# Market Liquidity, Capitalization and the Random Walk Behavior of Stock Prices

Kamil Yilmaz*

Koç University

First Draft: March 2004
Revised: December 2005

**Abstract**

Variance ratio based tests are applied to moving windows of weekly NYSE-AMEX market indices and the capitalization-based decile indices from July 1962 to September 2003. The graphical and regression analysis of test statistics and market indicators demonstrate that serial correlation in returns is inversely related to liquidity and size throughout most of the sample. Stock prices tend to converge towards random walk as market capitalization and liquidity increase. However, this relationship between market indicators and serial correlation in returns has weakened or, as in the case of large-capitalization deciles, been reversed during the internet bubble of late 1990s and 2000.

**JEL classification:** G10, G14.
**Key words:** Serial correlation in stock returns; Joint variance ratio tests; Market development; Market indicators.

* This paper was written while I was a Visiting Professor at the Department of Economics, University of Pennsylvania. I am grateful to Frank Diebold, Celso Brunetti, Craig MacKinlay and participants at the Econometrics Lunch Seminar for helpful comments.
Correspondence Address: Kamil Yilmaz, Department of Economics, Koç University, Rumelifeneri Yolu, Sarıyer 34450 Istanbul Turkey. email: kyilmaz@ku.edu.tr.

## I. Introduction

The objective of this paper is to empirically study the link between market development indicators, such as market capitalization and liquidity measures, and the behavir of stock prices from 1962 to 2002.[1] Both in terms of size and liquidity (see Figure 1) as well as trading technology and the effectiveness of regulatory system US stock markets have evolved remarkably since 1960s. Total market value of all stocks traded in the NYSE and AMEX markets together increased from $1.66 trillion in July 1962 to $7.8 trillion (in constant 1995 prices) in December 2002. During the same time interval, trade volume increased from 92 million to 35.3 billion shares a month and the value of shares traded in a month increased from $15.4 billion to $748 billion (in constant 1995 prices).

An analysis of short-horizon stock returns over a 40-year period of substantial development and change needs to take into account the possible effects of the market development on the behavior of stock prices. In their recent book, Andrew Lo and Craig MacKinlay (Lo and MacKinlay, 1999) recognize this possibility while re-evaluating the results of their previous research in light of the recently available data. In their frequently cited paper Lo and MacKinlay (1988) show that between 1962 and 1985 the behavior of equal-weighted index as well as the small- and medium-sized portfolio indices was not consistent with the random walk behavior. At the time they conclude that the rejection of random walk behavior was an indication of the availability of profitable opportunities in the U.S. stock markets. In Lo and MacKinlay (1999) they repeated the same test and failed to reject the random walk behavior for the period 1986-1996. The authors interpreted this finding as the result of investors' better exploitation of profit opportunities (see Lo and MacKinlay, 1999, pg. 16). They argued that using better trading techniques

[1] Following the common approach in the literature we use "random walk" in place of "martingale", even though it is well known that random walk is a more restrictive model than the martingale. For example, risk neutrality of all agents implies the martingale but not the random walk behavior (Leroy 1989).

[2] Lo and MacKinlay (1989) reported Monte Carlo calculations showing that variance ratio test had better size and power performance compared to two alternative unit root test, namely, Dickey-Fuller's *t*-test and Box-Pierce portmanteau Q-test. In other words, when the focus is the absence of correlation among the increments the variance ratio test is preferred.

(“statistical arbitrage”) and strategies, investment companies and investors helped bring the profit margins down and made the market even a more competitive environment in which the stock prices converged towards the random walk.

In a cross country context, market indicators are used as a measure of the development level stock markets reached over time. The more developed a stock market is the more efficient it is expected to be and hence contribute positively to the economic growth of the country through facilitating investment (see Demirgüç-Kunt and Levine, 1996, Levine and Zervos, 1998).

This paper is closely related to the literature on the relationship between trading volume and the serial correlation in stock returns. Morse (1980) was the first to analyze this relationship. Using daily price data for 50 US stocks between 1973 and 1976, Morse (1980) shows that individual stock returns tended to be positively serially correlated during periods of high-volume. Morse (1980) explains these results with an asymmetric information framework. When trading volume is high, price adjustment to new information is not instantenous because during periods of high trading volume investors with very different information sets operate in the market. Investors with informational disadvantages act after the more-informed investors. This process by itself generates serial correlation in stock returns.

Subsequent work on the topic obtained results that were not in agreement with Morse’s (1980) findings. Using daily data on S&P 500 index, Dow-Jones Industrial Average index, and 32 large individual stock prices, Campbell, Grossman and Wang (1993) show that the first-order serial correlation of daily returns is lower when trading volume is high. They develop a model of a stock market in which trading volume acts as a measure of the total demand of liquidity traders. In this model, the interaction between the informed and uninformed (noise or liquidity) traders generates serial correlation of returns that declines with trade volume.

Using monthly data, Duffee (1992) also finds evidence in support of an inverse relationship between trade volume and serial correlation in stock returns. In both 1915-1945 and 1946-1989 periods positive shocks to trading volume in NYSE generated substantial degree of return reversal, implying a lower serial correlation for monthly stock returns. Conrad, Hameed and Niden (1992) study the relationship between the lagged trading volume and serial correlation of returns in a cross section of stocks. Their results show that while stocks with high lagged trading volume experience return reversals, stocks with low lagged trading volume have positive serial correlation in returns. Finally, LeBaron (1992) shows that serial correlation of daily and weekly return series tended to decrease during times of high volatility. To the extent that trading volume and volatility are positively correlated, the results of LeBaron (1992) are consistent with the findings of Campbell et. al. (1993).

With the exception of Morse (1980) all studies we summarized above have found support for an inverse relationship between trading volume and the predictability of stock returns. One reason for the differences in findings could be the choice of stocks/indices and the time period. In our framework, we apply random walk test procedures to value- and equal-weighted market indices for NYSE and AMEX as well as the capitalization-based decile indices over 500-week long moving windows. Our framework, therefore, allows for the possibility of variation in the trading volume-stock return relationship at different time periods and for different stocks/indices.

Following Fong *et al.* (1997) we use two joint variance ratio test procedures. The first one is the multiple comparison test (MCT) proposed by Chow and Denning (1993). MCT is based on comparisons among variance ratios of different lags and chooses the variance ratio test statistics with the highest absolute value as the joint test statistic. In calculating the variance ratio test statistics for different return horizons, we follow Lo and MacKinlay (1988) and obtain heteroscedasticity-consistent variance ratio test statistics. The VR test statistic can be used to test the weakest form of the random walk hypothesis: Increments to exchange rates are serially uncorrelated at all leads and lags. The second joint VR test is the Wald test developed by Richardson and Smith (1991). Unlike MCT, Richardson-Smith Wald test (RSWT) explicitly incorporates the serial correlation among variance ratios caused by overlapping observations in the process of calculating the test statistic. RSWT does not necessarily dominate MCT, because unlike MCT it does not allow for the possibility of heteroscedastic increments.

The rest of the paper is organized as follows. Section II presents the empirical methodology and the test procedures used. Section III presents test results for the full sample as well as for the moving subsample windows. Section IV concludes the paper.

## II. The Conceptual Framework and Tests of Random Walk Behavior

There are several versions of the random walk hypothesis (See Lo and MacKinlay, 1988). In this paper, the weakest form of the random walk hypothesis, namely, the increments to stock prices are uncorrelated (but not independent), is adopted. All tests of the weak-form random walk hypothesis are related to the correlogram of stock returns and evaluate if the autocorrelation coefficients at different lags and leads are equal to zero. Since tests of random walk do not run the risk of misspecification of the alternative hypothesis, they are expected to be theoretically reliable. In practice, however, they were found to have quite low statistical power. Consequently, even when stock prices follow random walk behavior, random walk hypothesis can be on occasion rejected. Among the random walk tests that rely on alternative representations of the autocorrelogram of the return series are the variance ratio test (Cochrane, 1987, Diebold, 1988, Lo and MacKinlay, 1988, and Poterba and Summers, 1988), Fama and French's (1988) regression test and Jegadeesh's (1991) regression test.

Variance ratio test is a weighted-sum of estimated autocorrelation coefficients, with the weights declining in return horizon. Being a two-tailed test, the rejection by the variance ratio test reveals information about autocorrelation structure. If the variance ratios at different return horizons are greater (smaller) than one, then one cannot reject the hypothesis that stock returns are positively (negatively) serially correlated. Accordingly, a value of one for the variance ratio means that stock prices follow random walk.

Lo and MacKinlay's variance ratio test differs from others (mainly from the one used by Cochrane, 1987, and Poterba and Summers, 1988) because it takes into account the possibility that stock returns are heteroscedastic. If the returns (also called as the increments to stock prices) are uncorrelated, the sum of the variances of the increments should be equal to the sum of their variances and the variance ratio should move closer to one even with heteroscedastic disturbances. The asymptotic variance will depend on the degree and type of the heteroscedasticity present. Rather than specifying the form of heteroscedasticity in increments, Lo and MacKinlay (1988) followed White (1980) to derive variance ratio estimates that allow for general forms of heteroscedasticity. Lo and MacKinlay (1988) made use of the relationship between the variance ratio and autocorrelation coefficients to derive the asymptotic distribution of the variance ratio estimator under heteroscedastic disturbances.

Lo and MacKinlay's heteroscedasticity-consistent variance ratio test statistic, $z^*(q)$, is used to test the null hypotheses for a specific aggregation value (holding period), $q$. If $z^*(q)$ is greater than the critical value of the standard normal distribution, then the random walk hypothesis is rejected. However, because variance ratios may be statistically close to 1 for some $q$, and different from 1 for others, variance ratio test procedure based on various holding periods can easily lead to inconclusive results. [2]

Chow and Denning (1993) proposed a solution to this problem. They used Hochberg's (1974) theorem on multiple comparison tests and extended Lo and MacKinlay variance ratio test to incorporate joint comparison of selected variance ratios with one. Taking $k$ Lo-MacKinlay variance ratio test statistic, $z^*(q_i)$s, for $i=1,2,...,k$, that have standard normal distribution under the random walk null hypothesis, and using Bonferroni probability inequality, Hochberg (1974) test amounts to picking up the test statistic $z^*(q_i)$ with the largest absolute value. Hochberg (1974) showed that the largest absolute value of these $k$ standard normal variates has a Studentized Maximum Modulus (SMM) distribution with $k$ and $nq$ (sample size) degrees of freedom.

Critical values for the SMM distribution are greater than the critical values for the standard normal distribution. This is not surprising given that the MCT statistic is the maximum of the variance ratio test statistic for all selected holding periods. Chow and Denning (1993) applied MCT to U.S. stock market indices between 1962 and 1985 and found statistical evidence to reject the random walk hypothesis for the equal-weighted index, but not for the value-weighted index.

The other joint variance ratio test used in this paper is developed by Richardson and Smith (1991), and makes explicit use of the serial correlation among variance ratios when the observations used to calculate variance ratios overlap. When one wants to calculate variance ratios for four-day return horizons using a sample of 100 observations, s/he can obtain 25 variance ratios if the return horizons are not allowed to overlap. Alternatively, if the return horizons are allowed to overlap then one could obtain 97 variance ratios. Obviously, using overlapping observations will substantially increase the sample-size from which to calculate variance ratios. However, the distribution of variance ratios of different return horizons, calculated from overlapping data, is likely to be nonnormal, because of the serial correlation among the variance ratios. Taking this fact into account, Richardson and Smith (1991) developed a variance-ratio-based Wald test which corrects for the nonnormality of the overlapping variance ratios.

## III. Empirical Analysis: Joint Variance Ratio Tests on Moving Subsample Windows

In the empirical analysis weekly rather than daily or monthly stock returns data are used. Monthly stock price series are not used because that would reduce the number of observations significantly, the use of which will lead to small sample bias in the multiple comparison test. On the other hand, daily returns are not used because of the high-degree of spurious correlation that might be generated by infrequent trading of many stocks. Following Lo and MacKinlay (1988), random walk is tested using weekly Wednesday-to-Wednesday excess stock returns.

### A. The analysis over the full-sample period

Before the analysis of the returns for moving subsample windows, first descriptive statistics for weekly Wednesday returns are presented in Table 1 to highlight the characteristics of stock return series for the full sample. Average weekly stock returns for size-based deciles vary from 0.10 percent for Decile 10 to 0.25 percent for Decile 1. The average return for the bottom size-based decile portfolio is two and a half time the return for the top decile portfolio. Volatility is the highest for the bottom decile and the lowest for the top decile of stocks. Altogether returns for decile indices are not normally distributed. Jarque-Bera test rejects normality strongly. The returns for all decile groups have excess kurtosis and some degree of skewness.

Table 2 presents the variance ratios and heteroscedasticity-consistent variance ratio test statistic ($z^*$) for 2, 4, 8, 16 and 32-week return horizons as well as the MCT test statistics for the full sample. For each index MCT statistic is the maximum of the $z^*$ statistics for 5 return horizons considered. To give an example, the MCT statistic for Decile 5 is 9.23, being the VR test ($z^*$) statistic for 4-week return horizon, it's the highest absolute value among $z^*$ for Decile 5. The variance ratio for 4-week return horizon is 1.51 which indicates that the decile 5 stock index returns are positively serially correlated. Having a studentized maximum modulus distribution, MCT statistic is above the critical value and hence rejects the random walk. The same is true for the RSWT, which is presented in the last column of Table 2.

As can be seen from the first two rows of Table 2, both tests reject the random walk hypothesis for the equal-weighted market index, but not for the value-weighted market index. Consistent with this result, the random walk hypothesis is rejected for all capitalization-based decile indices, expect the top-decile. The behavior of stock prices from the top decile dominates the value-weighted index but not the equal-weighted index. It is also important to note that with the exception of value-weighted index and the top decile index, variance ratios are greater than one at all return horizons (holding periods) considered. This implies that throughout the 1962-2003 period returns for these stock indices were positively serially correlated, a result consistent with Lo and MacKinlay's findings for 1962-1985 sample.

In the rest of the paper, we move beyond the results in Table 2 and conduct tests of random walk behavior on moving sub-sample windows. Based on power calculations by Lo and MacKinlay (1989) we choose 500-weeks as the length of the moving windows in order to insure that test procedures do not suffer from inadequate statistical power. In the implementation of the 500-week long moving windows analysis, we include the observations for the first 500 weeks in the first subsample (July 1962 - February 1972) and calculate the test statistic. Moving the 500-week window one-week ahead we recalculate the test statistic and repeat this exercise until the end of the sample, September 2003, is reached.

## B. Moving windows analysis of value- and equal-weighted indices

We first apply the moving windows approach to value- and equal-weighted price indices for all stocks traded in the NYSE and AMEX markets. However, before proceeding further with the analysis of value- and equal-weighted indices, it is imperative to discuss the role of outliers in random walk tests. ~~Yilmaz (2003) showed that the presence of outliers could have significant impact on MCT and RSWT results, generating big jumps in the test statistic for moving windows.~~ The removal of outliers creates a smoother trajectory of the test statistics as the windows are rolled over. In the case of U.S. stock markets, the crash of October 1987 generated outlier returns that affect the test results. For that reason, we report the moving window MCT results after dropping three observations during the market crash in October 1987 (October 21, 28 and November 4). MCT results for value- and equal-weighted indices after dropping outliers are presented in Figure 2. Aside from the results without outliers, in the appendix we report MCT results for value- and equal-weighted indices using all observations in order to make sure the reasons for dropping the outliers are clear (see Figure A1).

