Chapter 5

Evidence on the Stability of Serial Dependencies within Taiwan Stock Returns

5.1. The Question of Temporal Stability

A maintained assumption of all the tests used in the previous sections of this chapter is that whatever stochastic process underlies the data is a stable one, i.e., that the form of any serial dependencies within a data series remains stable. In other words, there is one correct model that describes the stochastic process, and the parameters of this correct model remain constant throughout the time period from which the data are drawn. For example, if the underlying process is a simple linear, autoregressive process, such as an AR(1) process, then the autocorrelation function (ACF), along with the model parameters for the process whose values are functions of the ACF, do not vary over time but remain constant throughout the entire time series. Due to the effects of random variation in the observed data, the estimated ACF will be an imperfect reflection of this stable underlying ACF.

If the underlying stochastic process is nonlinear, then the story becomes a bit more complicated. For example, an ARCH(q) process empirically mimics a time-varying parameter MA(q) process, so the apparent ACF for such a process will change over time. Nevertheless, the evolution of such a process can be described by equations whose parameters are stable or constant over time. Thus, such a nonlinear process could still be considered a stable process. (Note that the term "stable" is used here not in an engineering systems theory sense, but in terms of the parameterization of the process.)

If the stochastic process underlying stock returns is stable, then it may be feasible to model their progression over extended periods of time. Of course, many stable nonlinear processes would still be extremely difficult to model. But if the underlying process is not stable to begin with, e.g., if the form of any serial dependencies within the data series does not remain stable, then it would be impossible to model the process accurately over any extended period of time, thereby rendering prediction impossible and rendering invalid many empirical tests resting on specific distributional or memory (dependence) assumptions. The fact that many researchers have found it necessary to examine their results both with and without data from the period around October 19, 1987, and that such a period of presumed transient instability can drive some empirical results while obscuring others, clearly demonstrates both the possibility of and the problems associated with such process instability. The purpose of this section is to examine how stable the linear and nonlinear serial dependency structures of Taiwanese stock and stock index returns are, or, conversely, whether the observed departures, in terms of linear and nonlinear dependencies, of these returns from white noise are persistent or can be attributed instead to strong but episodic occurrences of such dependencies that appear within the data only infrequently.

5.2. Testing the Stability of Serial Dependencies via Hinich and Patterson's Windowed Test Procedure

The tool used to examine the issue of the stability of serial dependencies is the windowed test procedure of Hinich and Patterson (1996), which is designed to detect episodes of transient serial dependencies within a data series. Their procedure entails breaking the full sample down into smaller subsamples or "windows" of data and then testing each individual window for the presence of linear and nonlinear serial dependencies. Under the null hypothesis that the process underlying the data is a white noise process, the expected proportion of windows with significant results for any given test for serial dependencies within the data will be equal to the size, α, of the test.

Thus, if the full data sample does not exhibit any significant linear or nonlinear serial dependencies, a small proportion of the windows of data within this data set may nonetheless exhibit such dependencies due to chance, as a consequence of random variation. If, on the other hand, the full sample does exhibit significant serial dependencies but there are still only a few windows that are significant, then this suggests that the data may instead be characterized by episodes of transient dependencies and that it is the activity of these few windows that is actually driving the results for the overall sample.

Within each window, Hinich and Patterson's procedure makes use of two separate tests, one for detecting linear serial dependencies and one for detecting nonlinear serial dependencies. An autocorrelation portmanteau test similar to the Box-Pierce Q-statistic is developed for the detection of linear serial dependencies within a window. Under the null hypothesis that the data follow a white noise process, the autocorrelation test statistic and its asymptotic distribution are as follows:

$$H_N = L^{-1}\sum_{s=2}^{L}\sum_{r=1}^{s-1}[G^2(r,s)-1] \xrightarrow{D} N(0,1),$$

where:

$$L = N^c,\ 0 < c < .5,$$

$$G(r,s) = (N-s)^{-.5}\sum_{k=1}^{N-s}u(t_k)u(t_k+r)u(t_k+s).$$

In calculating C_T, the β parameter is typically set equal to 0.4. The C_T statistic is then translated into a percentile (or one less the p-value) for the χ^2_L distribution, and it is this percentile that is reported as the "C" statistic for each window in timeplots of these statistics.

For detecting nonlinear serial dependencies within a window, the procedure uses a bicorrelation portmanteau test that is a time-domain analog of the bispectrum test statistic to generate the "H" statistic that is reported for the window. Under the null hypothesis that the observations within a given window are white noise, the bicorrelation portmanteau test statistic and its distribution are as follows:

$$H_T = \frac{1}{L}\sum_{s=2}^{L}\sum_{r=1}^{s-1}[G^2(r,s)-1] \xrightarrow{D} N(0,1),$$

where:

$$L = N^{\beta},\ 0 < \beta < .5,$$

$$G(r,s) = (N-s)^{-.5}\sum_{k=1}^{N-s} u(t_k)u(t_k+r)u(t_k+s).$$

The final reported "H" statistic, then, is the percentile in which this H_T statistic falls within the standard normal distribution.

As a final note, the null hypothesis for Hinich and Patterson's test procedure is that the time series follows white noise, so the procedure looks for time periods during which the time series exhibits behavior that departs significantly from white noise. With the procedure testing for departures from white noise in terms of both linear serial dependencies (autocorrelation) and nonlinear serial dependencies (bicorrelation), a significant result for either or both of these tests will flag a window as exhibiting significant non-white noise behavior. The actual size for the test procedure, then, is not the same as the size used for the individual tests used in the procedure; rather, it is a function of the sizes of the two individual tests used in the procedure. If the two tests are independent of each other, then the size of the test procedure within a given window is:

$$\alpha_{Window} = 1 - [(1-\alpha_C)(1-\alpha_H)].$$

For example, if a test threshold of 0.005 is used for each of the two tests within the procedure, then the actual size for the window would be 0.00998, or approximately 0.01. Thus, while each of the individual tests would falsely reject white noise in approximately one out of every 200 windows, for both tests considered together the false rejection rate almost doubles, climbing to approximately one out of every 100 windows, with the significant windows showing significant results for autocorrelation, bicorrelation, or both. Alternatively, if the test threshold were set to a relatively high level of 0.20, so that the chance of obtaining a false rejection of white noise from a given test is one in five, then the chance of a false rejection increases to 0.36, or more than one time or window out of three, when a rejection can come from either or both tests.

As discussed above, Hinich and Patterson's windowed test procedure breaks the full sample down into a number of short windows, and then examines the linear (autocorrelation) and nonlinear (bicorrelation) dependency structure for each window. A stationary process should generate similar test results across most windows. But before the test can be applied, three important elements of the testing procedure must first be decided upon. These elements are whether or not to clip the data to remove the effects of outliers, what test threshold or significance level to use to decide whether a given test statistic is significant within a given window, and, finally, how wide these windows should be.

