the following simple model of nontrading.¹⁸

Suppose our universe of stocks consists of N securities indexed by i , each with the return generating process:

$$R_{it} = R_{Mt} + \varepsilon_{it} \quad i = 1, \dots, N. \quad (21)$$

R_{Mt} represents a factor common to all returns (e.g., the market) and is assumed to be an independently and identically distributed random variable with mean μ_M and variance σ_M^2 . The ε_{it} term represents the idiosyncratic component of security i 's return and it is also assumed to be i.i.d. (over both i and t), with mean 0 and variance σ_M^2 . The return-generating process may thus be identified with N securities each with a unit beta such that the theoretical R^2 of a market model regression for each security is 0.50.

Suppose that in each period t there is some chance that security i does not trade. One simple approach to modelling this phenomenon is to distinguish between the observed returns process and the virtual returns process. For example, suppose security i has traded in period $t-1$; consider its behavior in period t . If security i does not trade in period t , we define its virtual return as R_{it} (which is given by (21)), whereas its observed return R_{it}^0 is 0. If security i then trades at $t+1$, its observed return R_{it+1}^0 is defined to be the sum of its virtual returns R_{it} and R_{it+1} , hence non-trading is assumed to cause returns to cumulate. The cumulation of returns over periods of non-trading captures the essence of spuriously induced correlations due to the non-trading lag.

To calculate the magnitude of the positive serial correlation induced by non-trading, we must specify the probability law governing the non-trading event. For simplicity, we assume that whether or not a security trades may be

modelled by a Bernoulli trial, so that in each period and for each security there is a probability p that it trades and a probability $1 - p$ that it does not. It is assumed that these Bernoulli trials are i.i.d. across securities and, for each security, they are i.i.d. over time. Now consider the observed return R_t^O at time t of an equally-weighted portfolio:

$$R_t^O \equiv \frac{1}{N} \sum_i^N R_{it}^O . \quad (22)$$

The observed return R_{it}^O for security i may be expressed as:

$$R_{it}^O = X_{it}(0) \cdot R_{it} + X_{it}(1) \cdot R_{it-1} + X_{it}(2) \cdot R_{it-2} + \dots \quad (23)$$

where $X_{it}(j)$, $j = 1, 2, 3, \dots$ are random variables defined as:

$$X_{it}(0) \equiv \begin{cases} 1 & \text{If } i \text{ trades at } t. \\ 0 & \text{Otherwise.} \end{cases} \quad (24a)$$

$$X_{it}(1) \equiv \begin{cases} 1 & \text{If } i \text{ does not trade at } t-1 \text{ and } i \text{ trades at } t. \\ 0 & \text{Otherwise.} \end{cases} \quad (24b)$$

$$X_{it}(2) \equiv \begin{cases} 1 & \text{If } i \text{ trades at } t \text{ and does not trade at } t-1 \text{ and } t-2. \\ 0 & \text{Otherwise.} \end{cases} \quad (24c)$$

$$\vdots$$

The $X_{it}(j)$ variables are merely indicators of the number of consecutive periods before t in which security j has not traded. Using this relation, we have:

$$R_t^O = \frac{1}{N} \sum_i^N X_{it}(0) \cdot R_{it} + \frac{1}{N} \sum_i^N X_{it}(1) \cdot R_{it-1} + \frac{1}{N} \sum_i^N X_{it}(2) \cdot R_{it-2} + \dots \quad (25)$$

security's return is idiosyncratic and has zero expectation, the following approximation obtains:

$$R_t^o \approx \frac{1}{N} \sum_i X_{it}(0) \cdot R_{Mt} + \frac{1}{N} \sum_i X_{it}(1) \cdot R_{Mt-1} + \frac{1}{N} \sum_i X_{it}(2) \cdot R_{Mt-2} + \dots \quad (26)$$

It is also apparent that the averages $\frac{1}{N} \sum_i X_{it}(j)$ become arbitrarily close, again for large N , to the probability of j consecutive no-trades followed by a trade, i.e.:

$$\text{plim}_N \frac{1}{N} \sum_i X_{it}(j) = p \cdot (1 - p)^j \quad (27)$$

The observed equal-weighted return is then given by the approximation:

$$R_t^o \approx p \cdot R_{Mt} + p \cdot (1 - p) \cdot R_{Mt-1} + p \cdot (1 - p)^2 \cdot R_{Mt-2} + \dots \quad (28)$$

Using this expression, the general j^{th} -order autocorrelation coefficient $\rho(j)$ may be readily computed as:

$$\rho(j) \equiv \frac{\text{COV}[R_t^o, R_{t-j}^o]}{\text{VAR}[R_t^o]} = (1 - p)^j \quad (29)$$

Assuming that the implicit time interval corresponding to our single period is one trading day, we may also compute the weekly (five-day) first-order autocorrelation coefficient of R_t^o as:

$$\rho^W(1) = \frac{\rho(1) + 2\rho(2) + \dots + 5\rho(5) + 4\rho(6) + \dots + \rho(9)}{5 + 8\rho(1) + 6\rho(2) + 4\rho(3) + 2\rho(4)} \quad (30)$$

By specifying reasonable values for the probability of non-trading, we may calculate the induced autocorrelation using equation (30). To develop some intuition for the parameter p , observe that the total number of securities

which trade in any given period t is given by the sum $\sum_i^N X_{it}(0)$. Under our assumptions, this random variable has a binomial distribution with parameters (N, p) hence its expected value and variance are given by Np and $Np(1-p)$ respectively. Therefore, the probability p may be interpreted as the fraction of the total number of N securities which trades on average in any given period. A value of 0.90 implies that, on average, 10 percent of the securities do not trade in a single period.