Figure 2 presents MCT statistics and the corresponding variance ratios (the maximum of Lo and MacKinlay's $z^*$ test statistics that are calculated for 2, 4, 8, 16, and 32 week return horizons) for moving windows of value- and equal-weighted market indices. In the case of value-weighted index, the plot of MCT statistics (Panel b) shows that random walk is rejected for the windows that cover the observations for the 1960s. After the 1960s, however, the value-weighted price index behaved very much like a random walk until the observations for 1990s are included in the subsample window. As the data for 1990s are included in the windows, the MCT starts to move closer to the rejection region. For all windows that cover the period before 1980s, the variance ratio is greater than one (see Panel A), implying positive serial correlation, but for the most of these windows it is not statistically different from one except for the early 1960s. The behavior of value-weighted index changed somewhat in the 1990s (Figure 2, Panel A). The variance ratios slowly moved from above one to below one (not necessarily statistically different from one) once the data for 1990s are included in the subsample windows. The plot of the MCT statistics shows that there was deviation from random walk in the earlier part of the sample and the test statistic moved closer and closer to the rejection region towards the end of the sample (Figure 2, Panel B).

The analysis of equal-weighted index leaves no room for alternative interpretations. MCT statistic rejects random walk hypothesis for equal-weighted market index in all subsample windows considered. Variance ratio is always above 1.0, indicating that weekly returns of equal-weighted index are positively correlated. Even though the test statistic is always greater than the 5% critical value it declines towards the non-rejection region as the observations for 1991 and the subsequent years are dropped.

Before moving further in the analysis we compare the plots in Figure 2 (based on a sample after dropping three observations pertaining to the October 1987 market crash) with the plots without dropping any observations (Figure A1). The case for dropping the outliers is clear in the case of equal-weighted indices. In panel (d) of Figure A1 there is a downward jump in the MCT statistics as soon as the subsample windows are moved to include data pertaining to the October 1987 market crash. The downward jump is large enough that all of a sudden the MCT statistic falls below the critical region. As soon as these observations are dropped from the subsample window the test statistic jumps up again. These jumps are not observed once we drop three outliers from the full sample.

The impact of outlier observations on test statistics is more subtle in the case of value-weighted index compared to the equal-weighted index. The exclusion of outliers results in higher test statistics reaching the rejection region faster. When the full data set is used, the test statistics for windows with end-points from 1992 to 1997 stay significantly lower than 1.0 (panel (b) of Figure A1), but when the outliers are dropped the test statistics for the same windows are all above 1.0 and moving closer to the rejection region as the windows are moved further.

Even though the impact of the presence of outliers of the October 1987 crash on test results are negligible in the case of the value-weighted index, because of the substantial impact on test results for the equal-weighted index, in the rest of the paper we exclude the observations for October 21, 28 and November 4, 1987 from the return series.

After analyzing the behavior of test statistics for the equal- and value-weighted indices over time, we turn to the analysis of test results along with the market indicators. We plot the MCT statistics for the value- and equal-weighted indices and the major market indicators. Since stock market indicators are expected to be exogenous to the test statistics, it is not wrong to interpret any relationship present to be a causal one from market indicators to test statistics. As we have already discussed above, the test statistic is expected to move toward the non-rejection region as markets develop over time. Figure 3a and 3b present the scatter plots of MCT statistics for value- and equal-weighted indices, respectively, and market statistics.

In the case of the value-weighted index it is difficult to discern any relationship between average market indicators and MCT statistic for moving windows (see Figure 3a). While the test statistic sometimes increases with the market indicators, in some other instances we observe a negative impact of market indicators on test statistics. Even though, the MCT statistic sometimes increase with market indicators it for the most part lies in the non-rejection region.

The case is quite different for the equal-weighted index in Figure 3b. There is definitely an inverse relationship between the average market indicators and the MCT statistics for moving windows. At low levels of MC/GDP, the relationship tends to be strongly negative. Yet, as the MC/GDP increases and hence the MCT statistic moves closer to the non-rejection region, the relationship weakens. It is possible to interpret this result as, the market capitalization and other market indicators become less crucial for the serial correlation in stock returns as the level of market development reached a certain threshold. However, it is too soon to reach a conclusion without analyzing the behavior of test statistics for size-based decile portfolios.

Figures 4a and 4b present scatter plots of MCT statistics over the average of major market indicators for value- and equal-weighted indices over the subsample window. There is direct relation between the average market capitalization and the MCT statistic. After slightly increasing for low levels of market indicators, MCT statistic declines as the market capitalization and liquidity increase. However, as the market indicators continue to increase the relationship weakens, as can be observed in the flat region of scatter plots in Figure 3b. The test statistics falls below the 5% critical value in a few instances only, which can be claimed to be exceptions rather than the rule. The stocks tend to move towards random walk behavior as the market liquidity and capitalization increase, yet the random walk behavior is not dominant among the stocks with with lower market capitalization and liquidity. We then ask the question: How widespread is the convergence towards random walk behavior among the NYSE/AMEX stocks? In order to seek an answer to this question, in the next section we apply test procedures to market-capitalization-based decile portfolio indices.

## C. Moving windows analysis of market-capitalization-based deciles

Our analysis of the test statistics for the value- and equal-weighted indices shows that there had been convergence towards the random walk behavior among the NYSE/AMEX stocks as the major market indicators increase over time. In order to study the extent of the move towards random walk behavior we conduct the random walk tests on market-capitalization-based decile portfolio indices. For each decile portfolio, we analyze the relationship between test statistics and the market indicators.

Time series plots of MCT and RSWT statistics for 500-week fixed-length moving windows of size-based decile portfolio indices are presented in Figure 4a and 4b, respectively. There are 10 sub-graphs each of which belongs to a market-capitalization-based deciles of stocks traded in the NYSE and AMEX markets. The test statistics for each moving window is measured on the y-axis. As the subsample window is moved forward, one weekly observation is added to the end of the subsample window while one weekly observation is dropped from the beginning of the window. The straight line indicates the 5% critical value for each test.[3]

In Figure 4a there is a downward trend in the MCT statistic for all but the top decile as the 500-week long window is moved forward in time. During the earlier parts of the full sample, covered by windows with end-points up to February 1984 only the stock price index for the top decile could be classified as following random walk. The trend becomes even more pronounced in the decile portfolios with larger capitalization (deciles 5 through 9). Before the downward trend starts, however, the test statistic first increases slightly for windows with starting points between July 1962 and mid-1965 (end points between February 1972 and February 1975). Despite the ensuing downward trend, the MCT statistic for deciles 1 through 5 never falls below the 10% critical value. In the case of deciles 6 through 9, the downward trend leads to the non-rejection region. Especially in the case of deciles 8 and 9, the test statistic fails to reject random walk hypothesis for windows with starting points that cover the period from 1978 to 1994 (with end points that cover the period from 1987 and 2003).

Figure 4a establishes that over time large-capitalization decile indices (especially deciles 7 through 9) started converged towards random walk behavior. However, there is a slight reversal in the

---

[3] The critical values for MCT are obtained from Hahn and Hendrickson (1971) and for the RS Wald test they are the chi-square value for 0.05 and 5 degrees of freedom (for 5 different variance ratio statistics are used for 2, 4, 8, 16 and 32 weeks).

downward trend of the MCT statistics. After declining for a long period, with the inclusion of data that pertain to 1990s the test statistic starts to increase. For deciles 8 and 9, the increase in MCT statistic does not lead to all the way up to the rejection region. In the case of the top decile portfolio index, however, the upward trend starts as early as the windows with starting points in 1990 and the upward trend leads to the rejection region as the subsample windows is moved in time to include data for 1996 and later. This is an interesting result by itself. While US stock markets get better and better in terms of pricing stocks of almost all sizes, they become worse in terms of pricing the largest capitalization stocks.

The reversal of the downward trend is even more pronounced in the case of RSWT (Figure 4b). Despite the recurrent upward spikes in the plots, RSWT statistics also has a downward trend for windows with ending-points after the mid-1970s. RSWT plots differ from MCT plots only for deciles 8 and 9. Even for decile 8 and 9 indices, RSWT started to reject the random walk hypothesis once the data for 1998 and 1999 are included in the subsample window.

Time series plots provide evidence about the downward trend in the test statistics. However, as we have seen in the case of equal-weighted index, the test statistic is inversely related to major market indicators. In order to reach more conclusive results about the random walk behavior of stock prices we analyze the link between market indicators and test statistics for decile portfolios. As the underlying data to obtain market indicators for decile portfolios are available on a monthly frequency only, we first transform the MCT and RSWT statistics from weekly to monthly frequency by simply using the average of the test statistics obtained from the moving-windows ending in that month. Then we obtain the monthly market indicators for each decile portfolio using the monthly CRSP data on number of shares outstanding, value and number of shares traded. The market indicators that we use are the market capitalization/GDP ratio, the trade volume (number of shares traded) and the turnover ratio (defined here as the value of traded shares/market capitalization ratio).[4] Finally, taking the average of each indicator

[4] CRSP tapes include monthly data on market value, trade volume (number of traded shares) and value (value of traded stocks) for each stock. Aggregating these values over stocks in each decile portfolio and month we obtain the

over the length of each subsample window (so that they correspond to the test statistic in time) we create three series of monthly frequency.

Having created separate monthly market indicators for each decile portfolio, we will next generate scatter plots of test statistics over average market statistics for moving subsample windows. However, before moving to scatter plots we plot time series graphs of both variables. Figure 5a and Figure 5b present separate plots of MCT and RSWT statistics at monthly frequency along with the average market capitalization/GDP ratio for moving windows. Figure 5a and 5b reveal two major trends. Average MC/GDP ratio declines starting with the first 500-week-long window in the sample (July 1962-February 1972) through the window that covers March 1973-October 1982. The decline in MC/GDP ratio is faster in the case of smaller capitalization deciles, but slower for the larger capitalization deciles. In the case of deciles 2 through 9, as the average MC/GDP ratio is declining the MCT statistic first increases then stalls for a while.

With the inclusion of post-1982 observations in the windows (that is, subsample windows following the March 1973-October 1982 window), the average MC/GDP ratio starts to increase and this trend continues until the end of the last window that ends in December 2002. The average MC/GDP ratio for larger capitalization deciles increases more significantly compared to smaller capitalization deciles. Test statistics, on the other hand, make a completely reverse move, and as the MC/GDP ratio starts to increase both MCT and RSWT statistics start to go down. Again the rate of downward move in both test statistics is faster for large capitalization stocks. But the decline in the test statistics lasts only up to windows that cover mid-1990s. As the observations for the second half of 1990s are included in the subsample windows the test statistics either stall or start to move upwards.

market indicators for each decile on a monthly basis from July 1962 and September 2003. In addition, we obtain the monthly turnover ratio by dividing value of stocks traded to the value of outstanding stocks (market capitalization). In obtaining the ratios with GDP we use annual GDP figures.

Time series plots of the test statistics and market capitalization/GDP ratio in Figures 5a and 5b indicates that there is an inverse relationship between market capitalization/GDP ratio and the test statistics. In order to analyze the nature of this relationship more carefully we generate separate scatter plots of the MCT statistics for moving windows with each of the three market statistics (Figures 6, 7 and 8 for MC/GDP ratio, trade volume, and turnover ratio, respectively). As we have already shown above the similarity between MCT and RSWT results, we leave the scatter plots of RSWT with market indicators to the appendix (Figures A2, A3 and A4) and do not discuss these plots seperately.

In the case of market capitalization (Figure 6), for the most part we observe a negative relationship between MC/GDP ratio and both test statistics. The negative relationship is the most visible for deciles 4 through 9. While there are flat regions for these decile portfolios (which implies that the test statistic has not changed much while MC/GDP ratio changed), the overall relationship is negative. The upper flat region corresponds to the windows with starting points between 1966 and 1973. The lower flat region corresponds to the windows with starting-points after 1986 to the end of our sample period. In the interim, there is a strong inverse relationship between the MC/GDP ratio and both test statistics. We can make similar observations for the smallest three decile portfolios. Even though, these portfolios also have negatively sloped portions of the test statistics and MC/GDP ratio plots, they also have slightly positively sloped portions that mostly correspond to the windows at the beginning of the sample period.

So far, the above analysis of the relationship between test statistics and the MC/GDP ratio conspicuously left one decile group aside. That is the top decile group with stocks that have very large market capitalization. While the average MC/GDP ratio for the top decile followed a path more or less similar to other deciles, the paths that MCT and RS test statistics followed as the windows are moved in time are different from other decile groups. For the whole period, both test statistics follow a path very similar to MC/GDP ratio. Test statistics decline with MC/GDP ratio for windows covering 1960s and 1970s. As the MC/GDP ratio started to increase test statistics started to move upwards as well. The increase in the test statistics was so significant that with the data for the second half of the 1990s included in the subsample windows, the test statistic started to reject random walk for the top decile. Even though for the most part the test statistic was in the non-rejection region, a positive relation between the MC/GDP ratio and the test statistic is inconsistent with our initial conjecture. At this point it is not possible with the current data set to uncover factors that may help explain the positive relationship. However, given the emerging consensus on the presence of a US stock market bubble towards the end of the decade and especially in 1999 (see Malkiel, 2003), it is quite possible that the stock market bubble of the period could be in effect especially in the top decile stocks.

When we look at the measures of stock market liquidity (Figures 7 and 8), we observe that unlike the case with MC/GDP ratio, the relationship between liquidity measures (the trading volume and the turnover ratio) with test statistics are consistently inverse for all decile portfolios except the top decile portfolio. These graphs leave no room for a misunderstanding. As the subsample windows move over time, average trading volume and, especially, the average turnover ratio increase, hence, the markets become more liquid over time. At the same time, both test statistics decline substantially, moving closer to the non-rejection region for the random walk hypothesis. Especially the plots of test statistics over the turnover ratio clearly show an inverse relationship for all deciles and over most of the subsample windows. In the case of decile 7, and especially deciles 8 and 9, test statistics eventually move below the critical values, failing to reject random walk as the data for late 1980s and early 1990s are included in the subsample windows. Even though test statistics for the first through the sixth decile portfolios continue to reject random walk the relative decline in test statistics with increased market capitalization and liquidity cannot be ignored.

The difference between the liquidity measures and the market capitalization-GDP ratio is basically due to the price effect. The decline in aggregate market capitalization between 1972 and 1975 was for the most part due to the decline in stock prices. As a change in stock prices affects the numerator only, MC/GDP ratio declines with stock prices. As can be seen in Figure 1, a similar price effect is observed in the case of trading value/GDP ratio. Scatter plots of test statistics on the traded value/GDP ratio (we do not present them to save space), look very similar to scatter plots with MC/GDP ratio. In the case of other liquidity measures either the change in stock prices does not affect the liquidity measure (the number of shares traded) or it affects both the numerator and the denominator, with a negligible net effect on the measure (the turnover ratio) itself.

## D. Regression Analysis

Plots of test statistics along with major market indicators provide ample evidence about the relationship between the market indicators and test statistics for random walk behavior. An increase in one of the market indicators (more so for average trading volume and turnover ratio) are accompanied with a decline in the test statistics for size-based decile portfolio returns. As a final step in the analysis, we use OLS and fixed-effect regressions to obtain summary measures for the relationship between the market indicators and random walk behavior. We regress logs of the MCT and RSWT statistics for each fixed-length subsample on the logs of four major market indicators used above. The results of separate and pooled regressions of MCT and RSWT statistics on market indicators are presented in Tables 3a, 3b, 4.

For an overwhelming majority of cases (the first through the ninth deciles) in Tables 3a and 3b an inverse relationship between market indicators and the test statistics is obtained. Adjusted $R^2$s are in general high (especially for deciles 5 through 9) indicating that the relationship between market indicators and the convergence of stock indices towards random walk behavior is rather strong. The exact values of coefficient estimates are not of direct concern. However, it is important to emphasize that as one moves from the bottom decile up to the ninth decile the slope coefficients tend to increase in absolute value, while the constant term declines. In other words, in the higher decile portfolio test statistics tend to be closer to the non-rejection region to start with and, as we have already pointed out above, the decline in test statistics towards the non-rejection region is faster in response to an increase in market indicators.