The first element, clipping the data, is undertaken to prevent presumably anomalous observations, such as that of October 19, 1987, from affecting the test results. Even for long data series, such anomalous observations, or "outliers," can overwhelm any statistical regularities among the rest of the data and dramatically affect the results of statistical tests, whether by masking or obscuring any regularities that do exist among the data or, alternatively, by creating the appearance of statistical regularities where none in fact exist. In other words, a sufficiently large outlier at the right location in the data could either drive or mask significant test results within even very large data sets. Within a small data set, such as the data within a narrow sampling window from a larger data set, the effects of any such outliers are exponentially greater. Thus, when using sample data windows, it is especially important to try to insulate the test statistics, hence the test results, from the effects of any such outliers. The tool used to accomplish this task is the data clipping procedure.

The clipping procedure entails replacing the values of the most extreme observations in the data set with those of somewhat less extreme observations. I.e., if 1% of the data points are clipped, then the values of the 0.5% most extreme low or negative observations will be replaced with the value of the observation at the 0.5^{th} percentile, while the values of the 0.5% most extremely large observations are substituted with the value of the observation at the 99.5^{th} percentile. Clipping the data in this manner will prevent anomalous data from affecting the results, but at the cost of preventing the effects of some legitimate observations from being reflected in the results.

The next element that must be decided upon in the windowed test procedure, the choice of test threshold to use to determine whether the results for a given window are significant, entails a similar set of tradeoffs. If the threshold is set too low, then, assuming that the data are white noise data, a false rejection of the null hypothesis that the data within a given window follow a white noise process will be unlikely, but the test would also be less likely to reject the null hypothesis if the data are in fact subject to linear or nonlinear serial dependencies, unless these dependencies are fairly strong. Weak serial dependencies would be less likely to affect the data to a sufficient degree to enable it to register a significant test statistic. A high test threshold, on the other hand, would increase the statistical power of the test procedure, better enabling any such weak dependencies to be registered via a significant test statistic, but the cost of this increased power is, of course, an increased likelihood of obtaining false rejections of the null hypothesis when there are no dependencies underlying the data. Furthermore, as noted in the previous section, this likelihood of false rejections is multiplied when there are multiple tests (e.g., for autocorrelation, for bicorrelation, etc.) that can lead to the triggering of a significant window.

The final, and perhaps most important, decision that must be made in applying Hinich and Patterson's windowed testing procedure is the choice of window width. Similar to the situation in choosing a test threshold, statistical power is an issue in deciding what window width to use. In general for statistical tests, the greater the number of observations used in performing statistical tests, the greater the power of those tests. So including the full data set in one large window of data would result in the greatest possible power for the tests used. But such an approach would average the test statistics out across all of the data, thereby precluding the detection of transient dependencies within the data and defeating the purpose of using a windowed test procedure.

Thus the tradeoff in this case is between having windows containing a sufficient number of data points to provide adequate power and having a large enough number of sufficiently narrow windows to be able to pinpoint the arrival and disappearance of transient dependencies. If dependencies are transient but appear with sufficient frequency, then the choice of wider windows could result in having significant results for every window, giving the appearance of a strong, stable dependency structure, despite the fact that the specific dependencies that are driving the results may be different for each window or may even vary within each window. Conversely, if the dependencies that do appear in the data persist for some time but are of a relatively low magnitude, then a larger number of observations would be necessary to detect them, and if the windows are not wide enough, these dependencies may not trigger significant test results even for the windows in which their presence is manifested most strongly.

Thus, the choice of window width must be guided by the investigator's ideas about both how strongly and how transiently serial dependencies appear within the data. For the Taiex data, the extremely high significance levels ($p < 0.0005$) for each of the nonlinearity tests applied to this data suggest that if dependencies within the data are transient, they are likely to be very strong and so should be detectable even within fairly narrow windows. Moreover, the results of other studies indicate that the duration of serial dependencies within financial time series can be very short. For example, in the Hinich and Patterson (1996) study of DJIA stocks, significant linear and nonlinear serial dependencies were found within the overall sample, but when the sample was broken down into relatively narrow, two-week-long, windows, such dependencies appear extremely strongly within only a few windows but then quickly disappear altogether, or at least become too weak to be detected, in subsequent windows. Therefore, strong serial dependencies, at least within intradaily data, can appear strongly and then quietly disappear even within as short a time span as two weeks.

Note that clear and unambiguous results regarding the transience of serial dependencies are possible in this case because Hinich and Patterson were using intradaily data, so even as seemingly short a time span as two weeks would still contain a sufficiently large number of observations to yield fairly powerful tests. With daily data, on the other hand, much larger windows of data would need to be used in order to obtain similar power levels. But aside from the issue of power, these results do illustrate just how transient the serial dependencies within financial time series can be. Thus, in order to clearly detect exactly when such transient dependencies appear, it is necessary to use windows that are as narrow as possible. Windows that are too wide, moreover, would cover a much wider variety of economic circumstances, thereby obscuring or averaging out not only any transient patterns of serial dependence but also much more general information that a windowed testing approach could potentially convey.

5.3. Results of Windowed Testing of Serial Dependencies in Taiex Returns

As a consequence of the numerous factors described in the previous section, there are a number of decisions to make in applying Hinich and Patterson's windowed testing procedure, and a good deal of information can be obtained about the variability across time of the stochastic process underlying the time series. In using this test procedure for the Taiwan stock index data, the goal of this section will be to use this procedure to try to learn as much as possible about the time-variability of the stochastic process underlying the Taiex returns.

Possibly the most important of the decisions to be made in the windowed test procedure is that of the window width to use. To make the tradeoff between the ability to quickly detect changes in the serial dependency structure and the power to detect the dependencies that exist within a given window, a rule of thumb was used of setting the window width approximately equal to the square root of the full sample size. For the Taiex daily data, the full sample size is 3,142 observations, a number for which the square root is 56.05. This figure was then rounded downward slightly to obtain a window width of 54 days, which would include nine full weeks (at six trading days per week) of trading activity. Incidentally, this window width also covers just over two months of trading activity, so while Hinich and Patterson (1996) use two-week windows in examining intradaily return data, the present study uses two-month windows in examining daily return data. Even so, using just 54 observations per window does raise questions of statistical power, which will be discussed and examined in more detail in subsequent sections of this chapter.