Table 4 presents the theoretical daily and weekly autocorrelations induced by non-trading for non-trading probabilities of 10 to 50 percent. The first row shows that when (on average) 10 percent of the stocks do not trade each day, this induces a weekly autocorrelation of only 2.1 percent! Even when the probability of non-trading is increased to 50 percent (which is quite unrealistic), the induced weekly autocorrelation is 17 percent.¹⁹ We conclude that our rejection of the random walk hypothesis cannot be solely attributed to infrequent trading.

The positive autocorrelation of portfolio returns and the negative autocorrelation of individual securities is puzzling. Although our stylized model suggests that infrequent trading cannot fully account for the 30 percent autocorrelation of the equal-weighted index, the combination of infrequent trading and Roll's (1984) bid-ask effect may explain a large part of the small negative autocorrelation in individual returns.

One possible stochastic model which is loosely consistent with these observations is to let returns be the sum of a positively autocorrelated common component and an idiosyncratic white noise component. The common component induces significant positive autocorrelation in portfolios since the idiosyncratic component is trivialized by diversification. The white noise component reduces the positive autocorrelation of individual stock returns,

and the combination of infrequent trading and the bid-ask spread effects drive the autocorrelation negative. Of course, explicit statistical estimation is required to formalize such heuristics and, ultimately, what we seek is an economic model of asset prices which might give rise to such empirical findings. This is beyond the scope of our present paper, but is the focus of current investigation.

5. THE MEAN-REVERTING ALTERNATIVE TO THE RANDOM WALK.

Although the variance ratio test has shown weekly stock returns to be incompatible with the random walk model, the rejections do not offer any explicit guidance towards a more plausible model for the data. However, the pattern of the test's rejections over different base observation intervals and aggregation values q does shed considerable light on the relative merits of competing alternatives to the random walk. For example, one currently popular hypothesis is that the stock returns process may be described by the sum of a random walk and a stationary mean-reverting component, as in Summers (1986) and Fama and French (1987).²⁰ One implication of this alternative is that returns are negatively serially correlated for all holding periods. Another implication is that, up to a certain holding period, the serial correlation becomes more negative as the holding-period increases.²¹ If returns are in fact generated by such a process, then their variance ratios should be less than unity when $q = 2$ [since negative serial correlation is implied by this process]. Also, the rejection of the random walk should be stronger as q increases [larger $z^*(q)$ values for larger q].²² But Tables 1 and 2 and those in Lo and MacKinlay (1987a) show that both these implications are contradicted by the empirical evidence.²³ Weekly returns do not follow a random walk, but do not fit a stationary mean-reverting alternative any better

Of course, the negative serial correlation in Fama and French's (1987) study for long (three- to five-year) holding-period returns is, on purely theoretical grounds, not necessarily inconsistent with positive serial correlation for shorter holding-period returns. However, our results do indicate that the sum of a random walk and a mean-reverting process cannot be a complete description of stock price behavior.

6. CONCLUSION.

We have rejected the random walk hypothesis for weekly stock market returns using a simple volatility-based specification test. These rejections cannot be completely explained by infrequent trading or time-varying volatilities. The pattern of rejections indicate that a stationary mean-reverting model of Shiller and Perron (1985), Summers (1986), Poterba and Summers (1987), and Fama and French (1987) cannot account for the departures of weekly returns from the random walk.

As we stated in the introduction, the rejection of the random walk model does not necessarily imply the inefficiency of stock price formation. Our results do, however, impose restrictions upon the set of plausible economic models for asset pricing; any structural paradigm of rational price formation must now be able to explain this pattern of serial correlation present in weekly data. As a purely descriptive tool for examining the stochastic evolution of prices through time, our specification test also serves a useful purpose, especially when an empirically plausible statistical model of the price process is more important than a detailed economic paradigm of equilibrium. For example, the pricing of complex financial claims often depend critically upon the specific stochastic process driving underlying asset returns. Since such models are usually based upon arbitrage

of less consequence. One specific implication of our empirical findings is that the standard Black-Scholes pricing formula for stock index options is misspecified.

Although our variance-based test may be used as a diagnostic check for the random walk specification, it is a more difficult task to determine precisely which stochastic process best fits the data. The results of French and Roll (1986) for return variances when markets are open versus when they are closed adds yet another dimension to this challenge. The construction of a single stochastic process which fits both short and long holding-period returns data is one important direction for further investigation. However, perhaps the more pressing problem is to specify an economic model which might give rise to such a process for asset prices, and will be pursued in subsequent research.