In the case of the top decile, however, there exists a direct relationship between market indicators and test statistics. We know that test statistics for the top decile was much lower than the critical value to start with.  As the turnover ratio, trade volume, market capitalization and the value of traded stocks increased, test statistics for the top-decile moved closer to the region of rejection of the random walk hypothesis.

There is a caveat in order.  The MCT and the RS Wald test statistics for the top decile was quite low to start with (compare the constant term for the top decile with others).  Even after the upward trend becomes stronger in the late 1990s, the test statistic (MCT or RSWT) barely reaches the rejection level in the late 1990s.  In any case, however, these test statistics continue to be much lower compared to the test statistics for deciles 1 through 5.

In the analysis of the graphs above we observed that the test statistics started to increase in the 1990s (early 1990s for the top decile and mid-1990s for deciles 8 and 9) along with market indicators. Based on these observations we repeat OLS regressions of MCT on market indicators for 1962-1994 (1962-1989 in the case of decile 10) and 1995-2002 (1990-2002 in the case of decile 10), separately.  The relationship between all four market indicators and MCT statistics for the top three deciles are now all positive, with high degrees of fit.  In In the case of decile 7 and decile 2, the slope estimates continue to be negative, whereas in all other deciles the slope coefficients are not significantly different from zero. These regression results are consistent with what we observed in Figures 5 through 8.  Based on these results it is reasonable to claim that the relationship between market indicators and random walk test statistics are not always negative.

## IV. Conclusions

In this paper we analyzed the relationship between major market indicators and the random walk behavior of stock prices in NYSE & AMEX over a period of 40 years.  We applied variance-ratio-based tests to 500-week long moving windows of value- and equal-weighted market indices as well as equal-weighted capitalization-based decile indices. Time series plots of test statistics reveal a downward trend in the test statistics from 1960s to mid-1990s for the equal-weighted indices of all stocks and the first through the ninth decile indices. Test statistics for the value weighted market index as well as the equal-weighted index for the top decile portfolio, on the other hand, are below the critical value for most of the moving subsample windows. However, similar to test statistics for other indices they are subject to an upward move towards the rejection region in the second half of 1990s and early 2000s.

Scatter plots of test statistics and major market indicators leave no doubt that the downward moving test statistics are closely linked to the increasing trading volume, turnover ratio and market capitalization in the US markets since 1970s. Separate OLS regressions of test statistics on each market indicator also support the conclusions reached by the analysis of graphs.

Based on the graphs and regressions we conclude that it is not justified to assume that the behavior of US stocks has been homogeneous over such a long period. As suggested by Lo and MacKinlay (1999), over time stock market indices tend to converge towards random walk behavior. Our prior expectations about the results of the variance ratio tests have been for the most part supported by the evidence: As the market capitalization, trading volume and the turnover ratio increase over time, the NYSE/AMEX stock prices converge towards random walk behavior.

These findings in general support earlier studies (Campbell, et. al., 1993; Duffee, 1992; Conrad, et. al, 1992; and LeBaron, 1992) that have found evidence for an inverse relationship between trading volume and serial correlation in stock returns. Moving beyond the contributions of the earlier literature, our results also show that there is not always an inverse relationship between market indicators and test statistics (hence serial correlation in returns). Serial correlation in returns for large-capitalization deciles have increased along with market indicators in the second half of the 1990s, and especially during the internet bubble of late 1990s.

## References


Campbell, J., S. Grossman, and J. Wang, 1993, "Trading Volume and Serial Correlation in Stock Returns," *Quarterly Journal of Economics* 108, 905-939.

Chow, K. V., and Denning, K. C., 1993, "A Simple Multiple Variance Ratio Test," *Journal of Econometrics,* 58, 385-401.

Cochrane, J., 1991, "Volatility Tests and Efficient Markets," *Journal of Monetary Economics* 27, 463-485.

Conrad, J. S., A. Hameed and C. Niden, 1992, "Volume and Autocovariances in the Short-Horizon Individual Security Return," *Journal of Finance* 49(4), 1305-1329.

Demirgüç-Kunt, A. and R. Levine, 1996, "Stock Market Development and Financial Intermediation: Stylized Facts," *World Bank Economic Review* 10, 291-322.

Diebold, F. X., 1989, "Random Walks versus Fractional Integration: Power Comparisons of Scalar and Joint Tests of the Variance-Time Function," in *Advances in Econometrics and Modeling, ed.* Baldev Raj, Kluwer Academic Publishers: Needham, MA, 29-45.

Duffee, G. R., 1992, "Trading Volume and Return Reversals," Board of Governors of the Federal Reserve System, Finance and Economic Discussion Paper Series, No. 192.

Fama, E. F. and K. R. French, 1988, "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy* 96, 246-273.

Fong, W. M., Koh, S. K., and Ouliaris, S., 1997, "Joint Variance-Ratio Tests of Martingale Hypothesis for Exchange Rates," *Journal of Business and Economic Statistics* 15, 51-59.

Hahn, G.R. and R.W. Hendrickson, 1971, "A Table of Percentage Points of the Distribution of Large Absolute Value of *k* Student *t* Variates and its Applications," *Biometrika* 58, 323-332.

Hochberg, Y., 1974, "Some Generalizations of T-method in Simultaneous Inference," *Journal of Multivariate Analysis* 4, 224-234.

Jegadeesh, N., 1991, "Seasonality in Stock Price Mean Reversion: Evidence from the US and the UK," *Journal of Finance* 66, 1427-1444.

LeBaron, B., 1992, "Some Relations between Volatility and Serial Correlation in Stock Market Returns," *Journal of Business* 65(2), 199-219.

Leroy, S. F., 1989, "Efficient Capital Markets and Martingales," *Journal of Economic Literature* 27(4), 1583-1621.

Levine, R., and S. Zervos, 1998, "Stock Markets, Banks, and Economic Growth," *American Economic Review* 88, 537-558.

Lo, A. W. and A. C. MacKinlay, 1988, "Stock Market Prices do not Follow Random Walks: Evidence from a Simple Specification Test," *Review of Financial Studies* 1(1), 41-66.

Lo, A. W. and A. C. MacKinlay, 1989, "The Size and Power of the Variance Ratio Test in Finite Samples a Monte Carlo Investigation," *Journal of Econometrics* 40, 203-238.

Lo, A. W. and A. C. MacKinlay, 1999, *A Non-Random Walk Down Wall Street*, Princeton University Press.

Malkiel, B. G., 2003, "The Efficient Market Hypothesis and its critics," *Journal of Economic Perspectives* 17(1), 59-82

Morse, D., 1980, "Asymmetric Information in Securities Markets and Trading Volume," *Journal of Financial and Quantitative Analysis* 15, 1129-1146.

Poterba, J. M., and L. H. Summers, 1988, "Mean Reversion in Stock Prices: Evidence and Implications," *Journal of Financial Economics* 22, 27-59.

Richardson, M., and Smith, T., 1991, "Tests of Financial Models in the Presence of Overlapping Observations," *Review of Financial Studies* 4, 227-254.

White, H., 1980, "A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity," *Econometrica* 48, 817-838.

# Appendix A.

## Variance Ratio Based Test Procedures

Variance ratio is a weighted-sum of estimated autocorrelation coefficients, with the weights declining in return horizon. Being a two-tailed test, the rejection by the variance ratio test reveals information about autocorrelation structure. If the variance ratios at different return horizons are greater (smaller) than one, one can conclude that stock returns are positively (negatively) correlated. Accordingly, a value of one for the variance ratio means that stock prices follow random walk. Random walk series possesses a unit root and random walk increments are required to be uncorrelated.

Lo and MacKinlay (1988) used the idea behind variance ratios to test for independently and identically distributed Gaussian increments first, and than extended it to the case with uncorrelated but heteroscedastic increments. Lo and MacKinlay (1989)'s Monte Carlo power tabulations show that variance ratio test yields higher power under both approximations compared to Dickey-Fuller's t-test and Box-Pierce portmanteau Q-test. The variance ratio test is preferred when the focus is the absence of correlation among the increments.

Variance ratio is computed with an aggregation value of $q$. It is a combination of the first $q-1$ autocorrelation coefficient estimators for the returns with arithmetically declining weights. However, the Box-Pierce test gives equal weighting to all autocorrelation coefficients. When $q$ becomes large relative to the sample size, the rejection of the Variance Ratio-test occurs due to upper tail. The $z$ statistic for the efficiency of the market seems to increase slightly above its normal value and then fall back to it. If $q$ is large relative to time, then the tests have little power. As the differencing interval increases, so does the autocorrelation of the increments, and it becomes more difficult to distinguish between this process and random walk.

## I. Variance Ratio Test (Lo and MacKinlay)

The rest of this section introduces and discusses in detail Lo and MacKinlay's variance ratio tests. A stochastic process $X_t$ is defined as:

$$X_t = \mu + X_{t-1} + \varepsilon_t \text{ and } E[\varepsilon_t] = 0 \text{, for all } t.$$

The same stochastic process can also be represented by: $\Delta X_t = \mu + \varepsilon_t$, where $\Delta X_t = X_t - X_{t-1}$ denotes first differences and $\mu$ is arbitrary. Random walk theory is based on the presumption that innovations ($\Delta X_t$) cannot be predicted using past innovations, and disturbances $\varepsilon_t$ are serially uncorrelated.

Lo and MacKinlay (1988) first developed the test statistic for Gaussian identically and independently distributed (i.i.d.) increments. Take $nq + 1$ observations, $(X_0, X_1, \ldots, X_{nq})$ of $X$, where both $n$ and $q$ are arbitrary integers greater than one. The unbiased estimators of the mean and variance of the one-period returns are given by $\mu$ and $\sigma^2$. Under the Gaussian random walk, the variance of the overlapping $q^{th}$ difference of $X_t$, $\sigma^2(q)$, is $q$ times the variance of the one-period returns, $\sigma^2$. The unbiased estimator for the variance of overlapping $1$-period and $q$-period differences of $X_t$ can be derived:

$$\hat{\sigma}^2 = \frac{1}{nq-1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2 \quad \textbf{(1)}$$

$$\hat{\sigma}^2(q) = \frac{1}{\Psi}\sum_{k=1}^{nq}(X_k - X_{k-q} - q\hat{\mu})^2 \quad \textbf{(2)}$$

where $\Psi = q(nq-q+1)(1-\frac{q}{nq})$. Using the unbiased estimators of $\hat{\sigma}^2$ and $\hat{\sigma}^2(q)$, an estimate of the variance ratio, $V_r(q)$, statistic is obtained:

$$\hat{V}_r(q) = \frac{\hat{\sigma}^2(q)}{\hat{\sigma}^2} - 1 \quad \textbf{(3)}$$

Even though the variance estimators are unbiased $\hat{V}_r(q)$ is not, but it is a consistent estimator of the variance ratio. Lo and MacKinlay (1988) notes that finite-sample properties of $V_r(q)$ is closer to its asymptotic value when the variance estimators are unbiased.

Lo and MacKinlay (1988) also show that the variance ratio can be asymptotically written as a weighted sum of the estimated autocorrelation coefficients:

$$\hat{V}_r(q) = \sum_{k=1}^{q-1} \tfrac{2(q-k)}{q}\, \hat{\gamma}(k) \qquad \textbf{(4)}$$

where $\hat{\gamma}(k)$ is the estimate of the $k^{th}$ autocorrelation coefficient. Using this asymptotic relation between the variance ratio statistics, $\hat{V}_r(q)$, and the autocorrelation coefficients Lo and MacKinlay (1988) derive the asymptotic distribution of $\hat{V}_r(q)$ under the Gaussian i.i.d. increments assumption:

$$\sqrt{nq}\, \hat{V}_r(q) \sim N(0, \tfrac{2(2q-1)(q-1)}{3q})$$

Lo and MacKinlay's variance ratio test procedure can be applied when returns ($\Delta X_t$ ) are heteroscedastic, given that they are uncorrelated with each other. If the increments are uncorrelated, the sum of the variances of the increments should be equal to the sum of their variances and the variance ratio should converge to the probability of one even with heteroscedastic disturbances. The asymptotic variance will depend on the degree and type of the heteroscedasticity present. Rather than specifying the form of heteroscedasticity in increments, Lo and MacKinlay (1988) follow White (1980) to derive variance ratio estimates which allow for general forms of heteroscedasticity. Again, Lo and MacKinlay (1988) make use of the relation between the variance ratio and the autocorrelation coefficients to derive the asymptotic distribution of the variance ratio estimator under heteroscedastic disturbances. Under the null hypothesis, we may obtain heteroscedasticity-consistent estimator of the variance, $\hat{\delta}(j)$, of the autocorrelations $\hat{\gamma}(j)$ of $\Delta X_t$. Under the assumption of heteroscedastic returns, asymptotic distribution of $\hat{V}_r(q)$ is given by:

$$\sqrt{nq}\,\hat{V}_r(q) \sim N(0, \theta(q))$$

where $\theta(j)$ *is* the asymptotic variance of $\hat{V}_r(q)$. Under the presence of heteroscedasticity it is defined as the weighted sum of the variances of the estimated autocorrelation coefficients, *δ(j)'s*. Once the consistent estimates for the variances of the estimated autocorrelations are derived, it is possible to obtain a consistent estimate of $\theta(j)$. Lo and MacKinlay (1988) show that the consistent estimate of *δ(j)* is given by:[1]

$$\hat{\delta}(k) = \frac{nq \sum_{j=k+1}^{nq} (X_j - X_{j-1} - \hat{\mu})^2 (X_{j-k} - X_{j-k-1} - \hat{\mu}))^2}{\left[ \sum_{J=1}^{nq} (X_j - X_{j-1} - \hat{\mu})^2 \right]^2} \qquad \textbf{(5)}$$

Using the consistent estimate of *δ(j),* the consistent estimate of the variance of the estimated variance ratios can be written as:

$$\hat{\theta}(q) = \sum_{k=1}^{q-1} \left[\tfrac{2(q-k)}{q}\right]^2 \hat{\delta}(k) \qquad \textbf{(6)}$$

Dividing $\sqrt{nq}\,\hat{V}_r(q)$ by its asymptotic standard deviation under homoscedastic and heteroscedastic returns, Lo and MacKinlay (1988) obtained the standardized test statistics $z_1(q)$ and $z_2(q)$,

$$z_1(q) = \sqrt{\frac{nq\,(3q)}{2(2q-1)(q-1)}}\,\hat{V}_r(q) \sim N(0,1) \qquad \textbf{(7)}$$

---

[1] Equation (5) is the correct version of equation (19) in Lo and MacKinlay (1988), as reported in the Erratum in the *Review of Financial Studies*, 1990, vol. 3. Number 1, pg. 1.

$$z_2(q) = \sqrt{\frac{nq}{\hat{\theta}(q)}}\,\hat{V}_r(q) \sim N(0,1) \qquad \textbf{(8)}$$

## II. Multiple Comparison Test

Lo and MacKinlay's variance ratio test statistics $z_1(q)$ and $z_2(q)$ are used to test the null hypothesis of random walk under homoscedastic and heteroscedastic returns assumption for a specific aggregation value, $q$. If $z_1(q)$ and $z_2(q)$ are greater than the critical value of the standard normal distribution, then the random walk hypothesis is rejected. However, because variance ratios may be statistically close to 1 for some $q$, and different from 1 for others, the variance ratio test procedure based on several aggregation values can easily lead to inconclusive results.