For the weekly Taiex returns, there are far fewer observations (538 versus 3,142), so the rule of setting the window width equal to the square root of the sample size was not followed, because this would only allow 23 observations per window, far too few observations to obtain any reasonable statistical results. Furthermore, a two-month window as is used for the daily returns would contain even fewer observations. Instead, the window width for the weekly return data is set to 50 weeks. This still entails fewer observations than the windows for the daily returns, but it does include one whole year's worth of trading, after accounting for the fact that the Taiwan Stock Exchange is closed one week each for the New Year's and Chinese New Year's holiday seasons.

After window width, the next decision to be made is the test threshold to use. Because the goal of the test procedure is typically to detect pockets of very strong nonlinear activity, a very low test threshold is generally used, such as 0.005, so that there is little chance of a 'false positive' test result indicating the presence of nonlinearity where it does not really exist. The potential problem with such a low test threshold, as was noted in the previous section, is that if serial dependencies are present in the data but are not particularly strong, it may not be possible for them to generate a large enough test statistic to cross this threshold, in which case they will remain undetected. However, the extremely low p-values that are typically obtained when testing for nonlinear serial dependencies in financial time series, as is illustrated by the results of the previous chapter, indicate that the use of as low a test threshold as 0.005 should not create too many problems in this regard. But with only 54 observations per window for the daily data and 50 observations per window for the weekly data, questions of power will nevertheless arise. Thus, the results for both the daily and weekly returns will be reported for a wide range of test thresholds, including 0.005 at the strictest, on through 0.01, 0.05, and 0.10, and finally to 0.20 at the least strict.

The third decision to make is whether or not to clip the data to control for outliers. Given the tradeoffs entailed in this choice, namely eliminating valid observations that actually reflect nonlinearities within the data versus keeping all the observations as is and potentially having results that are driven by truly anomalous observations, the windowed test procedure will be performed both on the original data series and on the series with 1% of its most extreme observations clipped, which will allow a comparison between these two alternatives. A similar approach will be taken with a final decision to be made, whether or not to use windows that overlap one another. Use of overlapping windows can provide greater information about the "fleetingness" of any transient dependencies, especially in comparison to the results using only adjacent windows. Thus, results for both overlapping and non-overlapped windows will be reported. For the daily return data, a 54-day window width results in a total of 58 separate, adjacent windows or a total of 115 overlapping windows. For the weekly data, there is a total 10 non-overlapping windows or 20 overlapping windows.

A summary of the results of the windowed test procedure for the Taiex daily and weekly returns is given in Table 5.1, and plots of the results across windows are given in Figures 5.1 through 5.4. The top set of results in Table 5.1 are the autocorrelation (C_T) and bicorrelation (H_T) test statistics and their respective p-values for the full data sets. The first set of results gives the values for these statistics when testing out to a number of lags equal to the 0.4^{th} root of the number of observations. For the daily returns, with 3,142 observations, the C_T and H_T statistics were calculated utilizing the estimated autocorrelations and bicorrelations out to 25 lags. For the 538 observations of weekly returns, these statistics incorporated the autocorrelations and bicorrelations out to 12 lags. This means that the C_T statistics for the daily returns are compared to a Chi-Squared distribution with 25 degrees of freedom, while the C_T statistics for the weekly returns are compared to a Chi-Squared distribution with 12 degrees of freedom. The H_T statistics, on the other hand, are normalized, so they are compared to a standard normal distribution regardless of the number of lags used.

In either case, the statistics are highly statistically significant, indicating the presence of strong linear and nonlinear dependencies within both time series. Of the two test statistics, the nonlinearity statistic, H_T, appears to lead to the strongest rejections of the null hypothesis of no serial dependencies within the data. For the daily data, though, both the autocorrelation and bicorrelation statistics entail p-values that are much less than 0.0001. For the weekly data, on the other hand, the C_T statistic is only marginally significant at a 5% level, with a p-value of 0.048. Overall, these results are very similar to those obtained in Chapter Four, despite the differences in specific test statistics used.

The results for the C_T and H_T statistics are reported not only for the original data, but also for the data after 1% clipping. For the daily return data, there is little difference between the two sets of results, and the significance levels for the test statistics remain virtually unchanged. Interestingly, although the same proportion (1%) of observations were clipped in both cases, clipping had a more noticeable impact on the results for the weekly return data. After clipping the data, the autocorrelation test statistic for the weekly data grew slightly larger, from 21.19 to 23.26. But because the original figure was only marginally significant, this increase in the test statistic had a more dramatic impact on the p-value, lowering it from 0.048 down to 0.026. On the other hand, while the autocorrelation test statistic increased slightly, the bicorrelation test statistic suffered a more substantial move in the opposite direction, from 33.00 to 25.87. These two sets of results would seem to indicate that, at least for the weekly returns, outlying observations obscure some of the autocorrelation within the data while driving some of the magnitude of the nonlinear dependencies. However, even the lower value for the H_T statistic after clipping the data, 25.87, is still an extremely large value for a Z-statistic, so there is no question that outlying observations are actually driving the results, only that they are amplifying the magnitude of these results.

The results described above take lags all the way out to 25 for the daily returns and 12 for the weekly returns into account for calculating the autocorrelations and bicorrelations in the test statistics. For the tests within each window, however, the shorter sample sizes necessitate cutting off the autocorrelations and bicorrelations after the fifth lag. To the extent that the overall results discussed above may be driven by results from longer lags, comparing these results to the window test results would be like comparing apples and oranges. Thus, the next set of results in Table 5.1 are the autocorrelation and bicorrelation test results calculated only out to lag five.

Restricting the tests to lags no greater than the fifth lag has a substantial impact on the magnitude of the test statistics. The autocorrelation test statistics, for both the daily and the weekly and both the original and clipped data sets, fall by between 33% and 40%, from magnitudes of about 186 down to about 115 for the daily data and from 22 or 23 down to about 14 for the weekly data. Thus, about a third of the overall magnitude of the autocorrelation within these data sets is driven by autocorrelation at lags greater than 5. On the other hand, this means that about two-thirds of the overall autocorrelation within these series is embodied in autocorrelation within the first five lags, and this autocorrelation is still highly significant. In fact, despite their smaller test statistics, the p-values for this autocorrelation actually decrease (i.e., become more significant), because these reduced overall measures of autocorrelation are being averaged out over a much smaller number of lags. Thus, for the original weekly data series, for example, as the test statistic falls from 21.19 to 13.76, the p-value also falls, from a marginally significant 0.048 to a much more clearly significant 0.017.

For the bicorrelation test statistics, moving from using 12 or even 25 lags worth of bicorrelations (for total numbers of bicorrelations used in these test statistics of 66 and 300, respectively) down to only five lags worth of bicorrelations (or a total of 10 bicorrelations) results in a proportionately much greater reduction in the magnitude of the test statistic. For the daily data, reducing the number of lags used (reducing the total number of bicorrelations tested from 300 down to 10) results in an 80% reduction in the bicorrelation test statistic, down to 24.94 for the original data and 23.65 for the clipped data. For the weekly data, there is a smaller reduction in the number of bicorrelations tested (from 66 to 10), but the bicorrelation test statistic still declines in magnitude by about two-thirds, down to 9.29 for the original data and 8.84 for the clipped data. Nonetheless, these are still very large values for Z-statistics, so all of these bicorrelation test statistics remain highly significant, even when only the nearest 10 bicorrelations are considered.