FOOTNOTES

¹See, for example, the studies in Jensen's (1978) volume on anomalous evidence regarding market efficiency.

²The use of variance ratios is, of course, not new. Most recently, Campbell and Mankiw (1987), Cochrane (1987a, b), Fama and French (1987), French and Roll (1986), and Huizinga (1987) have all computed variance ratios in a variety of contexts. However, those studies do not provide any formal sampling theory for our statistics. Specifically, Cochrane (1987a), Fama and French (1986), and French and Roll (1986) all rely upon Monte Carlo simulations to obtain standard errors for their variance ratios under the null. Campbell and Mankiw (1987) and Cochrane (1987b) do derive the asymptotic variance of the variance ratio but only under the assumption that the aggregation value q grows with (but more slowly than) the sample size T . Specifically, they use Priestley's (1981, p. 463) expression for the asymptotic variance of the estimator of the spectral density of ΔX_t at frequency zero with a Bartlett window as the appropriate asymptotic variance of the variance ratio. But Priestley's result requires (among other things) that $q \rightarrow \infty$, $T \rightarrow \infty$, and $q/T \rightarrow 0$. In this paper, we develop the formal sampling theory of the variance ratio statistics for the more general case.

Our variance ratio may, however, be related to the spectral density estimates in the following way. Letting $f(0)$ denote the spectral density of the increments ΔX_t at frequency zero, we have the following relation:

$$\pi f(0) = \gamma(0) + 2 \cdot \sum_{k=1}^{\infty} \gamma(k)$$

where $\gamma(k)$ is the autocovariance function. Dividing both sides by the variance $\gamma(0)$ then yields:

$$\pi f^*(0) = 1 + 2 \cdot \sum_{k=1}^{\infty} \rho(k)$$

where f^* is the normalized spectral density and $\rho(k)$ is the autocorrelation function. Now in order to estimate the quantity $\pi f^*(0)$, the infinite sum on the right-hand side of the preceding equation must obviously be truncated. If, in addition to truncation, the autocorrelations are weighted using Newey and West's (1987) procedure, then the resulting estimator is formally equivalent to our $\bar{M}_r(q)$ statistic. Although he does not explicitly use this variance ratio, Huizinga (1987) does employ the Newey and West (1987) estimator of the normalized spectral density.

³Briefly, Hausman (1978) exploits the fact that any asymptotically efficient estimator of a parameter θ , say $\hat{\theta}_e$, must possess the property that it is asymptotically uncorrelated with the difference $\hat{\theta}_a - \hat{\theta}_e$ where $\hat{\theta}_a$ is any other estimator of θ . If not, then there exists a linear combination of $\hat{\theta}_e$ and $\hat{\theta}_a - \hat{\theta}_e$ which is more efficient than $\hat{\theta}_e$, contradicting the assumed efficiency of $\hat{\theta}_e$. The result follows directly then since:

$$\begin{aligned} \text{AVAR}[\hat{\theta}_a] &= \text{AVAR}[\hat{\theta}_e + \hat{\theta}_a - \hat{\theta}_e] = \text{AVAR}[\hat{\theta}_e] + \text{AVAR}[\hat{\theta}_a - \hat{\theta}_e] \\ \Rightarrow \text{AVAR}[\hat{\theta}_a - \hat{\theta}_e] &= \text{AVAR}[\hat{\theta}_a] - \text{AVAR}[\hat{\theta}_e] \end{aligned}$$

where $\text{AVAR}[\cdot]$ denotes the asymptotic variance operator.

⁴Note that if $(\hat{\sigma}_a^2)^2$ is used to estimate σ_0^4 , then the standard 't-test' of $J_d = 0$ will yield inferences identical to those obtained from the corresponding test of $J_r = 0$ for the ratio since

$$\frac{J_d}{\sqrt{2\hat{\sigma}_a^4}} = \frac{\hat{\sigma}_b^2 - \hat{\sigma}_a^2}{\sqrt{2} \hat{\sigma}_a^2} = \frac{J_r}{\sqrt{2}} \sim N(0, 1) .$$

⁵Proofs of all the theorems are given in the Appendix.

⁶According to the results of Monte Carlo experiments in Lo and MacKinlay (1987b), the behavior of the bias-adjusted M statistics [which we denote as $\bar{M}_d(q)$ and $\bar{M}_r(q)$] does not depart significantly from that of their asymptotic limits even for small sample sizes. Therefore, all our empirical results are based upon the $\bar{M}_r(q)$ statistic.

⁷See equations (A2-2) in the Appendix.

⁸Note the similarity between these variance ratios and the Box-Pierce Q-statistic which is a linear combination of squared autocorrelations with all the weights set identically equal to unity. Although we may expect the finite-sample behavior of the variance ratios to be comparable to that of the Q-statistic under the null hypothesis, they can have very different power properties under various alternatives. See Lo and MacKinlay (1987b) for further details.

⁹See, for example, Merton (1980), Poterba and Summers (1985), and French, Schwert, and Stambaugh (1987).