Taking this into account, Chow and Denning (1993) proposed to apply Hochberg's (1974) multiple comparison test to variance ratios to incorporate the joint comparison of all selected variance ratio estimates with one. Multiple comparison test allows the researcher to examine a vector of individual test statistics while controlling for the overall test size, which in our case is equal to the number of variance ratios being tested against unity:

$$\hat{V}_r(q_i) = 0, \quad i = 1, \cdots, m$$

MCT focuses on the largest absolute value of the *z(q)* statistic. Taking a set of VR estimates $\left[\hat{V}_r(q_i) \| i = 1, \ldots, m\right]$ MCT amounts to taking $z(q_i)$ , for $i=1,2,\ldots,m$, as $m$-standard normal variates. Using Bonferroni probability inequality, Chow and Denning (1993) show that the largest absolute value of $z(q_i)$s $z^*(q) = Max_{1 \le i \le m} \left| z(q_i) \right|$ have Studentized Maximum Modulus (SMM) distribution with parameter $m$ and $N$ degrees of freedom, $SMM(\alpha, m, N)$.

The critical values for the SMM distribution are larger than the standard normal distribution, which is not surprising given that the test statistic is the maximum of variance ratio statistics for all selected aggregation values. Chow and Denning (1993) test US stock market indices between 1962 and

1985 and they conclude that the random walk hypothesis is rejected for the equally-weighted index, but not rejected for the value-weighted index.

## III. Richardson-Smith's Wald test

The distribution of variance ratios of different return horizons calculated from overlapping data is likely to be non-normal, because of the serial correlation among the variance ratios. Richardson and Smith (1991) proposed a Wald test that makes explicit use of the serial correlation among variance ratios when the observations used to calculate the variance ratios overlap.

For a given number of (say *m*) variance ratios with different return horizons, Richardson and Smith (1991) derive a Wald test procedure to test for the null hypothesis, which explicitly takes the serial correlation among *m* variance ratios into account. Consider an *m* x *1* vector of variance ratios

$$\mathbf{V}_m = \left[V_r(q_1),\ldots,V_r(q_m)\right]'$$

The joint hypothesis that $H_{03} : V_r(q_i) = 0, \quad i = 1,\cdots,m$ can be examined by the Wald statistic

$$nq \;\; \hat{\mathbf{V}}'_m \;\; \mathbf{\Phi}^{-1} \; \hat{\mathbf{V}}_m \sim \chi^2(m)$$

where $\mathbf{\Phi}$ is the covariance matrix of $\hat{\mathbf{V}}_m$.

Applying Hansen's (1982) GMM technique, which explicitly allows for serial dependence induced by overlapping observations, Richardson and Smith (1991) derived an analytical expression for $\mathbf{\Phi}$ which is asymptotically valid under stationary, ergodic and conditionally homoscedastic returns. For any lag *r* and *s*, variance-covariance matrix of $\mathbf{\Phi}$ is defined as:

$$\mathbf{\Phi} = \begin{pmatrix} \frac{2(2r-1)(r-1)}{3r} & \frac{2(3s-r-1)(r-1)}{3s} \\ \frac{2(3s-r-1)(r-1)}{3s} & \frac{2(2s-1)(s-1)}{3s} \end{pmatrix}$$

**Table 1. Descriptive Statistics for weekly Wednesday excess stock returns (July 1962 – Sep. 2003)**

Returns for October 1987 (Oct. 21 and 28, and Nov. 4) are dropped from the sample. Weekly Wednesday excess returns are defined over the 3-month T-Bill rate. Indices for size-based decile portfolios 1 through 10 are equal-weighted indices of all stocks in the portfolio. Columns 1 through 5 present the sample mean, median, maximum, minimum and standard deviation of the stock returns. The numbers in columns 6 and 7 are the skewness and kurtosis statistics for each stock market returns. Columns 8 and 9 give the Jarque-Bera test statistic for the normality of stock returns and the associated marginal significance level (p-value), respectively. The numbers in the last column are the number of weekly Wednesday return observations used in this paper.

| | Mean (1) | Median (2) | Max. (3) | Min. (4) | Std. Dev. (5) | Skewness (6) | Kurtosis (7) | Jarque-Bera Test (8) | J-B test p-value (9) | No of Obs. (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Value Weighted** | 0.0011 | 0.0023 | 0.0971 | -0.1049 | 0.0199 | -0.1602 | 4.62 | 244.4 | < 0.001 | 2148 |
| **Equal Weighted** | 0.0025 | 0.0038 | 0.1279 | -0.1015 | 0.0204 | -0.0874 | 5.80 | 705.3 | < 0.001 | 2148 |
| **Decile 1** | 0.0025 | 0.0021 | 0.2230 | -0.1073 | 0.0261 | 0.8195 | 9.16 | 3638.2 | < 0.001 | 2148 |
| **Decile 2** | 0.0018 | 0.0025 | 0.2185 | -0.0957 | 0.0229 | 0.3745 | 9.12 | 3403.8 | < 0.001 | 2148 |
| **Decile 3** | 0.0016 | 0.0027 | 0.1796 | -0.1089 | 0.0218 | 0.0074 | 7.36 | 1705.2 | < 0.001 | 2148 |
| **Decile 4** | 0.0015 | 0.0027 | 0.1499 | -0.1042 | 0.0212 | -0.0774 | 6.47 | 1079.0 | < 0.001 | 2148 |
| **Decile 5** | 0.0014 | 0.0031 | 0.1249 | -0.1058 | 0.0215 | -0.2702 | 5.42 | 550.4 | < 0.001 | 2148 |
| **Decile 6** | 0.0016 | 0.0032 | 0.1168 | -0.1120 | 0.0213 | -0.2904 | 5.20 | 464.1 | < 0.001 | 2148 |
| **Decile 7** | 0.0016 | 0.0034 | 0.1110 | -0.1232 | 0.0209 | -0.3851 | 5.30 | 526.6 | < 0.001 | 2148 |
| **Decile 8** | 0.0014 | 0.0033 | 0.0898 | -0.1207 | 0.0206 | -0.2404 | 4.79 | 308.4 | < 0.001 | 2148 |
| **Decile 9** | 0.0014 | 0.0030 | 0.0882 | -0.1278 | 0.0206 | -0.2204 | 4.75 | 292.2 | < 0.001 | 2148 |
| **Decile 10** | 0.0010 | 0.0019 | 0.1032 | -0.1010 | 0.0202 | -0.1058 | 4.67 | 253.2 | < 0.001 | 2148 |

**Table 2. Variance-ratio-based Multiple Comparison and RS Wald Test Statistics for NYSE/AMEX stock**

Returns for October 1987 (Oct. 21 and 28, and Nov. 4) are dropped from the sample. Weekly Wednesday excess returns are defined over the 3-month T-Bill rate. All indices for size-based decile portfolios are equal-weighted indices from CRSP. Variance ratio and the corresponding $z^*$ statistic are calculated for 2, 4, 8, 16 and 32 week return horizons. MCT and RSWT are based on a comparison of the variance ratios of these five weekly return horizons. $^{**}$ indicates that the test statistic exceeds the critical value at the 5% significance level, that are 2.56 and 11.1 for MCT and RSWT, respectively.

| | Variance Ratio | | | | | $z^*$ statistic | | | | | MCT | RS Wald |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Stock Indices** | **2 weeks** | **4** | **8** | **16** | **32** | **2 weeks** | **4** | **8** | **16** | **32** | **Statistic** | **Statistic** |
| **Value weighted (VW)** | 1.008 | 1.034 | 1.045 | 1.022 | 1.066 | 0.303 | **0.663** | 0.572 | 0.192 | 0.404 | 0.66 | 2.52 |
| **Equal weighted (EW)** | 1.244 | 1.54 | 1.809 | 1.902 | 1.900 | 8.030 | **9.668** | 9.436 | 7.350 | 5.297 | 9.67** | 190.6** |
| **Decile 1** | 1.341 | 1.800 | 2.236 | 2.37 | 2.315 | 9.907 | 13.398 | **13.859** | 10.923 | 7.805 | 13.86** | 426.9** |
| **Decile 2** | 1.333 | 1.762 | 2.178 | 2.322 | 2.317 | 10.181 | 12.904 | **12.977** | 10.343 | 7.586 | 12.98** | 386.6** |
| **Decile 3** | 1.277 | 1.624 | 1.961 | 2.104 | 2.23 | 8.597 | 10.688 | **10.782** | 8.707 | 7.041 | 10.78** | 258.7** |
| **Decile 4** | 1.254 | 1.552 | 1.841 | 1.945 | 1.995 | 8.137 | **9.669** | 9.614 | 7.581 | 5.782 | 9.67** | 203.3** |
| **Decile 5** | 1.240 | 1.51 | 1.753 | 1.829 | 1.85 | 8.039 | **9.228** | 8.849 | 6.789 | 5.023 | 9.23** | 171.5** |
| **Decile 6** | 1.205 | 1.44 | 1.65 | 1.712 | 1.732 | 7.103 | **8.221** | 7.877 | 6.000 | 4.430 | 8.22** | 127.3** |
| **Decile 7** | 1.176 | 1.378 | 1.558 | 1.612 | 1.623 | 6.197 | **7.129** | 6.84 | 5.218 | 3.816 | 7.13** | 93.7** |
| **Decile 8** | 1.132 | 1.275 | 1.401 | 1.438 | 1.452 | 4.857 | **5.402** | 5.092 | 3.836 | 2.811 | 5.40** | 50.0** |
| **Decile 9** | 1.087 | 1.189 | 1.263 | 1.253 | 1.219 | 3.215 | **3.736** | 3.342 | 2.210 | 1.356 | 3.74** | 23.7** |
| **Decile 10** | 0.969 | 0.955 | 0.933 | 0.903 | 0.975 | **-1.119** | -0.878 | -0.852 | -0.832 | -0.149 | 1.12 | 4.75 |

**Table 3. OLS Regressions of Log MCT & RSWT Statistic on Market Indicators for Capitalization-based Decile Portfolios (July 1962- Dec. 2002)** The dependent variable is the log of the MCT statistic with each observation being the average of the MCT statistics obtained from 500-weekly moving-window ending in that month. The explanatory variables are logs of market indicators with each observation being the average of the monthly market indicators over the corresponding 500-week moving-window. Standard errors are heteroscedasticity-consistent.

| | Capitalization-based decile portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Dep. Variable: Log MCT statistic** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| **Log Turnover ratio** | -0.152$^{**}$ | -0.110$^{**}$ | -0.147$^{**}$ | -0.180$^{**}$ | -0.273$^{**}$ | -0.339$^{**}$ | -0.322$^{**}$ | -0.651$^{**}$ | -0.588$^{**}$ | 0.171$^{**}$ |
| | [0.005] | [0.004] | [0.006] | [0.006] | [0.007] | [0.008] | [0.009] | [0.017] | [0.019] | [0.021] |
| **Adjusted $R^2$** | 0.69 | 0.64 | 0.66 | 0.72 | 0.80 | 0.86 | 0.83 | 0.78 | 0.74 | 0.16 |
| **Log Trade Volume** | 0.009 | -0.269$^{**}$ | -0.479$^{**}$ | -0.880$^{**}$ | -1.439$^{**}$ | -1.807$^{**}$ | -1.307$^{**}$ | -2.282$^{**}$ | -1.480$^{**}$ | 0.256$^{**}$ |
| | [0.025] | [0.026] | [0.034] | [0.030] | [0.044] | [0.036] | [0.028] | [0.057] | [0.047] | [0.046] |
| **Adjusted $R^2$** | 0.001 | 0.24 | 0.24 | 0.54 | 0.74 | 0.86 | 0.87 | 0.76 | 0.70 | 0.08 |
| **Log Market Capitalization/GDP** | 0.212$^{**}$ | 0.034$^{+}$ | 0.110$^{**}$ | -0.135$^{*}$ | -0.206$^{*}$ | -0.589$^{**}$ | -1.121$^{**}$ | -2.894$^{**}$ | -2.182$^{**}$ | 1.659$^{**}$ |
| | [0.013] | [0.020] | [0.038] | [0.054] | [0.080] | [0.108] | [0.119] | [0.184] | [0.182] | [0.065] |
| **Adjusted $R^2$** | 0.2 | 0.01 | 0.02 | 0.02 | 0.02 | 0.08 | 0.19 | 0.25 | 0.17 | 0.58 |
| **Log Traded Value/GDP** | 0.064$^{**}$ | -0.059$^{**}$ | -0.072$^{**}$ | -0.281$^{**}$ | -0.530$^{**}$ | -0.959$^{**}$ | -0.958$^{**}$ | -1.764$^{**}$ | -1.290$^{**}$ | 0.433$^{**}$ |
| | [0.010] | [0.016] | [0.026] | [0.027] | [0.026] | [0.020] | [0.023] | [0.050] | [0.051] | [0.033] |
| **Adjusted $R^2$** | 0.06 | 0.04 | 0.02 | 0.21 | 0.32 | 0.58 | 0.8 | 0.74 | 0.71 | 0.29 |
| **Dep. Variable: Log RSWT statistic** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| **Log Turnover ratio** | -0.218$^{**}$ | -0.080$^{**}$ | -0.220$^{**}$ | -0.219$^{**}$ | -0.386$^{**}$ | -0.542$^{**}$ | -0.498$^{**}$ | -0.905$^{**}$ | -0.771$^{**}$ | 0.138$^{**}$ |
| | [0.016] | [0.009] | [0.015] | [0.013] | [0.016] | [0.016] | [0.013] | [0.027] | [0.026] | [0.023] |
| **Adjusted $R^2$** | 0.34 | 0.15 | 0.39 | 0.46 | 0.65 | 0.77 | 0.81 | 0.75 | 0.71 | 0.11 |
| **Log Trade Volume** | -0.097$^{*}$ | -0.362$^{**}$ | -0.577$^{**}$ | -0.966$^{**}$ | -1.934$^{**}$ | -2.831$^{**}$ | -1.946$^{**}$ | -3.201$^{**}$ | -1.995$^{**}$ | 0.229$^{**}$ |
| | [0.048] | [0.030] | [0.069] | [0.068] | [0.096] | [0.091] | [0.059] | [0.093] | [0.065] | [0.052] |
| **Adjusted $R^2$** | 0.01 | 0.20 | 0.09 | 0.28 | 0.54 | 0.74 | 0.78 | 0.74 | 0.71 | 0.07 |
| **Log Market Capitalization/GDP** | 0.110$^{**}$ | -0.087$^{**}$ | 0.357$^{**}$ | -0.011 | 0.039 | -0.327$^{+}$ | -0.865$^{**}$ | -3.021$^{**}$ | -1.866$^{**}$ | 1.053$^{**}$ |
| | [0.027] | [0.029] | [0.069] | [0.080] | [0.124] | [0.182] | [0.195] | [0.277] | [0.249] | [0.081] |
| **Adjusted $R^2$** | 0.01 | 0.02 | 0.06 | 0.001 | 0.003 | 0.01 | 0.05 | 0.13 | 0.07 | 0.24 |
| **Log Traded Value/GDP** | 0.004 | -0.126$^{**}$ | -0.005 | -0.261$^{**}$ | -0.595$^{**}$ | -1.298$^{**}$ | -1.287$^{**}$ | -2.345$^{**}$ | -1.648$^{**}$ | 0.329$^{**}$ |
| | [0.020] | [0.019] | [0.046] | [0.045] | [0.051] | [0.050] | [0.049] | [0.085] | [0.071] | [0.035] |
| **Adjusted $R^2$** | 0.0001 | 0.09 | 0.0002 | 0.08 | 0.16 | 0.37 | 0.59 | 0.65 | 0.64 | 0.17 |
| **Number of Observations** | 371 | 371 | 371 | 371 | 371 | 371 | 371 | 371 | 371 | 371 |