The remaining, lower, sections of Table 5.1 show the key results for this section, the results for the windowed testing. These results are also presented graphically in Figures 5.1 through 5.4. The plots in these figures show the percentiles (i.e., one less the p-value) into which the autocorrelation and bicorrelation test statistics fall for each given window. All of the overlapped windows are shown; the results for non-overlapped windows can be obtained simply by looking at the first window and then every other window subsequent to the first window. Figures 5.1 show the results for the original Taiex daily returns, while Figures 5.2 show the results for the clipped Taiex daily returns. Similarly, Figures 5.3 and 5.4, respectively, show the results for the original and clipped weekly return series.

The above emphasis on detailing the results for the full data sets provides the necessary background for analyzing the results within each window (and vice versa). Interestingly, for the daily return series, despite the fact that both the autocorrelation and bicorrelation test statistics are highly significant, with extremely small p-values of less than 1×10^{-22}, only a very small proportion of the individual windows have significant test results for either of these two types of serial dependencies. For the strictest test threshold presented, 0.005 (or 5×10^{-3}), only a total of 5 out of 58, or 8.62%, of the total of non-overlapping windows and 11 out of 115, or 9.57%, of the overlapping windows exhibit significant linear or nonlinear serial dependencies. Of the five significant windows from the non-overlapping testing, two (3.45%) exhibit significant autocorrelation and three (5.17%) exhibit significant bicorrelation. Among the 11 significant overlapped windows, four (3.48%) exhibit significant autocorrelation while eight (6.96%) exhibit significant bicorrelation. Identical results are also found for the clipped data.

These percentages are all greater than the 0.5% of windows from a white noise series that would be expected by chance to exhibit significant autocorrelation or the similar percentage of windows that would be expected to exhibit significant bicorrelation. But, as indicated by the overall test statistics described previously, the full data series is far from white noise. And given the strength of these test statistics for the full data series, many more of the windows of this data would also be expected to exhibit strong serial dependencies. Instead, while overall average levels of autocorrelation and bicorrelation are very high, these dependencies seem to manifest themselves in only a relatively few windows, with most windows being relatively quiet in terms of the dependencies they exhibit.

This pattern continues for the less strict test thresholds examined, 0.01, 0.05, 0.10, and 0.20, and to a certain extent becomes even more pronounced as the test threshold increases. If the data were white noise and contained no serial dependencies, for example, then, at a test threshold of 0.20, approximately 20% of the windows would still be expected to exhibit significant test statistics for autocorrelation simply due to chance. However, for the Taiex daily return data, which does exhibit highly significant autocorrelation for the full data set, only about 16% of the individual windows exhibit significant test statistics at this level. Thus, despite the strong autocorrelation evident in the Taiex daily returns, this autocorrelation drives even fewer windows to be significant than would be expected, as a consequence of random variation, for an uncorrelated, white noise data set. This finding would tend to suggest that the existence of autocorrelation is largely limited to the few highly significant windows and that it is the autocorrelation exhibited within these few windows that is driving the autocorrelation test results for the full data series.

A similar conclusion could be argued for the nonlinearity within the daily returns. A greater proportion of windows exhibit significant nonlinearity than exhibit significant autocorrelation (6.96% versus 3.46%, respectively, for non-overlapped windows of the original data set with the test threshold established at 0.5%), but once again there is a situation in which there are evidently very strong serial dependencies within the full data set (with p-values less than 1×10^{-25}) that manifest themselves significantly within only relatively few windows. Compared with the autocorrelation, the nonlinear dependencies appear to be even stronger in the overall sample, and such nonlinear dependencies drive a larger proportion of windows to be significant, so that is no longer the case with the bicorrelations that fewer windows are significant than would be expected by chance within white noise data.

Nevertheless, despite the strength of the nonlinear behavior in the full sample, this nonlinearity apparently manifests itself only relatively infrequently and fleetingly. This "fleetingness" or "transience" is illustrated in Figures 5.1 and 5.2, in which windows with more highly significant test statistics are often adjacent to windows whose test statistics are far from being significant. The slightly lower percentages of significant windows for overlapping windows relative to non-overlapping windows tends to corroborate the idea of the transience of the nonlinear serial dependencies within the data. This disparity in percentages indicates that, more often than not, such dependencies appear significantly within one window of data without appearing significantly in either of the two overlapping windows. In other words, the nonlinearity that appears within one window appears and then dissipates too quickly to drive significant test results within either of its overlapping windows, even though each of the observations within the significant window would also be contained within one or the other of these two adjacent windows.

In addition to this transience, another interesting feature of the test results for both autocorrelation and bicorrelation that is visible in the plots is that the test statistics tend to be either highly significant or extremely low, with relatively few statistics falling in between. Under the assumption of strong serial dependencies that are persistent throughout the data, it would be expected that the test statistics would tend to be fairly high for all of the windows, though with a bit of variation due to random fluctuation. Thus, some of the test statistics would be large enough to be significant while others would be somewhat lower, but very few would be expected to fall in the lower percentiles. In general, data with a constant dependency structure would tend to have a distribution of test statistics that is shifted upward relative to that of white noise data. But contrary to this expectation, the Taiex daily data actually has a greater proportion of test statistics falling into the lower percentiles than would be expected for white noise data. For example, about 22% of the bicorrelation test statistics and an even greater 30% of the autocorrelation test statistics fall below the 20^{th} percentile of the null distribution. This distribution of test statistics suggests that, rather than there being a constant dependency structure within the Taiex daily returns, the dependency structure fluctuates broadly over time between very strong dependence and virtual independence.

For the weekly Taiex returns, the autocorrelations for the full data set are not as strong as those for the daily returns, and this weaker autocorrelation structure is reflected in the paucity of windows that exhibit significant autocorrelation. For the clipped data, one of the overlapping windows exhibits significant autocorrelation at a level of 0.20. For the original (non-clipped) data, a second overlapped window also exhibits significant autocorrelation at this level (see Figures 5.3 and 5.4 for more details). For the non-overlapped window tests, none of the windows exhibits significant autocorrelation, even at as high a level as 0.20. But no windows, for either the original or the clipped data or for either overlapped or non-overlapped window testing, exhibit significant autocorrelation at a level of 0.10 or less.