¹⁰Of course, second moments are still assumed to be finite otherwise the variance ratio is no longer well-defined; this rules out distributions with infinite variance such as those in the stable Pareto-Levy family (with characteristic exponent less than two) proposed by Mandelbrot (1963) and Fama (1965). We do, however, allow for many other forms of leptokurtosis, such as that generated by Engle's (1982) conditionally heteroscedastic ARCH process.

¹¹Condition (i) is the essential property of the random walk which we wish to test. Conditions (ii) and (iii) are restrictions on the degree of dependence and heterogeneity which are allowed and yet still permit some form of the law of large numbers and the central limit theorem to obtain. See White (1984) for the precise details.

asymptotically uncorrelated. This condition may be weakened considerably at the expense of computational simplicity; see footnote 12.

¹²Although this restriction on the fourth cross-moments of ϵ_t may seem somewhat unintuitive, it is satisfied for any process with independent increments (regardless of heterogeneity) and also for linear Gaussian ARCH processes. This assumption may be relaxed entirely, requiring the estimation of the asymptotic covariances of the autocorrelation estimators in order to estimate the limiting variance θ of $\bar{M}_r(q)$ via relation (18). Although the resulting estimator of θ would be more complicated than (20), it is conceptually straightforward and may be readily formed along the lines of Newey and West (1987). An even more general (and possibly more exact) sampling theory for the variance ratios may be obtained using the results of Dufour (1981) and Dufour and Roy (1985). Again, this would sacrifice much of the simplicity of our asymptotic results.

¹³The average (over all securities) fraction of the entire sample where this occurs is less than 0.5 percent of the time for the 1216-week sample period.

¹⁴Additional empirical results (304-week subperiods, larger q values, etc.) are reported in Lo and MacKinlay (1987a).

¹⁵Since the values of $z^*(q)$ are always smaller than the values of $z(q)$ in our empirical results, to conserve space we report only the more conservative statistics. Both statistics are reported in Lo and MacKinlay (1987a).

¹⁶We also performed our tests using value-weighted portfolios and obtained essentially the same results. The only difference appeared in the largest quintile of the value-weighted portfolio, for which the random walk hypothesis was generally not rejected. This, of course, is not surprising

given that the largest value-weighted quintile is quite similar to the value-weighted market index.

¹⁷See, for example, Scholes and Williams (1977) and Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983).

¹⁸Although our model is formulated in discrete time for simplicity, it is in fact slightly more general than the Scholes and Williams (1977) continuous-time model of non-trading. Specifically, Scholes and Williams implicitly assume that each security trades at least once within a given time interval by "ignoring periods over which no trades occur" (pg. 311), whereas our model requires no such restriction. As a consequence, it may be shown that, *ceteris paribus*, the magnitude of spuriously induced autocorrelation is lower in Scholes and Williams (1977) than in our framework. However, the qualitative predictions of the two models of non-trading are essentially the same. For example, both models imply that returns for individual securities will exhibit negative serial correlation, but that portfolio returns will be positively autocorrelated.

¹⁹Several other factors imply that the actual size of the spurious autocorrelations induced by infrequent trading are lower than those given in Table 4. For example, in calculating the induced correlations using equation (29), we have ignored the idiosyncratic components in returns due to diversification whereas, in practice, perfect diversification is never achieved. But any residual risk increases the denominator of (29) and does not necessarily increase the numerator (since the ϵ_{it} 's are cross-sectionally uncorrelated). To see this explicitly, we simulated the returns for 1000 stocks over 5120 days, calculated the weekly autocorrelations for the virtual returns and for the observed returns, computed the difference of those autocorrelations, repeated this procedure 20 times and then averaged the

differences. With a (daily) non-trading probability of 10 percent, the simulations yield a difference in weekly autocorrelations of 2.1 percent, 4.3 percent for a non-trading probability of 20 percent, and 7.6 percent for a non-trading probability of 30 percent.

Another factor which may reduce the spurious positive autocorrelation empirically is that, within the CRSP files, if a security does not trade its price is reported as the average of the bid-ask spread. As long as the specialist adjusts the spread to reflect the new information, even if no trade occurs the reported CRSP will reflect the new information. Although there may still be some delay before the bid-ask spread is adjusted, it is presumably less than the lag between trades.

Also, if it is assumed that the probability of no-trades depends upon whether or not the security has traded recently, it is natural to suppose that the likelihood of a no-trade tomorrow is lower if there is a no-trade today. In that case, it may readily be shown that the induced autocorrelation is even lower than that computed in our i.i.d. framework.

²⁰Shiller and Perron (1985) propose only a mean-reverting process (the Ornstein-Uhlenbeck process) whereas Poterba and Summers (1987) put forth the sum of a random walk and a stationary mean-reverting process. Although neither studies offer any theoretical justification for these processes, they both motivate their alternatives as models of investors' fads.