**Table 4. OLS Regressions of Log MCT Statistic on Market Indicators for Capitalization-based Decile Portfolios**

(see notes for Table 3)

| | Capitalization-based decile portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **July 1962 – December 1994** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10 (1962-89)** |
| **Log Turnover ratio** | 0.118** | -0.022 | -0.263** | -0.736** | -1.815** | -1.664** | -1.289** | -1.960** | -1.366** | -0.560** |
| | [0.013] | [0.019] | [0.055] | [0.057] | [0.062] | [0.057] | [0.035] | [0.090] | [0.064] | [0.050] |
| **Adjusted $R^2$** | 0.15 | 0 | 0.07 | 0.31 | 0.72 | 0.81 | 0.84 | 0.74 | 0.71 | 0.32 |
| **Log Trade Volume** | -0.121** | -0.058** | -0.211** | -0.201** | -0.338** | -0.330** | -0.292** | -0.587** | -0.578** | -0.376** |
| | [0.008] | [0.007] | [0.007] | [0.009] | [0.011] | [0.011] | [0.011] | [0.028] | [0.027] | [0.030] |
| **Adjusted $R^2$** | 0.44 | 0.21 | 0.74 | 0.65 | 0.79 | 0.78 | 0.74 | 0.73 | 0.73 | 0.39 |
| **Log Market Capitalization/GDP** | 0.121** | 0.068** | 0.190** | 0.038 | 0.228** | 0.210** | -0.13 | -0.859** | -0.204 | 1.985** |
| | [0.012] | [0.013] | [0.030] | [0.038] | [0.063] | [0.075] | [0.097] | [0.235] | [0.236] | [0.090] |
| **Adjusted $R^2$** | 0.17 | 0.07 | 0.09 | 0 | 0.03 | 0.02 | 0 | 0.03 | 0 | 0.64 |
| **Log Traded Value/GDP** | 0.062** | 0.022* | 0.037+ | -0.105** | -0.310** | -0.747** | -1.065** | -1.724** | -1.487** | -0.543** |
| | [0.006] | [0.008] | [0.021] | [0.028] | [0.053] | [0.057] | [0.035] | [0.083] | [0.064] | [0.075] |
| **Adjusted $R^2$** | 0.16 | 0.02 | 0.01 | 0.04 | 0.08 | 0.31 | 0.73 | 0.71 | 0.78 | 0.14 |
| **Number of Observations** | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 275 | 215 |
| **Jan. 1995 – December 2002** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10 (1990-2002)** |
| **Log Turnover ratio** | -0.04 | -0.592** | -0.343** | -0.144 | -0.051 | -0.452** | -0.697** | 1.986** | 2.518** | 1.037** |
| | [0.033] | [0.038] | [0.087] | [0.147] | [0.090] | [0.156] | [0.152] | [0.266] | [0.107] | [0.183] |
| **Adjusted $R^2$** | 0.01 | 0.54 | 0.09 | 0.01 | 0 | 0.05 | 0.15 | 0.28 | 0.84 | 0.11 |
| **Log Trade Volume** | -0.048 | -0.277** | -0.027 | 0.01 | 0.035 | -0.034 | -0.328** | 0.887** | 1.166** | 0.361** |
| | [0.035] | [0.021] | [0.037] | [0.041] | [0.033] | [0.041] | [0.062] | [0.092] | [0.056] | [0.042] |
| **Adjusted $R^2$** | 0.02 | 0.53 | 0 | 0 | 0.01 | 0 | 0.18 | 0.41 | 0.81 | 0.41 |
| **Log Market Capitalization/GDP** | -1.130** | -0.563** | 0.174* | 0.280** | 0.184* | 0.109 | -0.602** | 3.658** | 4.388** | 0.762** |
| | [0.309] | [0.047] | [0.085] | [0.103] | [0.079] | [0.098] | [0.163] | [0.364] | [0.251] | [0.079] |
| **Adjusted $R^2$** | 0.27 | 0.47 | 0.02 | 0.05 | 0.04 | 0.01 | 0.09 | 0.51 | 0.76 | 0.44 |
| **Log Traded Value/GDP** | -0.063+ | -0.317** | -0.043 | 0.067 | 0.046 | -0.017 | -0.334** | 1.398** | 1.641** | 0.506** |
| | [0.036] | [0.022] | [0.047] | [0.063] | [0.044] | [0.063] | [0.079] | [0.153] | [0.073] | [0.062] |
| **Adjusted $R^2$** | 0.03 | 0.55 | 0.01 | 0.01 | 0.01 | 0 | 0.12 | 0.39 | 0.83 | 0.34 |
| **Number of Observations** | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 96 | 156 |

**Figure 1. Major Market Indicators for NYSE and AMEX (monthly observations, July 1962 – Dec. 2002)**

Market capitalization is the total value of outstanding shares of all stocks traded in the NYSE and AMEX at the end of the month obtained from daily CRSP files. Number and value of shares traded are obtained from the monthly CRSP files. Value of shares traded in a month is annualized by multiplying with 12 so that it can be comparable to annual GDP. Turnover ratio is defined as annualized value of shares traded in a month divided by the market value of outstanding shares at the end of the month.

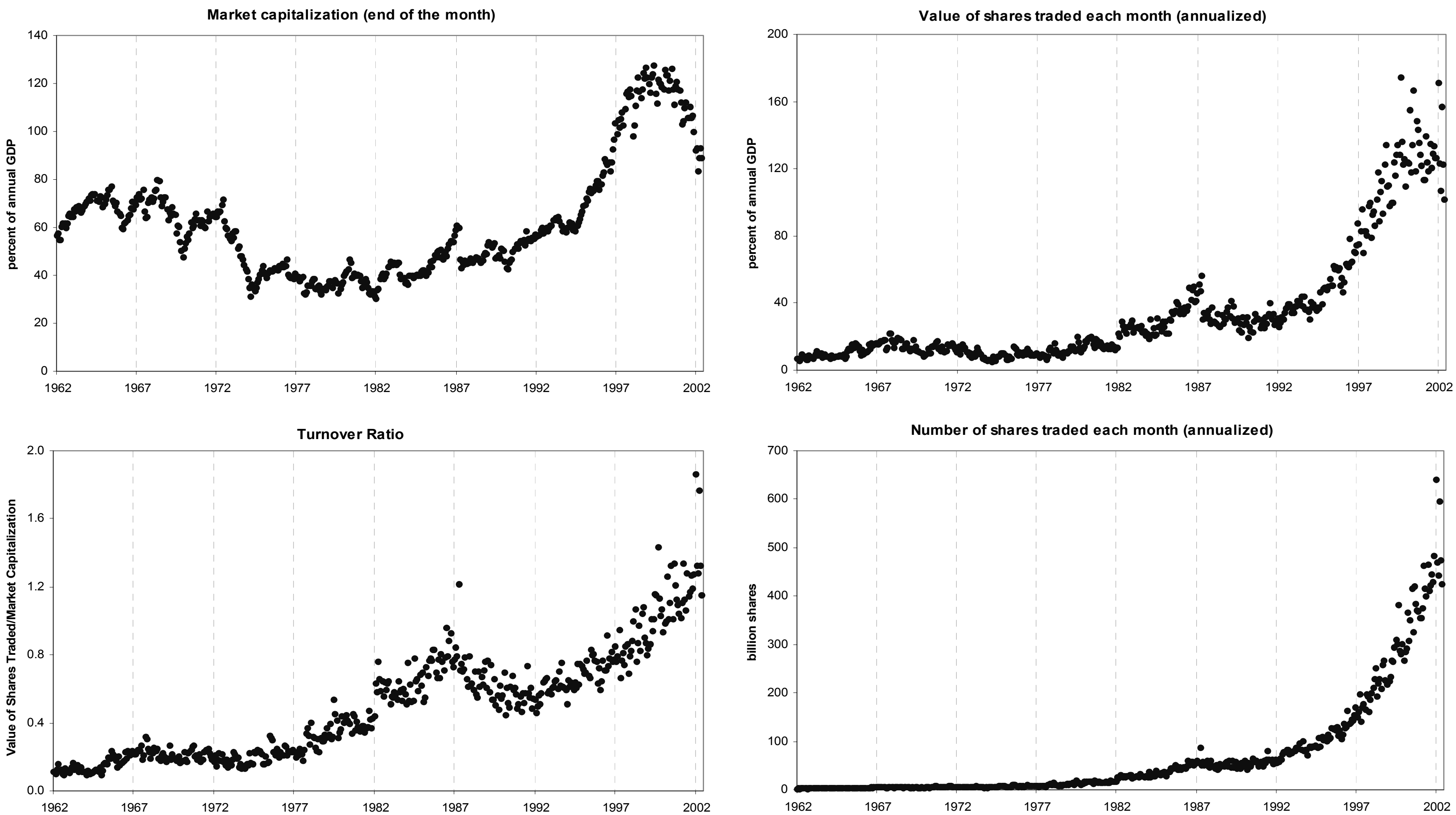


**Figure 2. MCT Statistic for Moving Windows and the Corresponding Variance Ratio – Value-weighted and Equal-weighted Indices of all NYSE/AMEX stocks**

Multiple comparison test statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns from July 1962 to September 2003. Three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. The straight line in Panels a) and c) is the benchmark value of 1.0 for the variance ratios that corresponds to MCT statistic (the maximum $z^*$-statistics among the ones calculated for 2, 4, 8, 16, and 32 week return horizons). Straight lines in Panels b) and d) indicate critical values at the 5% (upper bold line) and 10% significance levels, respectively.

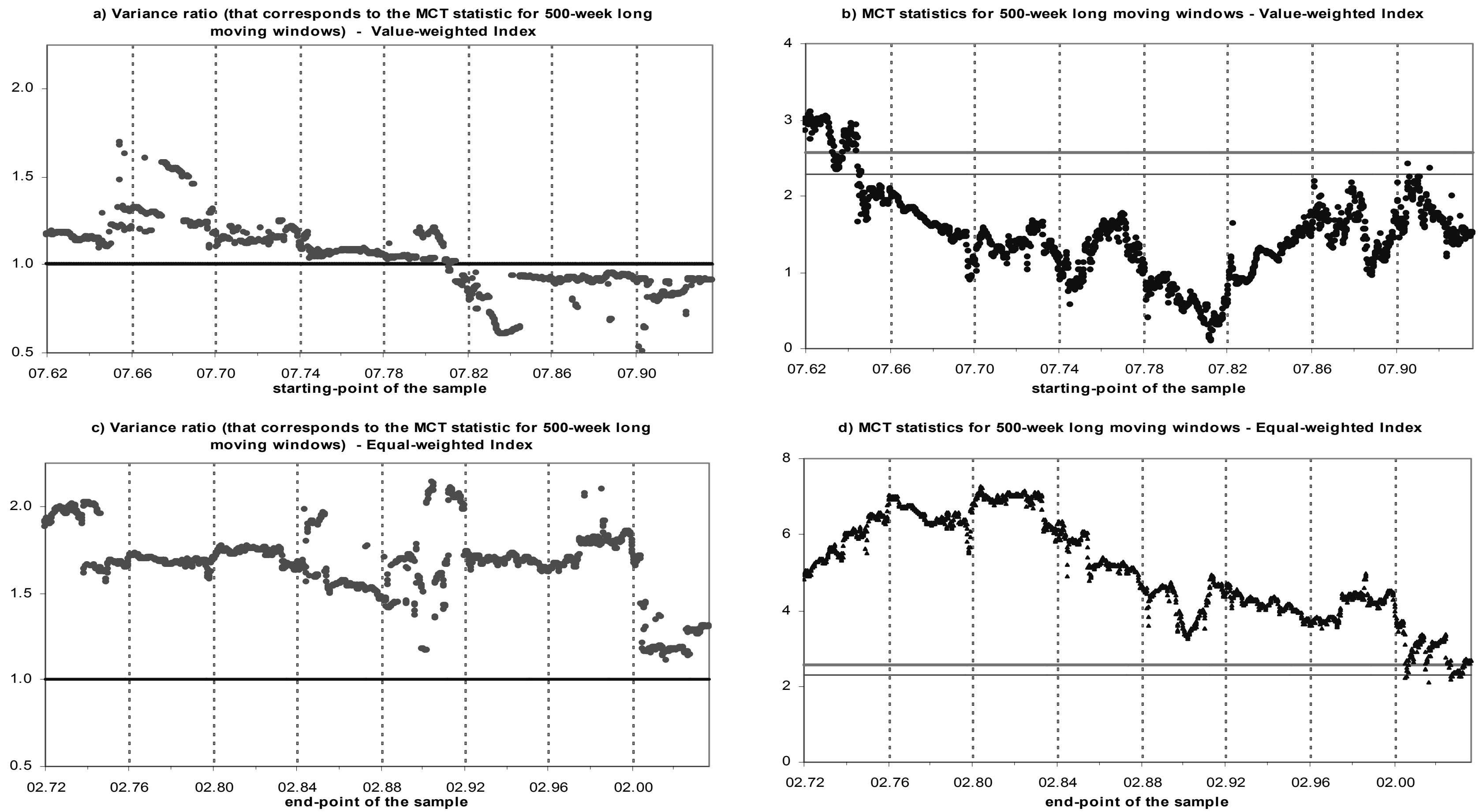


**Figure 3a. MCT Statistic for Moving Windows of Value-weighted Index and Market Indicators (July 1962 – December 2002, monthly observations)**

Multiple comparison test statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns from July 1962 to September 2003 after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each observation of the MCT statistic is the average of the MCT statistics obtained from 500-weekly moving-window ending in that month. The definition of market indicators are explained in detail in Figure 1. In each panel one observation of a market indicator is the average of the monthly indicators over the corresponding 500-week moving-window. Graphs cover the period up to December 2002 because of the market indicators for 2003 were not available at the time of the data download. Straight line in each panel indicates the 5% critical values for MCT statistic.

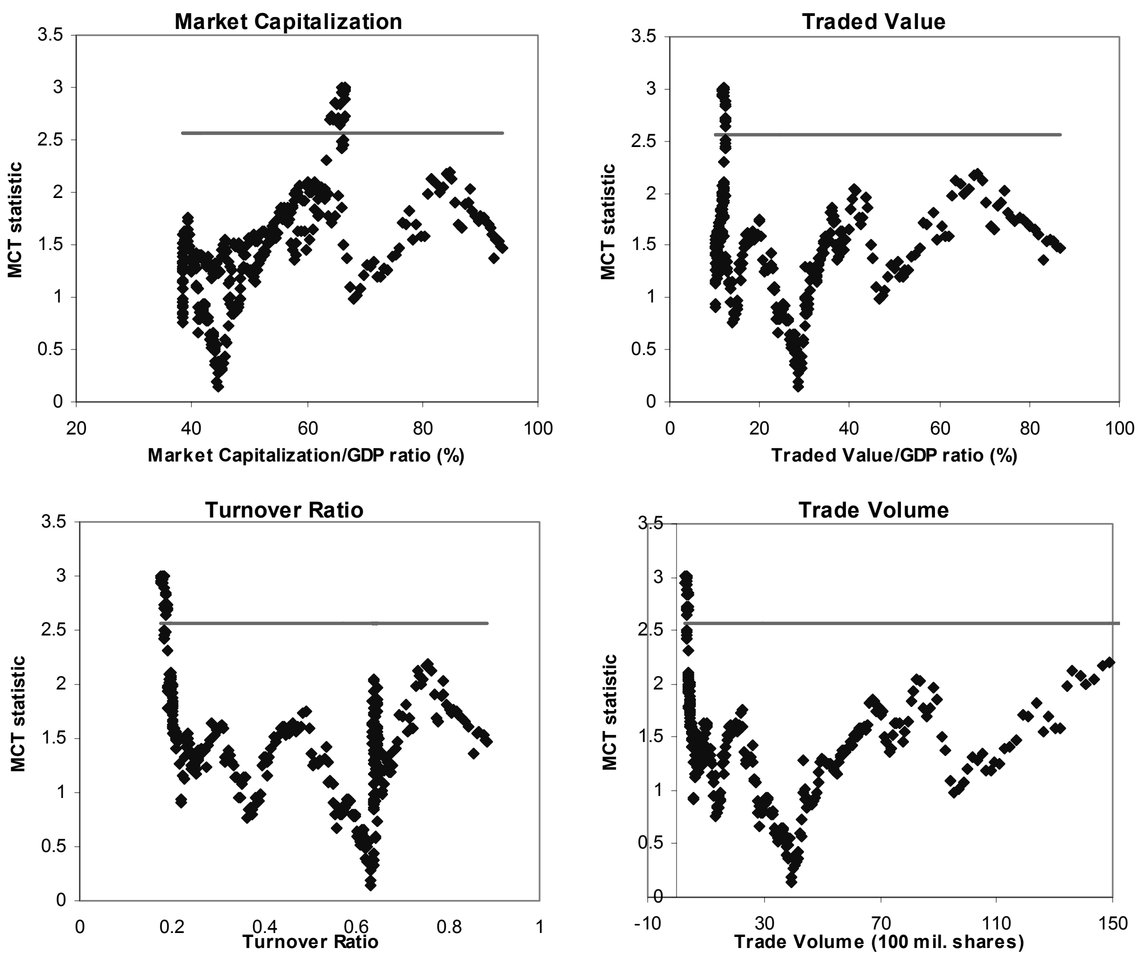


**Figure 3b. MCT Statistic for Moving Windows of Equal-weighted Index and Market Indicators (July 1962 – December 2002, monthly observations)**

Multiple comparison test statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns from July 1962 to September 2003 after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each observation of the MCT statistic is the average of the MCT statistics obtained from 500-weekly moving-windows ending in that month. The definition of market indicators are explained in detail in Figure 1. In each panel one observation of a market indicator is the average of the monthly indicators over the corresponding 500-week moving-window. Graphs cover the period up to December 2002 because of the market indicators for 2003 were not available at the time of the data download. Straight line in each panel indicates the 5% critical values for MCT statistic.