For the nonlinear dependencies, the full sample test statistics were much more highly significant, and this is reflected in a greater number of significant windows for bicorrelation than for autocorrelation. For a test threshold of 0.005, for the non-overlapped window tests, 10% of the windows exhibit significant bicorrelation, though this 10% figure entails only one single window. For the overlapped window tests, proportionately more windows exhibit significant bicorrelation (a trend opposite of that for the daily data), and the total comes to three significant windows. When the test threshold is increased to 0.05, another two of the overlapped windows become significant, for a total of five windows or 25.0% of the total, while, for the non-overlapped windows, the total remains at one. Increasing the test threshold to 0.10 causes the bicorrelation test statistics for two more windows to be categorized as significant, for a total of three significant windows for the non-overlapping window tests and seven significant windows for the overlapping window tests. Finally increasing the test threshold to 0.20 allows one additional window to become significant for the overlapping window tests, for a total of 40.0% of the overlapping windows being significant. At each step in increasing the test threshold, the number of significant windows for nonlinear dependencies is greater than would be expected by chance for white noise data, and the proportion of significant windows is greater out of the 20 overlapped windows than from the 10 non-overlapped windows. These two pieces of information suggest that the serial dependencies within the weekly returns may be less transient and more persistent than those within the daily returns.

For both the daily and weekly Taiex returns, though, the key finding from these tests is that significant test results for linear and nonlinear serial dependencies for the full data series are reflected in significant test results for only relatively few of the subsample windows from these series. However, although the emphasis in this chapter is on using these results to highlight the transience of such dependencies, it is important to note that a number of possible factors could lead to such results. The first possibility is that the serial dependencies within the data are episodic and transient, disappearing almost as quickly as they appear (possibly through the actions of quickly reacting traders). A second possibility is that dependencies within the data are persistent but of low magnitude, so that random variations in the data will cause them to appear too weakly to be detected in some windows, given the relatively high levels of statistical power necessary to detect them. A third possibility is that the relevant dependency structure, the memory within the data, is too long to be adequately captured within an individual window. These possibilities are not mutually exclusive, though; they could all exist within the same data set. For example, a data set could have both long- and short-term dependencies, and among the short-term dependencies, there could be persistent, low level dependencies that are augmented by much stronger dependencies on an episodic basis.

For the Taiex data, the results presented above suggest that some combination of these factors is present. The autocorrelation within the weekly data, which is only marginally significant in the full sample but is not significant in any of the individual windows at even as high a test threshold as 0.10, does not appear to be driven by any "pockets" of highly autocorrelated activity, and the autocorrelation within these returns could be an example of low-level but persistent serial dependencies. But for the other sets of dependencies examined, the bicorrelations within the weekly returns and both the autocorrelations and bicorrelations within the daily returns, the magnitudes of these dependencies within the full sample seem to be much too high for this to be the case, and the relative scarcity of significant windows in these cases is more likely the result of the appearance of transient dependencies within the data. Moreover, the substantial decline in the magnitude of the bicorrelation tests in moving from testing out to a number of lags based on the full sample size down to testing only out to five lags indicates that, in addition to the very strong bicorrelation out to five lags that would be detectable within the span of a single window, there is also strong bicorrelation whose lag structure is too long to be included in any of the single-window tests.

5.4. Effects of Trading Price Limits on Observed Serial Dependencies

One issue that has not yet received much attention is the specific pattern across time of the magnitudes of the dependencies within these return series. Of interest is whether there is any clustering in the appearance of stronger dependencies during any specific time period, or whether the appearance of such dependencies is more random. This would be a subject of interest for any market. But the existence of daily price limits on transactions on Taiwan's stock exchange creates particular interest in what effect these price limits, and the changes that have been made in them, have on the appearance of serial dependencies within the returns on this market. For reference, the price limits on the Taiwan Stock Exchange and the dates within the sample period during which they were in effect are given in the table below.

Price Limits	Start	End
5%	Beginning of Data	October 24, 1987
3%	October 27, 1987	November 11, 1988
5%	November 14, 1988	October 9, 1989
7%	October 11, 1989	End of Data

For the weekly Taiex returns, although the bicorrelation within the data is generally more highly significant than the autocorrelation within the data, both types of dependencies tend to make their strongest appearances simultaneously. There appear to be three main periods when these dependencies are at their strongest - the period at the beginning of the data set from July, 1987 through January, 1984, the period from March, 1987 through September, 1988, and the final two years of data, especially the window covering the period from November, 1990 through October, 1991. These periods of strong serial dependence among the weekly returns appear to be somewhat randomly spaced within the data and cover three different price limit regimes and three different types of markets, the quiet, pre-runup market, the more volatile market after the Taiex had begun its ascent, and the post-crash market. The only commonality between the three periods seems to be the fact that they are all characterized by both strong autocorrelation and strong bicorrelation. But between these three periods, the evolutionary paths of these two types of dependencies seem to differ somewhat, with the strength of the bicorrelations shifting more abruptly from very weak to very strong and with few windows exhibiting nonlinear dependencies of more moderate levels. The strength of the linear serial dependencies, on the other hand, tends to change more gradually from window to window, with fewer abrupt changes in strength.

For the daily Taiex returns, this relationship seems to be reversed. The autocorrelations tend to appear either very strongly within a window or very weakly, but with few windows exhibiting more moderate amounts of autocorrelation. A much greater proportion of windows, on the other hand, display more moderate levels of bicorrelation. Also in contrast to the situation for weekly Taiex returns, there seem to be few commonalities between the appearances of strong autocorrelation and the appearances of strong bicorrelation within the daily returns. Within the plot for the bicorrelations, it appears that there are pockets of strong nonlinear activity interspersed fairly persistently but somewhat randomly throughout the overall sample, although there does seem to be somewhat of a lull period near the end of the sample. The autocorrelations, on the other hand, appear significantly in much fewer windows. As with the weekly data, this could be a reflection of the somewhat greater strength exhibited by the nonlinear dependencies than by the linear dependencies within the full data series. But these relatively few windows exhibiting the strongest autocorrelation also appear to be more clustered than the strong bicorrelation windows, with all five of the windows that test positive for autocorrelation at test thresholds of 0.01 or less occurring during the two-year stock market runup period of 1987 and 1988. Thus, there is evidence that the stock return dynamics were different during this run-up than during other periods. One major factor that could lead to such a difference are the price limits, which were at their strictest during this time interval.