²¹If returns are generated by the sum of a random walk and a stationary mean-reverting process, their serial correlation will be a U-shaped function of the holding period; the autocorrelation becomes more negative as shorter holding-periods lengthen, but gradually returns to zero for longer holding-periods because the random walk component dominates. The curvature of this U-shaped function depends upon the relative variability of the random walk and

mean-reverting components. Fama and French's (1987) parameter estimates imply that the autocorrelation coefficient is monotonically decreasing for holding-periods up to three years, i.e., the minimum of the U-shaped curve occurs at a holding period greater than or equal to three years.

²²This pattern of stronger rejections with larger q is also only true up to a certain value of q . In view of Fama and French's (1987) results, this upper limit for q is much greater than 16 when the base observation interval is one week. See footnote 21.

²³See Lo and MacKinlay (1987b) for explicit power calculations against this alternative and against a more empirically relevant model of stock prices.

APPENDIX

Proof of Theorem 1:

Under the i.i.d. Gaussian distributional assumption of the null hypothesis H, $\hat{\sigma}_a^2$ and $\hat{\sigma}_b^2$ are maximum likelihood estimators of σ_0^2 with respect to data sets of every observation and every q-th observation respectively (the dependence of $\hat{\sigma}_b^2$ on q is suppressed for notational simplicity). Therefore, it is well-known that:

$$\sqrt{nq} (\hat{\sigma}_a^2 - \sigma_0^2) \stackrel{d}{\approx} N(0, 2\sigma_0^4) \quad (A1-1)$$

$$\sqrt{nq} (\hat{\sigma}_b^2 - \sigma_0^2) \stackrel{d}{\approx} N(0, 2q\sigma_0^4) . \quad (A1-2)$$

Since, under the null hypothesis H, $\hat{\sigma}_a^2$ is the maximum-likelihood estimator of σ_0^2 using every observation, it is asymptotically efficient. Therefore, following Hausman's (1978) approach, we conclude that the asymptotic variance of $\sqrt{nq} (\hat{\sigma}_b^2 - \hat{\sigma}_a^2)$ is simply the difference of the asymptotic variances of $\sqrt{nq} (\hat{\sigma}_b^2 - \sigma_0^2)$ and $\sqrt{nq} (\hat{\sigma}_a^2 - \sigma_0^2)$. Thus we have

$$\sqrt{nq} J_d(r) \equiv \sqrt{nq} (\hat{\sigma}_b^2 - \hat{\sigma}_a^2) \stackrel{d}{\approx} N(0, 2(q-1)\sigma_0^4) . \quad (A1-3)$$

The asymptotic distribution of the ratio then follows by applying the "delta-method" to the quantity $\sqrt{nq} (g(\hat{\sigma}_a^2, \hat{\sigma}_b^2) - g(\sigma_0^2, \sigma_0^2))$ where $g(u, v) \equiv \frac{v}{u}$, hence:

$$\sqrt{nq} J_r(q) = \sqrt{nq} \left(\frac{\hat{\sigma}_b^2}{\hat{\sigma}_a^2} - 1 \right) \stackrel{d}{\approx} N(0, 2(q-1)) . \quad (A1-4)$$

Q.E.D.

Proof of Theorem 2:

To derive the limiting distributions of $\sqrt{nq} M$ and $\sqrt{nq} M$ we require the

suppressed for notational convenience). Our approach is to re-express this variance estimator as a function of the autocovariances of the $(X_k - X_{k-q})$ terms and then employ well-known limit theorems for autocovariances. Consider the quantity:

$$\hat{\sigma}_c^2 = \frac{1}{nq^2} \sum_{k=q}^{nq} [X_k - X_{k-q} - q\hat{\mu}]^2 = \frac{1}{nq^2} \sum_{k=q}^{nq} \left[\sum_{j=1}^q (X_{k-j+1} - X_{k-j} - \hat{\mu}) \right]^2 \quad (\text{A2-1a})$$

$$= \frac{1}{nq^2} \sum_{k=q}^{nq} \left[\sum_{j=1}^q \hat{\eta}_{k-j+1} \right]^2 \quad (\text{A2-1b})$$

where $\hat{\eta}_{k-j+1} \equiv X_{k-j+1} - X_{k-j} - \hat{\mu}$. But then we have:

$$\hat{\sigma}_c^2 = \frac{1}{nq^2} \sum_{k=q}^{nq} \left[\sum_{j=1}^q \hat{\eta}_{k-j+1}^2 + 2 \sum_{j=1}^{q-1} \hat{\eta}_{k-j+1} \hat{\eta}_{k-j} + 2 \sum_{j=1}^{q-2} \hat{\eta}_{k-j+1} \hat{\eta}_{k-j-1} + \dots + 2 \hat{\eta}_k \hat{\eta}_{k-q+1} \right] \quad (\text{A2-2a})$$

$$= \frac{1}{nq^2} \left[q \sum_{k=1}^{nq} \hat{\eta}_k^2 - \sum_{k=1}^{q-1} ([q-k] \hat{\eta}_k^2 + k \hat{\eta}_{nq-q+k+1}^2) \right.$$

$$+ 2(q-1) \sum_{k=2}^{nq} \hat{\eta}_k \hat{\eta}_{k-1} - 2 \sum_{k=2}^{q-1} ([q-k] \hat{\eta}_k \hat{\eta}_{k-1} + [k-1] \hat{\eta}_{nq-q+k+1} \hat{\eta}_{nq-q+k})$$

$$+ 2(q-2) \sum_{k=3}^{nq} \hat{\eta}_k \hat{\eta}_{k-2} - 2 \sum_{k=3}^{q-1} ([q-k] \hat{\eta}_k \hat{\eta}_{k-2} + [k-2] \hat{\eta}_{nq-q+k+1} \hat{\eta}_{nq-q+k-1})$$