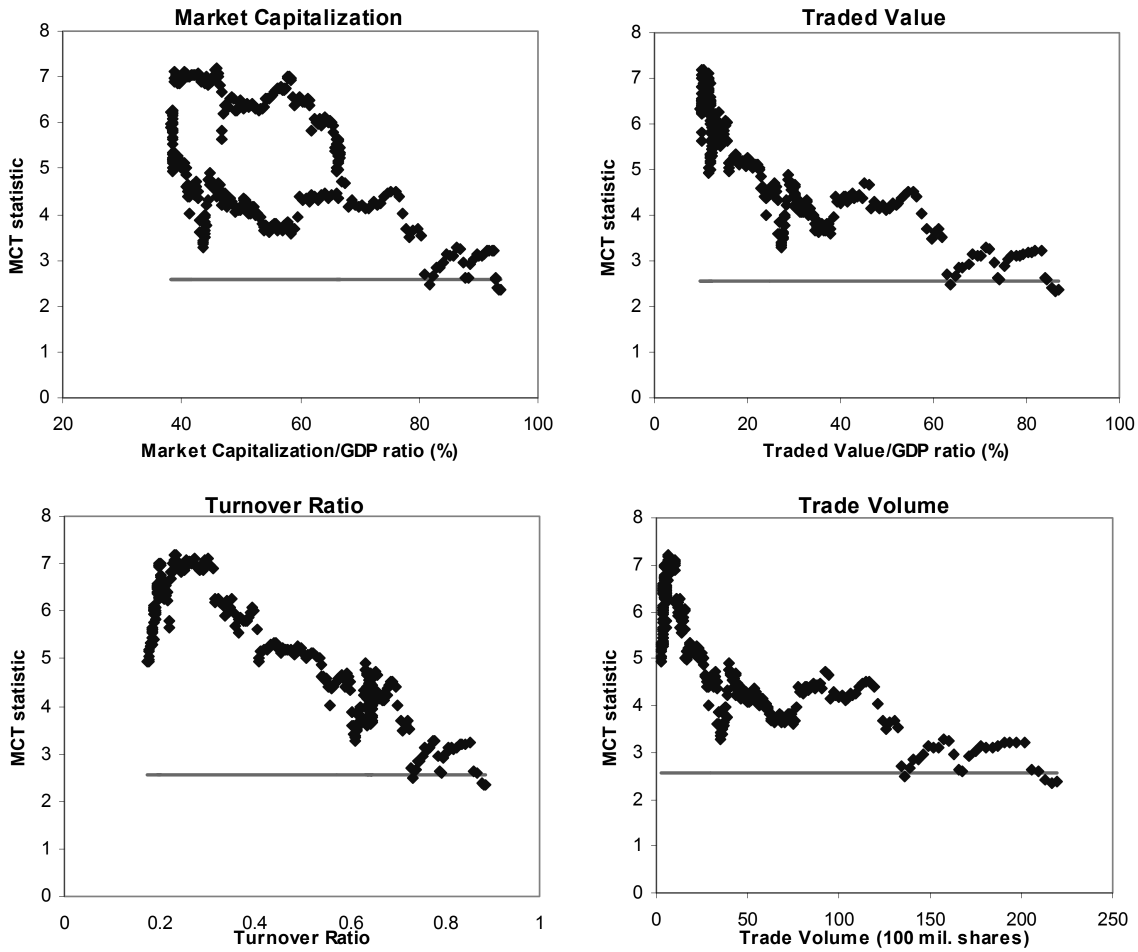


**Figure 4a. MCT Statistic for Moving Windows of Size-based Decile Portfolio Indices (July 1962 – Sep. 2003, weekly observations)**
MCT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Decile portfolio index data are from CRSP daily index files. Straight line in each panel indicates critical value at the 10% significance levels.

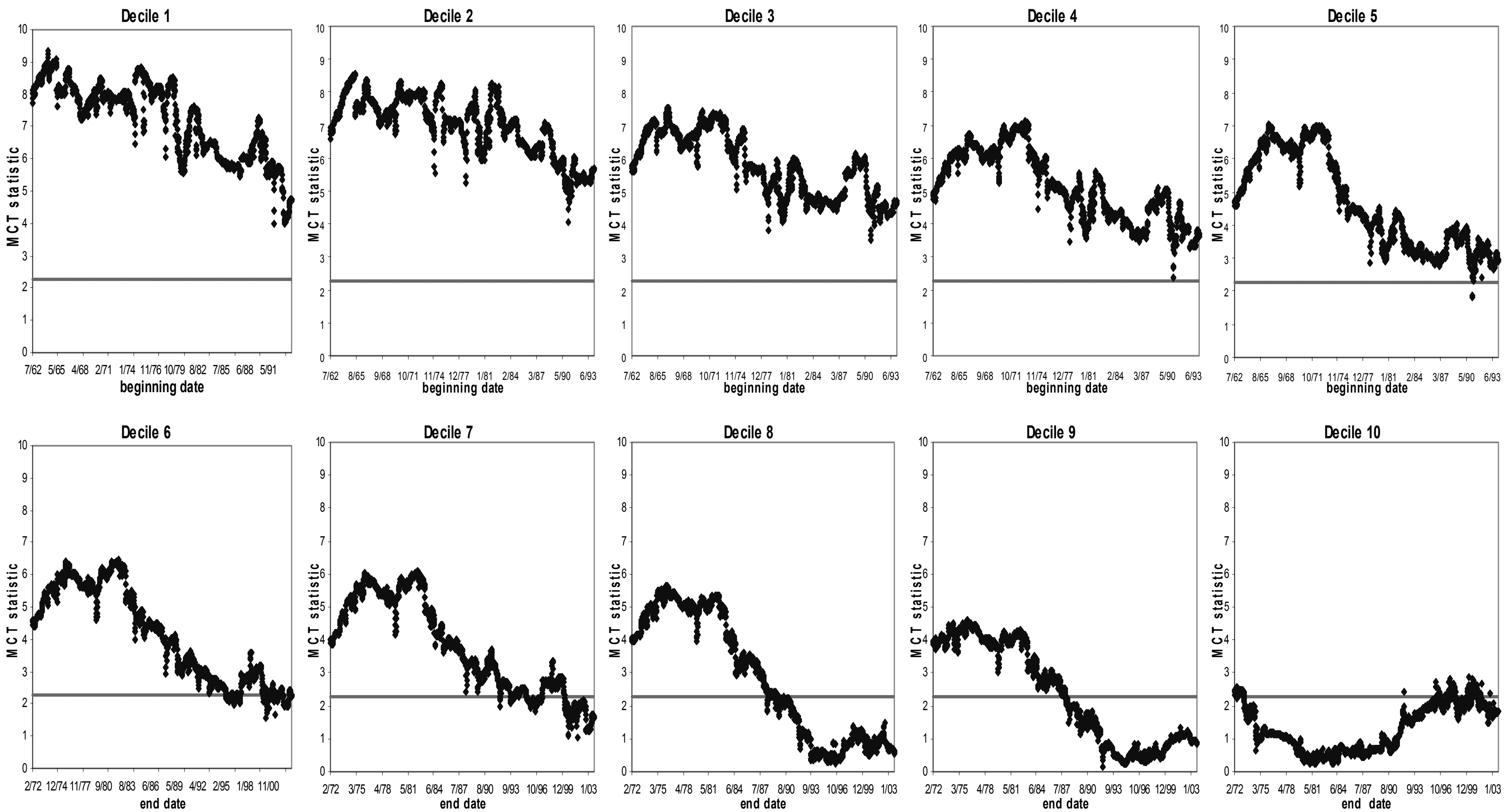


**Figure 4b. RSWT Statistic for Moving Windows of Size-based Decile Portfolio Indices (July 1962 – Sep. 2003, weekly observations)**
RSWT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Decile portfolio index data are from CRSP daily index files. Straight line in each panel indicates critical value at the 10% significance levels.

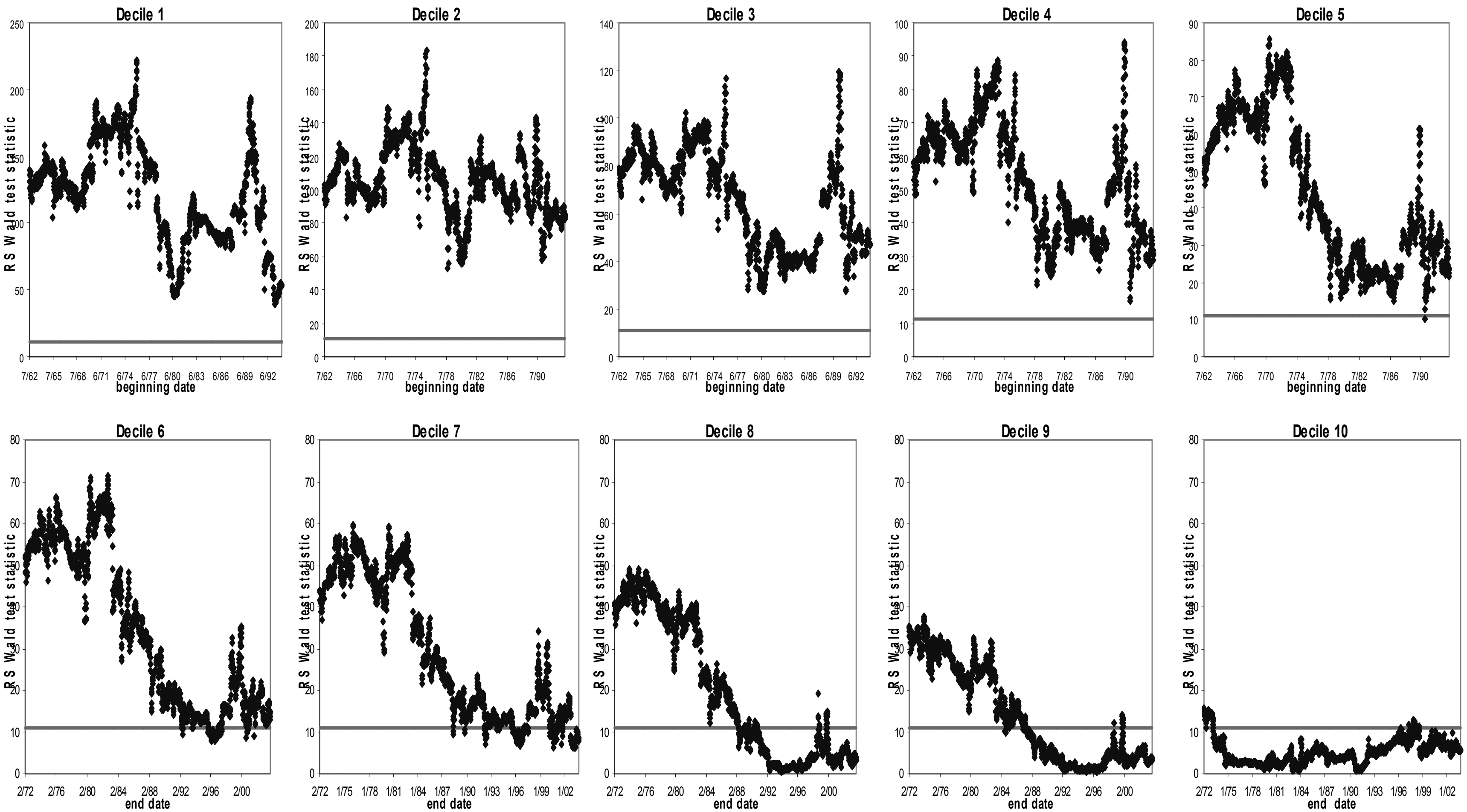


**Figure 5a. MCT Statistic and Market Capitalization/GDP Ratio for Moving Windows – Time Series Plots (July 1962 – Dec. 2002, monthly observations)** MCT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the MCT statistic is the average of the MCT statistics obtained from the moving-windows ending in that month. Each observation of the MC/GDP ratio (the smooth grey line) is the average of the monthly indicators over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download.

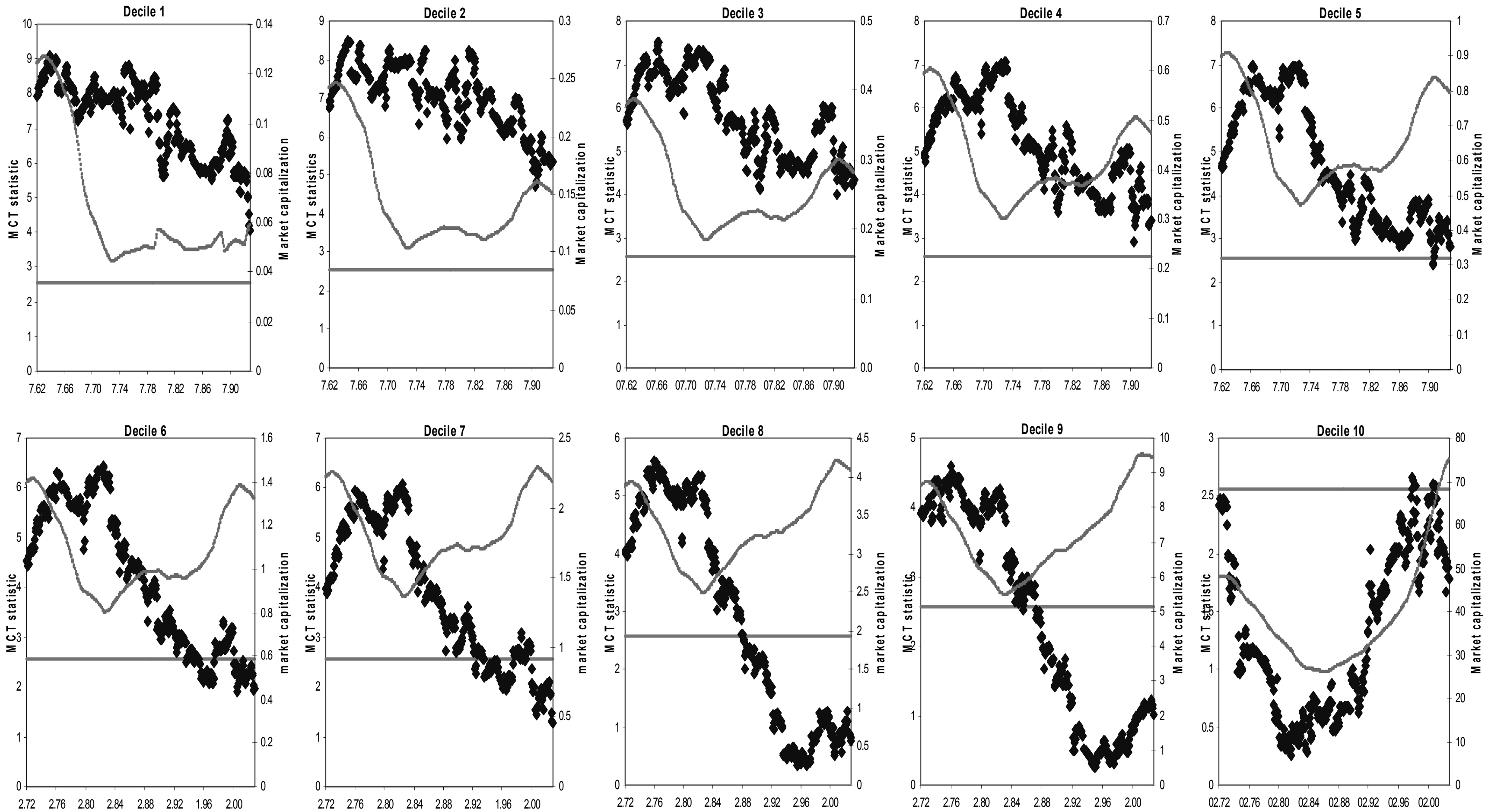


**Figure 5b. RSWT Statistic and Market Capitalization/GDP Ratio for Moving Windows – Time Series Plots (July 1962 – Dec. 2002, monthly observations)** RSWT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the RSWT statistic is the average of the RSWT statistics obtained from the moving-window ending in that month. Each observation of the MC/GDP ratio (the smooth grey line) is the average of the monthly indicators over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download.