Unfortunately, the tool being used up to this point, the use of test statistics tied to specific windows, can be too limited for use in examining this relationship more closely. This is a consequence of the long time lag, up to 27 trading days, between when an event occurs and when the test statistics are updated. Depending on what occurs in the meantime, a temporary jump in the strength of serial dependencies could lead to a significant value for the subsequent test statistic, or it could be averaged out by subsequent events, in which case its presence would never be known. Therefore, in order to obtain more detailed information about the time path of serial dependencies and its connection, if any, with the changes in price limits, the use of overlapping windows in the windowed test procedure was modified so that, rather than advancing half a window width at each step, the advance between calculations would instead be a single day. Thus, instead of using half-overlapped windows, 54-day sliding windows that were updated daily were used instead, with each of these daily updated windows containing a full 53 days' worth of data that was also included in the calculations for the preceding window.

These daily updated 54-day test statistics are shown in Figures 5.5. The top figure shows the time path for the autocorrelation test statistics (the actual C_t test statistics, rather than the percentiles for these statistics as shown in the previous plots) plotted against the value for the 99.5^{th} percentile of the Chi-squared distribution with five degrees of freedom. The middle figure shows the time path for the Z-statistics (or normalized test statistics) for the bicorrelation test, plotted against the 99.5^{th} percentile value for the standard normal distribution. The bottom figure contains the time path for the non-normalized test statistics for bicorrelation, plotted against the 99.5^{th} percentile value for the Chi-squared distribution with ten degrees of freedom.

This latter portmanteau bicorrelation test statistic is an alternative to the normalized test statistic given previously. It is recommended by Hinich and Patterson (1996) especially for cases in which the number of lags (L) used is less than 16. In these cases, the Chi-squared test statistic entails better tail properties than the normalized test statistic. For this variation of the bicorrelation portmanteau test, under the null hypothesis that the observations within a given window are white noise, the test statistic and its null distribution are as follows:

$$H_T = \sum_{s=2}^{L}\sum_{r=1}^{s-1} G^2(r,s) \xrightarrow{D} \chi^2_{\frac{L(L-1)}{2}},$$

where:

$$L = N^{\beta}, \ 0 < \beta < .5,$$

$$G(r,s) = (N-s)^{-.5} \sum_{k=1}^{N-s} u(t_k) u(t_k + r) u(t_k + s).$$

For this section, as for the previous window tests, the number of lags, L, is set at five, as a function of the 54-day window width that is used.

Comparing the results in Figures 5.5 for the two different sets of bicorrelation test statistics, the only major difference seems to be the significance levels of the results. The value of the 99.5th percentile of the null distribution seems to be somewhat higher relative to the test statistic values for the Chi-squared test statistics than for the normalized ones, and slightly fewer of the non-normalized test statistics achieve a sufficient magnitude to exceed this threshold. Thus, the windowed test results discussed above, for which used the normalized test statistic was used, may actually be overstating the number of windows that exhibit significant nonlinear dependencies. But the differences in the relative heights of the test thresholds is only very slight, and the patterns exhibited in the time paths of the two sets of test statistic data are virtually identical, so regardless of which method is used to tell the story, the story remains the same.

And the story that both of these test statistics tells is one of strong nonlinear dependencies appearing episodically throughout the data but typically driving the test statistic to be significant for only a few days at a time. On one occasion, around June, 1984, the sequence of test statistics remains greater than the 0.005 test threshold for over a month, but in most cases significant test statistics are followed within a few short days by test statistics that fall back below the test threshold. In contrast to the results shown in Figures 5.1, it is evident in these time paths that there are spikes in the level of bicorrelation concomitant with the two main periods of high autocorrelation, but these two spikes are only a few out of the many spikes in nonlinear activity that appear throughout the time series, across all different types of market behavior and all different levels of price limits. Closer to the end of the data series, about a year after the spike that is concurrent with the second spike in autocorrelation, there is a brief flurry of marginally significant nonlinear activity, after which the market seems to enter a three-year lull period during which the market is relatively quiet in terms of nonlinear activity. This lull is ended just before the end of the data sample by a final strong, though very brief, spike in the level of bicorrelation.

In terms of autocorrelation, on the other hand, the market is relatively quiet, with the test statistics remaining well below the 0.005 test threshold throughout most of the sample. Note that this does not mean that there is no autocorrelation within the returns of this period, only that whatever autocorrelation is extant in the data is too weak to be discernible within any 54-day period. The exception to this, when the levels of autocorrelation not only cross the test threshold but actually remain above it for extended periods of time, all occur during the relatively brief span from October 15, 1987 through December 7, 1988. Notably, and probably not coincidentally, this interval surrounds and largely coincides with the period during which the price limits were the strictest, at 3%.

This overlap between the period of greatest autocorrelation and the 3% price limit regime can be clearly seen by comparing the plot of the autocorrelation tests with the plot of the daily returns given at the top of Figures 5.6. The remaining two plots of Figures 5.6, showing recursive estimates for the variance and for the first-order autocorrelation within the Taiex daily returns, provide additional details in support of one possible explanation for the close relationship between the high autocorrelation and these strictest price limits.

The recursive estimates in Figures 5.6 are obtained by taking a small number of observations at the beginning of the data set, in this case the first 54 days' worth of data, and using these observations to estimate the parameter in question, here the variance of the daily returns and the first-order autocorrelation within these returns. Then, the next day's observation is added to the observations already used, and the values for the parameters are re-estimated, after which the following day's observation is added and the parameters are re-estimated again. This process continues until all the observations have been included and the final parameter estimate has been obtained. The series of parameter estimates is then output, and their behavior over time can be plotted and examined. The formulas used to estimate the variance (s_T^2) and first-order autocorrelation (ϕ_1^T) at time T are, respectively:

$$s_T^2 = \frac{\sum_{t=1}^{T}(y_t - \bar{y}_T)^2}{T-1},$$

and:

$$\phi_1^T = \frac{\sum_{t=2}^{T}(y_t - \bar{y}_T)(y_{t-1} - \bar{y}_T)}{\sum_{t=1}^{T}(y_t - \bar{y}_T)^2},$$

where:

$$\bar{y}_T = \frac{1}{T}\sum_{t=1}^{T} y_t .$$

The sequence of events that the time-plots of these statistics help illustrate is that, despite its relative financial isolation, in the days preceding the crash of '87, volatility on the Taiwan Stock Exchange, as on all world equity markets, started to increase. In response to this increase in volatility, the Taiwanese authorities imposed even stricter price limits, 3% versus the earlier 5%. This succeeded in ending the increase in single-day return variance, but of course had no effect on the underlying fundamental (information-based) volatility in the market, and the result was that this underlying 'natural' variance was transformed from measured daily return variance into autocorrelation among these daily returns. Even before the narrowing of the price limits, however, the increase in underlying volatility had started to lead to higher levels of induced autocorrelation under the 5% price limits. The narrowing of the price limits to 3% only exacerbated this problem.