+ ...

$$+ 2 \sum_{k=q}^{nq} \hat{\eta}_k \hat{\eta}_{k-q+1}] \quad (\text{A2-2b})$$

$$= \hat{\gamma}(0) - o_p(n^{-\frac{1}{2}}) + \frac{2(q-1)}{q} \hat{\gamma}(1) - o_p(n^{-\frac{1}{2}}) + \frac{2(q-2)}{q} \hat{\gamma}(2) - o_p(n^{-\frac{1}{2}})$$

$$+ \dots + \frac{2}{q} \hat{\gamma}(q-1)$$

where $\hat{\gamma}(j) \equiv \frac{1}{nq} \sum_{k=j+1}^{nq} \hat{\eta}_k \hat{\eta}_{k-j}$ and $o_p(n^{-\frac{1}{2}})$ denotes a quantity which is of order smaller than $n^{-\frac{1}{2}}$ in probability. Now define the $q \times 1$ vector $\hat{\gamma} \equiv [\hat{\gamma}(0) \hat{\gamma}(1) \dots \hat{\gamma}(q-1)]'$. A standard limit theorem for sample autocovariances $\hat{\gamma}$ of a stationary time series with independent Gaussian increments is [see, for example, Fuller (1976, Chapter 6.3)]:

$$\sqrt{nq} (\hat{\gamma} - \sigma_o^2 e_1) \stackrel{d}{\approx} N(0, \sigma_o^4 [I_q + e_1 e_1']) \quad (A2-3)$$

where e_1 is the $q \times 1$ vector $[1 \ 0 \ \dots \ 0]'$ and I_q is the identity matrix of order q . Returning to the quantity $\sqrt{nq} (\hat{\sigma}_c^2 - \sigma_o^2)$, we have:

$$\begin{aligned} \sqrt{nq} (\hat{\sigma}_c^2 - \sigma_o^2) &= \sqrt{nq} [(\hat{\gamma}(0) - \sigma_o^2) + \frac{2(q-1)}{q} \hat{\gamma}(1) + \dots \\ &+ \frac{2}{q} \hat{\gamma}(q-1)] - \sqrt{nq} o_p(n^{-\frac{1}{2}}) . \end{aligned} \quad (A2-4)$$

Combining (A2-3) and (A2-4) then yields the following result:

$$\sqrt{nq} (\hat{\sigma}_c^2 - \sigma_o^2) \stackrel{d}{\approx} N(0, V_c) \quad (A2-5a)$$

where

$$V_c \equiv 2\sigma_o^4 + \left[\frac{2(q-1)}{q}\right]^2 \sigma_o^4 + \dots + \left(\frac{2}{q}\right)^2 \sigma_o^4 = 2\sigma_o^4 \left[\frac{2q}{3} + \frac{1}{3q}\right] . \quad (A2-5b)$$

Given the asymptotic distributions (A1-1) and (A2-5), Hausman's (1978) method may be applied in precisely the same manner as in Theorem 1 to yield the desired result:

$$\sqrt{nq} M_d(q) \stackrel{d}{\approx} N\left(0, \frac{2(2q-1)(q-1)}{3q} \sigma_o^4\right)$$

$$\sqrt{nq} M_r(q) \stackrel{d}{\approx} N\left(0, \frac{2(2q-1)(q-1)}{3q}\right) .$$

The distributional results for $\bar{M}_d(q)$ and $\bar{M}_r(q)$ follow immediately since asymptotically these statistics are equivalent to $M_d(q)$ and $M_r(q)$ respectively.

Q.E.D.

Proof of Theorem 3:

(a) We prove the result for $\bar{M}_r(q)$; the proofs for the other statistics follow almost immediately from this case. Define the increment process

$Y_t \equiv X_t - X_{t-1}$ and define $\hat{\rho}(\tau)$ as:

$$\hat{\rho}(\tau) \equiv \frac{\frac{1}{nq} \sum_{t=\tau}^{nq} (Y_t - \hat{\mu}) \cdot (Y_{t-\tau} - \hat{\mu})}{\frac{1}{T} \sum_{t=1}^T (Y_t - \hat{\mu})^2} \equiv \frac{A(\tau)}{B(\tau)}. \quad (A3-1)$$