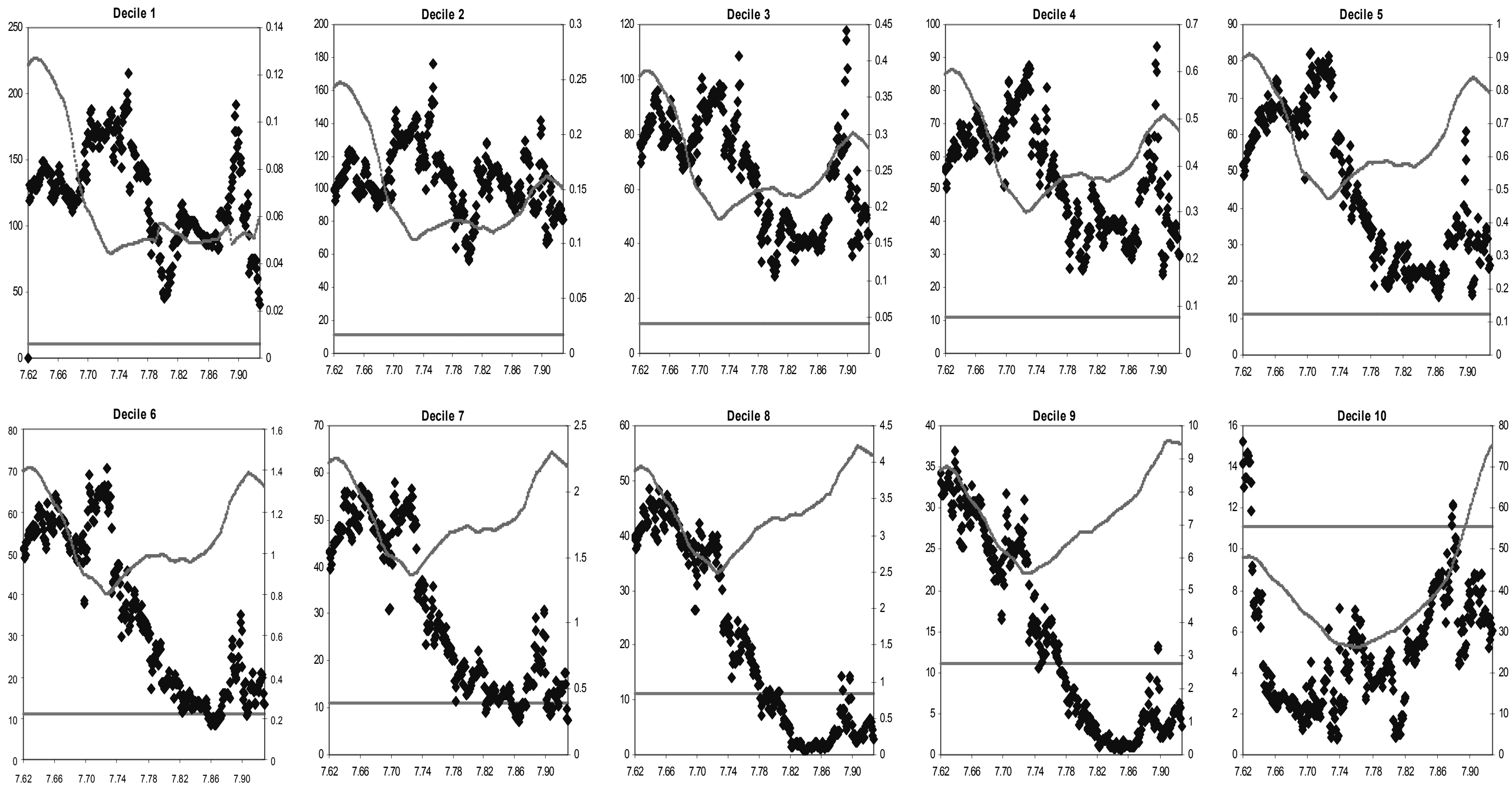


**Figure 6. MCT Statistic and Average Market Capitalization/GDP Ratio for Moving Windows– Scatter Plots (July 1962 – Dec. 2002, monthly observations)** MCT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the MCT statistic is the average of the MCT statistics obtained from the moving-window ending in that month. Each observation of the MC/GDP ratio is the average of the monthly indicators over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5%significance level.

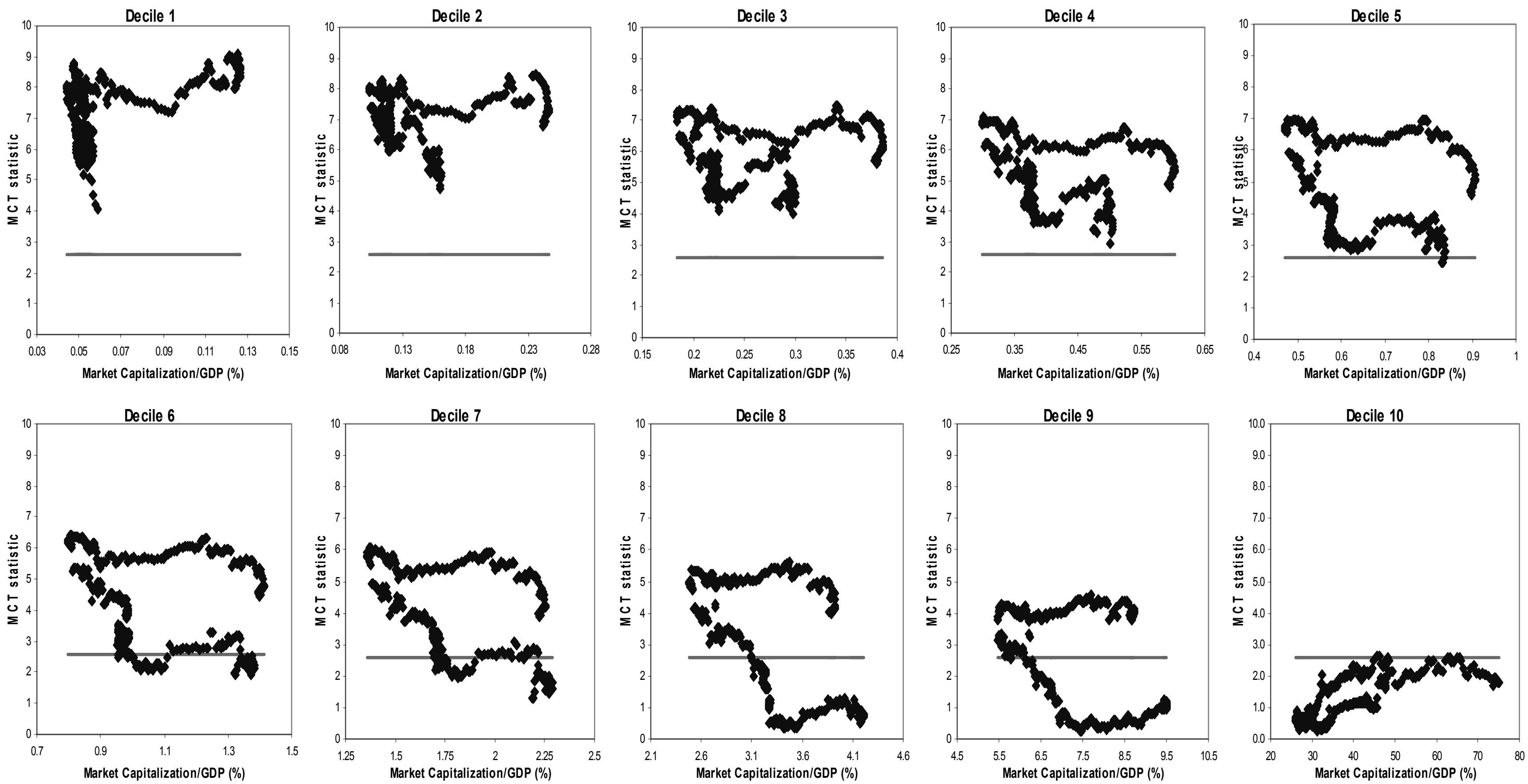


**Figure 7. MCT Statistic and Average Trade Volume for Moving Windows – Scatter Plots (July 1962 – Dec. 2002, monthly observations)**
MCT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the MCT statistic is the average of the MCT statistics obtained from the moving-window ending in that month. Each observation of the trade volume is the average of the monthly trade volume data over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5%significance level.

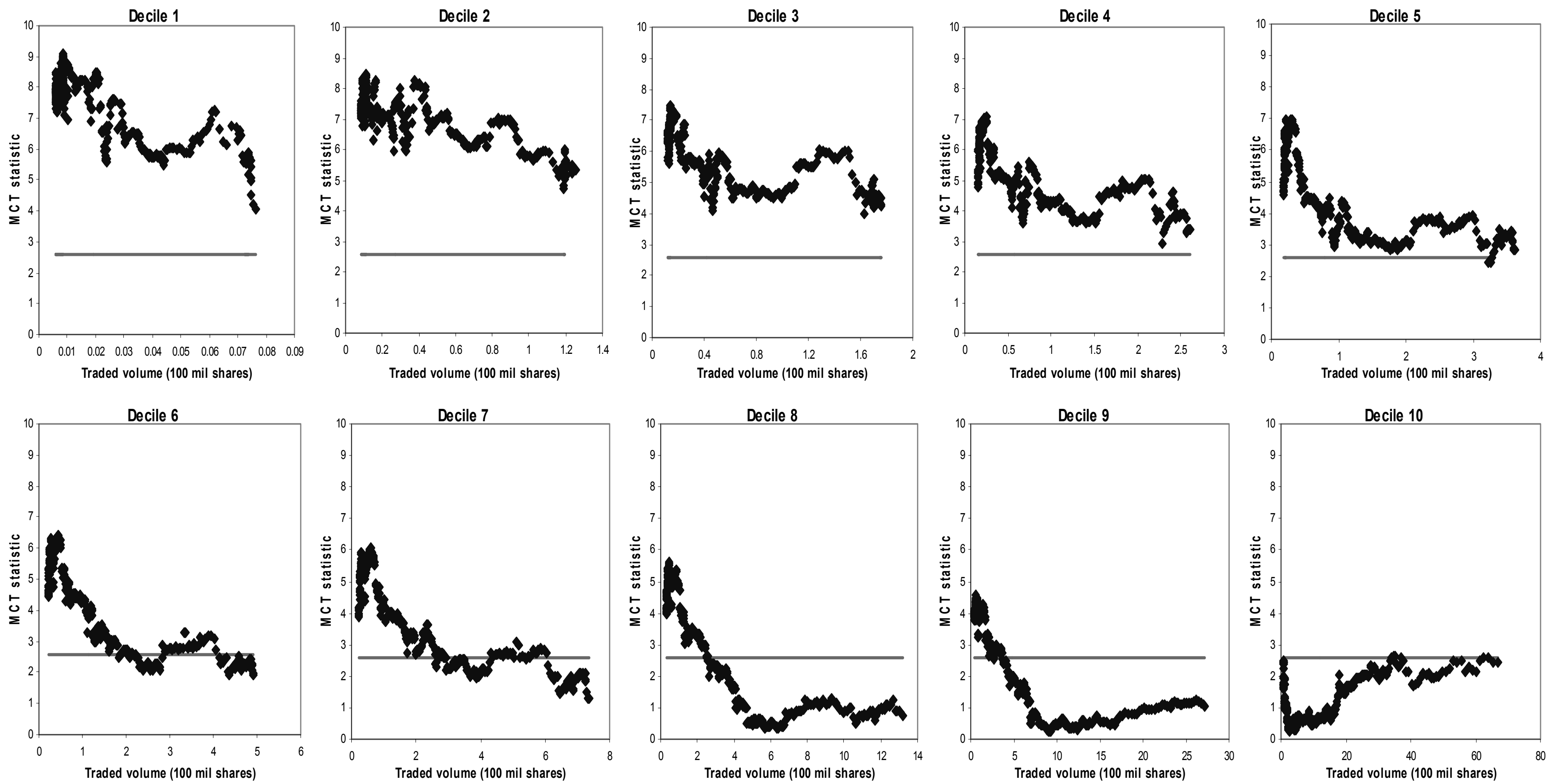
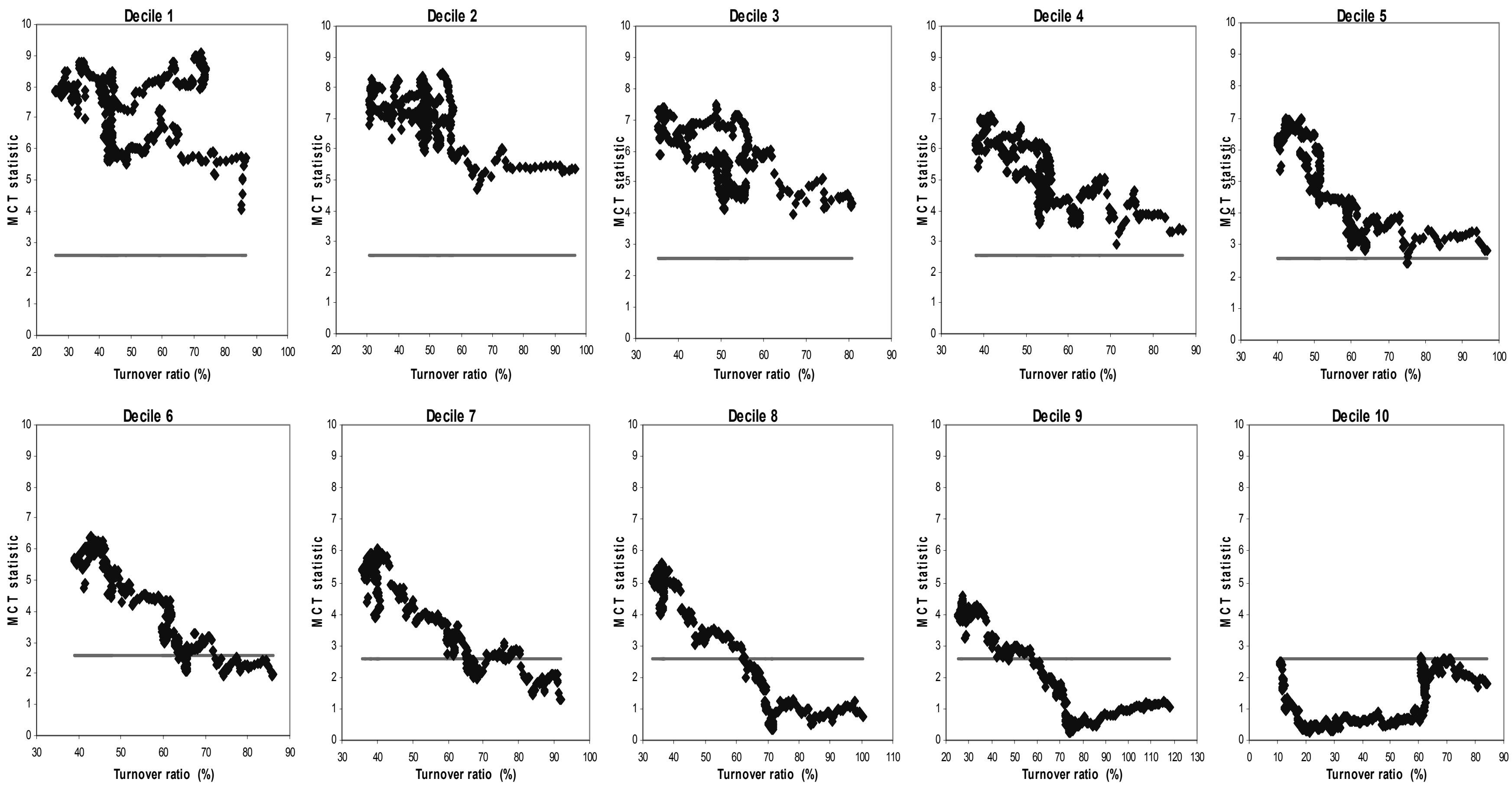


**Figure 8. MCT Statistic and Average Turnover Ratio for moving windows – Scatter plots (July 1962 – Dec. 2002, monthly observations)**
MCT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the MCT statistic is the average of the MCT statistics obtained from the moving-window ending in that month. Each observation of the turnover ratio is the average of the monthly turnover ratio data over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5%significance level.