There are a couple of ways of explaining this phenomenon. Looking at it from a signal processing framework, the price limits did not affect the underlying energy or volatility in the market (the plot in Figures 5.6 indicates that it was actually still in the process of increasing), but the tighter price limits forcibly suppressed the high frequency, short-term components of this energy and shifted this energy instead to the low frequency, long-term components of the power spectrum (although these are not shown, this shift is reflected in changes of the spectrum of Taiex returns over time).

In terms of plain English, what is happening is that when new information drives changes in stock prices, if this information is sufficient to push prices beyond the established price limits, the resultant moves will be halted for the day once the price limits have been reached and then will continue on the next trading day, moderated or enhanced, whichever the case may be, by any subsequent new information that arises. In other words, new information that is not too dramatic will be acted upon immediately, while the movements caused by more dramatic information must be dragged out overnight, or even over a few days, before the full impact of this information can be fully reflected in equity prices.

In addition, as noted by an investment banker interviewed in relation with this study, the relationship described above provided opportunities for market manipulation that would augment any naturally induced autocorrelation. Less informed investors, seeing the stocks hitting the price limits, could infer the existence of information about the stocks whose effects would likely continue on the following trading day. This inferred knowledge would lead these less informed investors to try to take positions in the stocks to attempt to gain from any remaining movement from the now-old information. Thus, in order to take advantage of and profit from these less informed traders, market manipulators would engage in what is known as "ramping," intentionally purchasing stocks (especially relatively illiquid ones) with the intention of pushing their prices up into the price limits. The fact of a stock's hitting the price limit would then gain some publicity for the stock and bring in less informed investors to purchase the stock. The buying pressure from these new, less informed investors would then push the stock's price still higher and allow the original manipulators to sell off their holdings at a profit.

Whatever the true impact of such alleged manipulation, it is nonetheless clear that the strict 3% price limits of the post-"Crash of 87" period led to substantially increased autocorrelation within the daily returns of the Taiex and that this autocorrelation quickly dropped back down to normal levels soon after the price limits were broadened back out to 5%. The levels of nonlinear serial dependencies, on the other hand, do not seem to have any direct relationship with the different price limit regimes. Rather, as also seems to be the case for equity returns on other markets throughout the world, the nonlinear dependencies within the Taiex daily returns are characterized by spikes of highly significant nonlinear activity that flare up at apparently random intervals throughout the data and then, as suddenly as they appear, quickly dissipate back down to levels that are undetectable within the span of a 54-day test period.

5.5. The Impact of Significant Windows on the Full Sample Results

As can be seen in the plot in Figures 5.6 showing the recursive estimates for first-order autocorrelation within the daily Taiex returns, the spikes in autocorrelation levels around the period of the 3% price limits had a substantial impact on the estimated level of first-order autocorrelation. However, the estimated levels of autocorrelation were already relatively high, greater than 0.10, even before the interaction of increased volatility and narrow price limits led to the jumps in autocorrelation levels that were reflected in the 54-day-window tests for autocorrelation. Given this earlier autocorrelation, it is clearly not the case that the subsequent episodes of transient (price-limit-driven) autocorrelation are completely driving the significant autocorrelation test results for the full data set. On the contrary, although the significant episodic autocorrelation appears to dramatically increase the magnitude of the full-sample results, there also seems to be some lower level autocorrelation within the daily returns that is not strong enough to be detected within a 54-day sample but is nevertheless of sufficient magnitude to show up significantly in larger samples.

The purpose of this section is to look more generally at the dependencies within the daily and weekly Taiex returns to obtain a deeper understanding of the relationship between the significant test results for the full samples and the transient, high-magnitude autocorrelation and bicorrelation that appear episodically throughout these data sets. Namely, to what extent are these extremely strong but transient dependencies driving the significance levels of test statistics for the full samples? Are these transient dependencies the sole factor underlying the significant test results for the full samples, or do there appear to be other contributing factors, such as more persistent, lower-level serial dependencies? If there are other such contributing factors underlying the full-sample test results, to what extent do the transient dependencies augment the effects of these other factors, or do the transient dependencies actually act to obscure or dampen the effects of these other factors? Or is it even the case that these other factors are driving all of the full-sample results, with the effects on these results of earlier episodes of strong, transient dependencies simply being reversed by the effects of later episodes?

These questions were examined separately for linear and nonlinear dependencies and for daily versus weekly Taiex returns. For each analysis, the data from (non-overlapping) windows showing significant test results at a given test threshold were removed from the sample. For each window removed, a dummy variable was created whose value was either one or zero, one for the observation immediately following the window of data that was removed and zero for all other observations. In order to remove some of the empirical effects caused by conjoining sets of observations that were originally separated by a window's worth of data, the data remaining in the sample were then regressed against these dummy variables. The residuals from this regression were then used as the input data for re-calculating the autocorrelation and bicorrelation test statistics. To aid in comparability throughout the analysis, regardless of the number of observations remaining in the sample, each of these test statistics was calculated for dependencies out to the fifth lag, rather than for a number of lags determined by the sample size.

The results for this analysis are provided in Table 5.2. The set of results at the top of the table show the effects of removing the windows exhibiting significant autocorrelation from the daily Taiex returns. Removing all of the windows that exhibit autocorrelation that is significant at a level of 0.20 or less leads to a substantial decline in the overall autocorrelation test statistic (C_T), from 115.026 (for which the associated p-value is 3.55×10^{-23}) to 54.295 (with a p-value of 1.82×10^{-10}), or a decline in magnitude of about 53%. The majority of this decline, from 115.026 to 73.868, approximately a 36% decline, occurs as a consequence of removing only the windows featuring the strongest autocorrelation. The decline from 73.868 down to 54.295 occurs relatively gradually as the windows exhibiting autocorrelation that is significant at progressively higher test thresholds are removed.

These results tend to confirm the observations made at the beginning of this section, namely that the data within the significant windows have a substantial impact on the overall test results for autocorrelation but that this impact seems to be in terms of increasing the magnitude or significance levels of these test results from significant to even more significant rather than in terms of driving these statistics to be significant in the first place. Also in the previous section it was noted that there seems to be little overlap between the episodes of significant transient linear dependencies and those of significant transient nonlinear dependencies. Thus, the windows removed for exhibiting high levels of autocorrelation tend to display relatively low levels of bicorrelation. Hence their removal would be expected to slightly increase the average levels of bicorrelation for the remaining data set. This possibility seems to be borne out by the bicorrelation test statistics (H_T), which tend to increase moderately in magnitude as autocorrelation windows significant at increasingly greater threshold levels are removed.