Consider first the numerator $A(\tau)$ of $\hat{\rho}(\tau)$:

$$A(\tau) \equiv \frac{1}{nq} \sum_{t=\tau}^{nq} (Y_t - \hat{\mu}) \cdot (Y_{t-\tau} - \hat{\mu}) = \frac{1}{nq} \sum_{t=\tau}^{nq} (\mu - \hat{\mu} + \epsilon_t) \cdot (\mu - \hat{\mu} + \epsilon_{t-\tau}) \quad (A3-2a)$$

$$= \frac{nq-\tau+1}{nq} (\mu - \hat{\mu})^2 + (\mu - \hat{\mu}) \cdot \frac{1}{nq} \sum_{t=\tau}^{nq} \epsilon_t + (\mu - \hat{\mu}) \cdot \frac{1}{nq} \sum_{t=\tau}^{nq} \epsilon_{t-\tau} + \frac{1}{nq} \sum_{t=\tau}^{nq} \epsilon_t \epsilon_{t-\tau}. \quad (A3-2b)$$

$\hat{\mu}$ a.s.

Since $\hat{\mu} \rightarrow \mu$, the first term of (A3-2b) converges a.s. to zero as $nq \rightarrow \infty$. Moreover, under Assumption (A2) it is apparent that $\{\epsilon_t\}$ satisfies the conditions of White's [1984] Corollary 3.48, hence H*'s Condition (i) implies that the second and third terms of (A3-2b) also vanish a.s. Finally, because $\epsilon_t \epsilon_{t-\tau}$ is clearly a measurable function of the ϵ_t 's, $\{\epsilon_t \epsilon_{t-\tau}\}$ is also mixing with coefficients of the same size as $\{\epsilon_t\}$. Therefore, under Condition (ii), Corollary 3.48 of White [1984] may also be applied to $\{\epsilon_t \epsilon_{t-\tau}\}$ for which Condition (i) implies that the

fourth term of (A3-2b) converges a.s. to zero as well. By similar arguments, it may also be shown that

$$B(\tau) \equiv \frac{1}{nq} \sum_{t=1}^{nq} (Y_t - \hat{\mu})^2 \xrightarrow{\text{a.s.}} \sigma_0^2. \quad (\text{A3-3})$$

Therefore, we have $\hat{\rho}(\tau) \xrightarrow{\text{a.s.}} 0$ for all $\tau \neq 0$, hence we conclude:

$$\bar{M}_r(q) \xrightarrow{\text{a.s.}} 0 \text{ as } nq \rightarrow \infty.$$

- (b) By considering the regression of increments ΔX_t on a constant and lagged increments ΔX_{t-j} , this follows directly from White and Domowitz (1984). Taylor (1984) also obtains this result under the assumption that the multivariate distribution of the sequence of disturbances is symmetric.
- (c) This result follows trivially from equation (14) and Condition (iv).

Q.E.D.

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TABLE 1a

Variance ratio test $\bar{M}_t(q)$ of the random walk hypothesis for CRSP equal and value weighted indexes using a one-week base observation interval for the sample period September 6, 1962 to December 26, 1985 and sub-periods. The actual variance ratios are reported in the main rows, with the $z^*(q)$ statistics given in parentheses immediately below each main row.

Time period	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Equal-Weighted CRSP NYSE-AMEX Index.					
620906-851226	1216	1.30 (7.51)*	1.64 (8.87)*	1.94 (8.48)*	2.05 (6.59)*
620906-740501	608	1.31 (5.38)*	1.62 (6.03)*	1.92 (5.76)*	2.09 (4.77)*
740502-851226	608	1.28 (5.32)*	1.65 (6.52)*	1.93 (6.13)*	1.91 (4.17)*
B. Value-Weighted CRSP NYSE-AMEX Index.					
620906-851226	1216	1.08 (2.33)*	1.16 (2.31)*	1.22 (2.07)*	1.22 (1.38)
620906-740501	608	1.15 (2.89)*	1.22 (2.28)*	1.27 (1.79)	1.32 (1.46)
740502-851226	608	1.05 (0.92)	1.12 (1.28)	1.18 (1.24)	1.10 (0.46)

*Indicates significance at the 5 percent level.

Note: Under the random walk null hypothesis the value of the variance ratio is 1.0 and the test statistic has a standard normal distribution (asymptotically).

TABLE 1b

Variance ratio test $\bar{M}_r(q)$ of the random walk hypothesis for CRSP equal and value weighted indexes using a four-week base observation interval for the sample period September 6, 1962 to December 26, 1985 and sub-periods. The actual variance ratios are reported in the main rows, with the $z^*(q)$ statistics given in parentheses immediately below each main row.

Time period	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Equal-Weighted CRSP NYSE-AMEX Index.					
620906-851226	304	1.15 (2.26)*	1.19 (1.54)	1.30 (1.52)	1.30 (1.07)
620906-740501	152	1.13 (1.39)	1.23 (1.32)	1.40 (1.46)	
740502-851226	152	1.15 (1.68)	1.11 (0.64)	1.02 (0.09)	
B. Value-Weighted CRSP NYSE-AMEX Index.					
620906-851226	304	1.05 (0.75)	1.00 (0.00)	1.11 (0.57)	1.07 (0.26)
620906-740501	152	1.02 (0.26)	1.04 (0.26)	1.12 (0.46)	
740502-851226	152	1.05 (0.63)	0.95 (-0.31)	0.89 (-0.42)	

*Indicates significance at the 5 percent level.