## Appendix – Figures

### Figure A1. MCT Statistic for Moving Windows and the Corresponding Variance Ratio – Value-weighted and Equal-weighted Indices of all NYSE/AMEX stocks

Multiple comparison test statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns from July 1962 to September 2003. The straight line in Panels a) and c) is the benchmark value of 1.0 for the variance ratios that corresponds to MCT statistic (the maximum $z^*$-statistics among the ones calculated for 2, 4, 8, 16, and 32 week return horizons). Straight lines in Panels b) and d) indicate critical values at the 5% (upper bold line) and 10% significance levels, respectively.

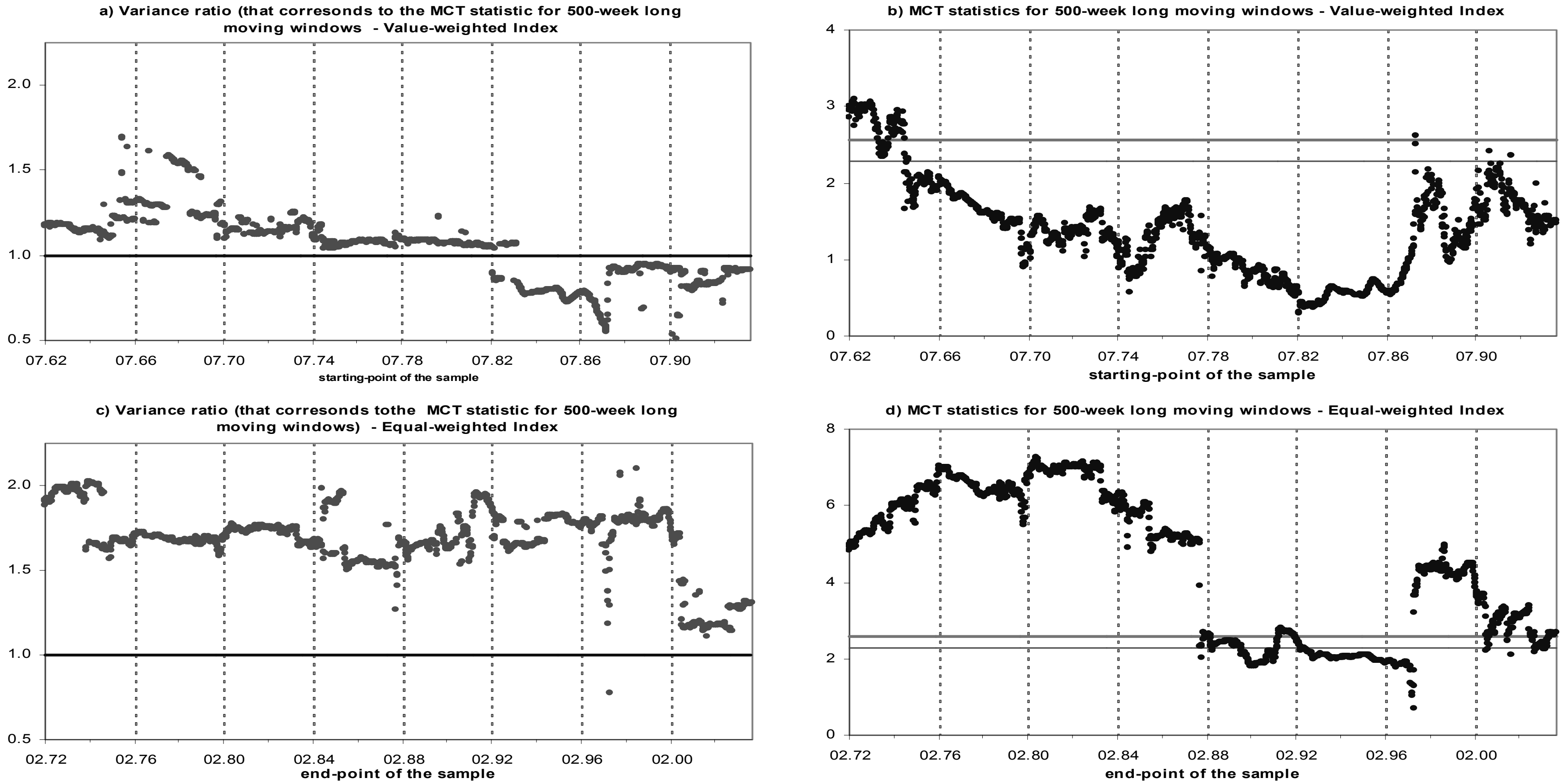


**Figure A2. RSWT Statistic and Average Market Capitalization/GDP Ratio for Moving Windows– Scatter Plots (July 1962 – Dec. 2002, monthly observations)** RSWT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the RSWT statistic is the average of the RSWT statistics obtained from the moving-window ending in that month. Each observation of the MC/GDP ratio is the average of the monthly indicators over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5%significance level.

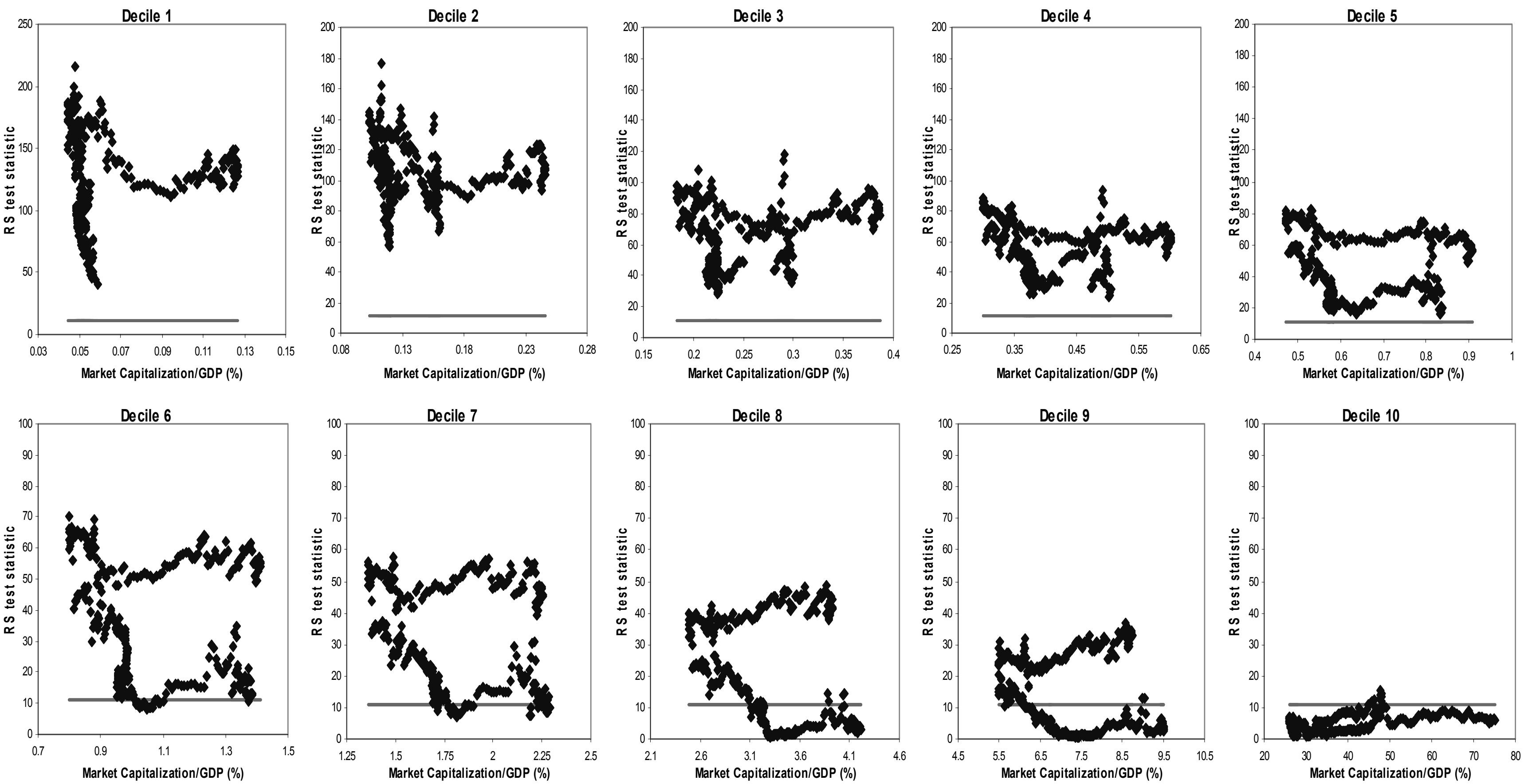


**Figure A3. RSWT Statistic and Average Trade Volume for moving windows – Scatter plots (July 1962 – Dec. 2002, monthly observations)** RSWT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the RSWT statistic is the average of the RSWT statistics obtained from the moving-window ending in that month. Each observation of the trade volume is the average of the monthly trade volume data over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5%significance level.

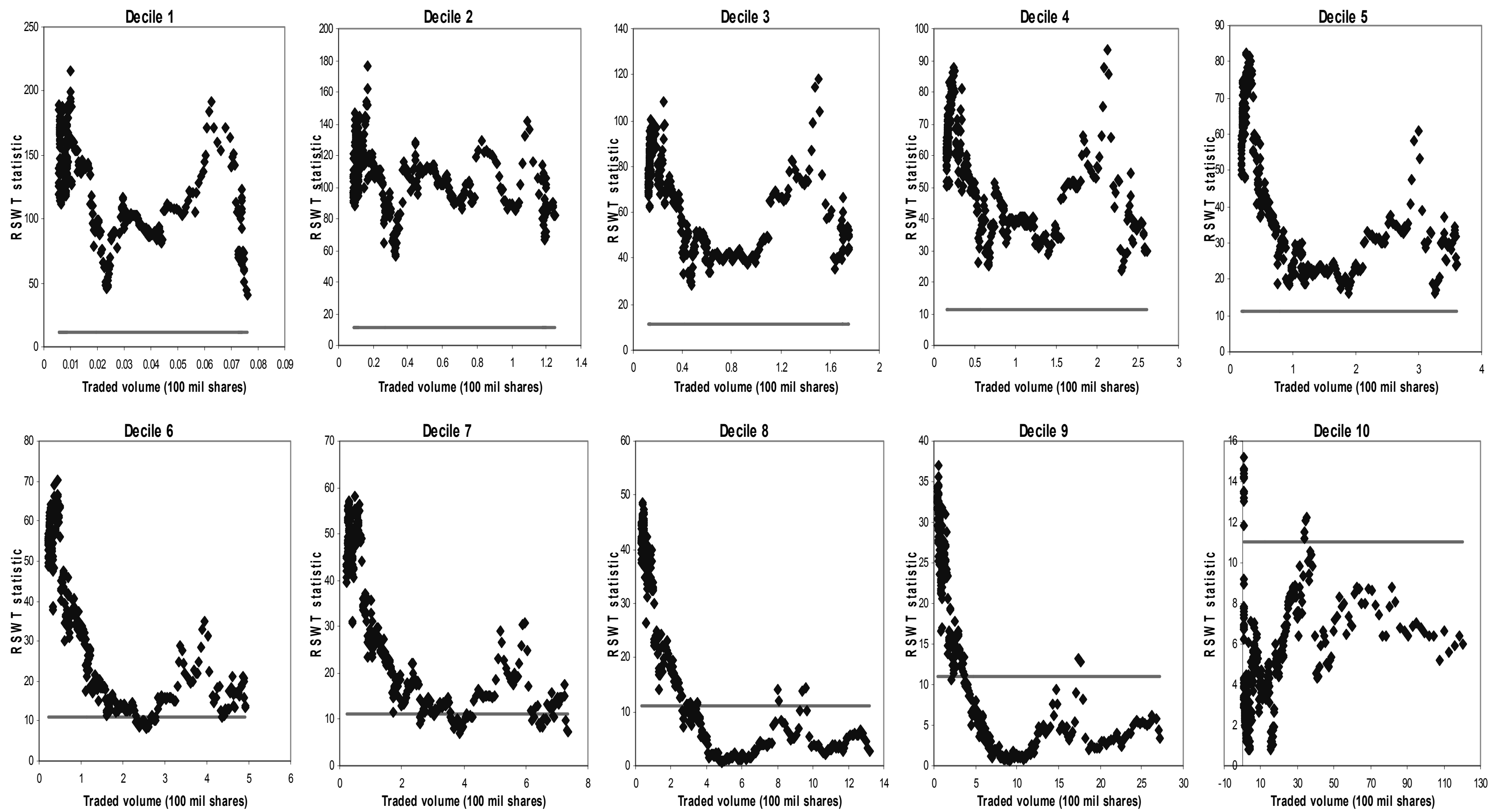


**Figure A4. RSWT Statistic and Average Turnover Ratio for Moving Windows – Scatter Plots (July 1962 – Dec. 2002, monthly observations)** RSWT statistics are calculated for 500-week long moving windows of weekly Wednesday excess returns for size-based decile portfolios after three outlier observations for October 1987 market crash (Oct. 21 and 28, Nov. 4) are dropped. Each monthly observation of the RSWT statistic is the average of the RSWT statistics obtained from the moving-window ending in that month. Each observation of the turnover ratio is the average of the monthly turnover ratio data over the corresponding 500-week moving-window. Decile portfolio index data are from CRSP daily index files. Graphs cover the period up to December 2002 because of the data on market indicators for 2003 were not available at the time of the data download. Straight line indicates the critical value at the 5% significance level.