Note: Under the random walk null hypothesis the value of the variance ratio is 1.0 and the test statistic has a standard normal distribution (asymptotically).

TABLE 2

Variance ratio test $\bar{M}_r(q)$ of the random walk hypothesis for size-sorted portfolios using a one-week base observation interval for the sample period September 6, 1962 to December 26, 1985 and sub-periods. The actual variance ratios are reported in the main rows, with the $z^*(q)$ statistics given in parentheses immediately below each main row.

Time period	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Portfolio of firms with market values in smallest NYSE-AMEX quintile.					
620906-851226	1216	1.42 (8.81)*	1.97 (11.58)*	2.49 (11.92)*	2.68 (9.65)*
620906-740501	608	1.37 (6.12)*	1.83 (7.83)*	2.27 (7.94)*	2.52 (6.68)*
740502-851226	608	1.49 (6.44)*	2.14 (8.66)*	2.76 (9.06)*	2.87 (7.06)*
B. Portfolio of firms with market values in central NYSE-AMEX quintile.					
620906-851226	1216	1.28 (7.38)*	1.60 (8.37)*	1.84 (7.70)*	1.91 (5.78)*
620906-740501	608	1.30 (5.31)*	1.59 (5.73)*	1.85 (5.33)*	2.01 (4.42)*
740502-851226	608	1.27 (5.31)*	1.59 (5.73)*	1.80 (5.33)*	1.69 (4.42)*
C. Portfolio of firms with market values in largest NYSE-AMEX quintile.					
620906-851226	1216	1.14 (3.82)*	1.27 (3.99)*	1.36 (3.45)*	1.34 (2.22)*
620906-740501	608	1.21 (4.04)*	1.36 (3.70)*	1.45 (2.96)*	1.44 (2.02)*
740502-851226	608	1.09 (1.80)	1.20 (2.18)*	1.27 (1.95)	1.18 (0.87)

*Indicates significance at the 5 percent level.

Note: Under the random walk null hypothesis the value of the variance ratio is 1.0 and the test statistic has a standard normal distribution (asymptotically).

TABLE 3

Means of variance ratios over individual securities with complete return histories from September 2, 1962 to December 26, 1985 (625 stocks). Means of variance ratios for the smallest 100 stocks, the middle 100 stocks, the largest 100 stocks, are also reported. For purposes of comparison, the final two rows report the variance ratios for equal and value weighted portfolios respectively of all 625 stocks. Parenthetical entries for averages over individual securities are standard errors of the cross-section of variance ratios. Parenthetical entries for portfolio variance ratios are the heteroscedasticity-robust $z^*(q)$ statistics. All variance ratios are computed with a base observation interval of one week.

SAMPLE	Number nq of base observations	Number q of base observations aggregated to form variance ratio			
		2	4	8	16
A. Averages of variance ratios over individual securities.					
All Stocks (625 Stocks)	1216	0.97 (0.05) ¹	0.94 (0.08)	0.92 (0.11)	0.89 (0.15)
Small Stocks (100 Stocks)	1216	0.94 (0.06)	0.91 (0.10)	0.90 (0.13)	0.88 (0.18)
Medium Stocks (100 Stocks)	1216	0.98 (0.05)	0.97 (0.09)	0.96 (0.12)	0.93 (0.15)
Large Stocks (100 Stocks)	1216	0.97 (0.04)	0.94 (0.07)	0.86 (0.11)	0.86 (0.17)
B. Variance ratios of equal and value weighted portfolios of all stocks.					
Equal-Weighted Portfolio (625 Stocks)	1216	1.21 (5.94)*	1.64 (6.71)*	1.65 (6.06)*	1.76 (4.25)*
Value-Weighted Portfolio (625 Stocks)	1216	1.04 (1.30)	1.08 (1.24)	1.12 (1.16)	1.12 (0.76)

*indicates significance at the 5 percent level.

¹Because the variance ratios are not cross-sectionally independent, the standard errors cannot be used to perform the usual significance tests; they are reported only to provide an indication of the cross-sectional dispersion of the variance ratios.

TABLE 4

Magnitudes of spurious autocorrelations of returns induced by the non-trading phenomena for daily non-trading probabilities $1 - p$ of 10 to 50 percent. The theoretical values of daily j -th order autocorrelations $\rho(j)$ and weekly first-order autocorrelation $\rho^W(1)$ are all zero in the absence of the non-trading problem.

Probability of Non-trading $1 - p$	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	$\rho^W(1)$
0.10	0.1000	0.0100	0.0010	0.0001	0.0000	0.0211
0.20	0.2000	0.0400	0.0080	0.0016	0.0003	0.0454
0.30	0.3000	0.0900	0.0270	0.0081	0.0024	0.0756
0.40	0.4000	0.1600	0.0640	0.0256	0.0102	0.1150
0.50	0.5000	0.2500	0.1250	0.0625	0.0312	0.1687