The next set of results, shown in the middle of Table 5.2, show the effects on daily Taiex returns of removing the windows displaying the strongest significant nonlinear dependencies. As with the autocorrelations, removing all the windows exhibiting significant bicorrelation at a threshold of 0.20 or less reduces the magnitude of the full sample test statistic by more than 50%. In this case the bicorrelation test statistic (H_T) falls from 24.940 for the full data set down to 12.109 (for a decline of 51.4%) when all of the windows with significant bicorrelation levels have been removed. However, contrary to the situation with the autocorrelations, almost all of this decline (from 22.037 to 12.109) occurs when the least significant windows ($0.10 < p < 0.20$) are removed; there is very little decline (24.873 versus 24.940) resulting from the removal of the most highly significant windows. Thus, these less highly significant windows appear to have a much greater impact on the full sample results than do the most highly significant windows. On the other hand, the removal of the more highly significant bicorrelation windows leads to a reduction in the autocorrelation test statistic from 115.026 to 102.485, while the final removal of the windows significant at the 0.20 threshold causes this test statistic to rise back up to 114.999, almost its original, full sample level. Of course, given the magnitudes of these test statistics, these movements indicate little real impact (as the relatively narrow range of p-values demonstrates) of the significant bicorrelation windows on the levels of autocorrelation.

The final set of results in Table 5.2 are for the weekly Taiex returns. Because no windows in the non-overlapped window testing exhibited significant autocorrelation at a level of 0.20 or less, only the removal of significant bicorrelation windows was examined. For the weekly returns, removing the windows displaying significant bicorrelation has a less substantial impact on the magnitude of the bicorrelation test statistic (from 9.292 to 5.941, down 36%) than did the removal of the equivalent windows from the daily returns. In terms of significance levels, on the other hand, the impact is much greater, as a glance at the change in p-values demonstrates. Also, unlike the situation for the daily returns, the removal of the significant bicorrelation windows has a substantial impact not only on the overall bicorrelation levels, but also on the overall autocorrelation levels, with the C_T statistic falling from 13.764, with a p-value of 0.017, down to 9.775, with a p-value of 0.082.

In all of three of these cases, removing the significant windows leads to a substantial reduction in the magnitude of the test statistic for the overall sample, but even after this decline these test statistics remain highly significant. In other words, although the dependencies of the significant windows do not completely drive the overall test results, they do contribute substantially to the magnitude of these test results. Thus, for the daily returns, for example, the dependencies within the relatively few significant windows contribute slightly more than half of the magnitude of the full sample autocorrelation and bicorrelation test statistics, while just under half of the magnitude of these statistics is contributed by remaining dependencies within the data that do not show up significantly in any given window.

Moreover, because the values of such test statistics are based on average magnitudes of dependencies across time, they tend to exaggerate the impact of low-level but persistent serial dependencies while understating the impact of any transient dependencies. This is especially true in cases where the sample size is very large. For the daily data, for example, the effects of any transient dependencies must be averaged out across, or diluted by, the effects of literally thousands of other observations before affecting the full sample test statistics. Therefore, these transient dependencies would need to be very strong indeed to be the sole factor underlying the significant test results for the full sample, or even to have a substantial impact upon the full sample test statistics, especially given the actual magnitudes of these full sample test statistics. On the other hand, given this very large number of observations within the full sample (or even the full sample less the windows that contain highly serially dependent returns), any persistent serial dependencies could show up very significantly in the full sample test results, even if the actual strength of such dependencies was relatively very small. Similarly, though the sample size for the weekly returns is much smaller, it still entails hundreds of observations, and the net effect remains the same. Thus, for both the daily and the weekly returns, while there does seem to be some base level of relatively weak but persistent serial dependencies throughout the data, the transient dependencies of the small proportion of significant windows nevertheless comprise the major component of the serial dependencies within these data sets.

5.6. Taiex Returns and Episodes of Transient Dependence - Confirmation from Recursive Estimation and Testing

Because the data within the significant windows does not appear to be the only factor driving the overall test results, so that the data exhibit significant results even after these windows have been removed, it is important to verify that such windows are indeed reflections of brief episodes of very strong but transient dependencies within the data, rather than merely periods during which the presumably stable latent dependency structure underlying the data happens to show up more strongly. One method for doing this, as described in Spanos (1986), for example, is through the use of recursive estimation and testing of the linear and nonlinear dependencies.

Recursive estimation, discussed above in Section 5.4, entails examining the time path of estimates underlying the estimated parameters for a full time series data set. That is, the intermediate estimates as more and more observations are included in the estimation, culminating in the final estimation in which all the observations in the full sample play a role, are compared with each other to explore how the estimated parameter evolves over time. This in turn yields information about whether the true value of the underlying parameter is constant or is undergoing radical changes over time. If the underlying parameter is constant, then the recursive estimates of this parameter will initially show a great deal of variability but will eventually converge to a constant value as more and more observations are included in the estimate. The initial volatility reflects the fact that the variance of estimates based on a small number of observations is quite large. But, for well behaved data sets, this variance, together with the confidence limits based upon it, quickly converges toward zero. Concomitantly, for data sets in which the underlying parameter is constant, the estimates for the parameter will converge in value to this constant.

This tendency of the variance of parameter estimates toward zero is also reflected in the time paths of the recursive portmanteau autocorrelation and bicorrelation test statistics for time series with stable dependency structures. If there is no autocorrelation, for example, so that the parameters of autocorrelation are all equal to zero, then the estimated autocorrelation parameters for each lag will be approximately equal to zero, remaining for the most part within their confidence intervals, and the portmanteau autocorrelation test statistics will likewise remain below their respective significance boundaries. Similarly for the case of zero bicorrelation. If, on the other hand, the data are either autocorrelated or bicorrelated, then as the parameter estimates tend toward their constant nonzero level while their variance tends toward zero, the number of standard errors that the parameter estimates lie away from zero will become progressively larger. Concomitantly, the portmanteau test statistics will become progressively larger and progressively more statistically significant, attaining progressively lower p-values as more observations are added.

Simulated Returns

To demonstrate these tendencies, two time series with stable dependency structures were simulated, and the recursive properties of their autocorrelation and bicorrelation parameters and portmanteau test statistics were examined. The two time series simulated include a strongly autocorrelated series and a less strongly autocorrelated series, neither of which entails any nonlinear dependencies. The specifications for the strongly autocorrelated time series (Simulated AR Series 1) are as follows:

$$\begin{aligned} y_t &= .3y_{t-1} + .2y_{t-3} + \varepsilon_t \\ \varepsilon_t &\sim NIID(0,1) \end{aligned},$$

and the specifications for the less strongly autocorrelated time series (Simulated AR Series 2) are:

$$\begin{aligned} y_t &= .14y_{t-1} + .06y_{t-3} + \varepsilon_t \\ \varepsilon_t &\sim NIID(0,1) \end{aligned}.$$

There are a number of different portmanteau test statistics that could be used to examine the dependency structures of these two time series, but to maintain consistency with the previous sections the autocorrelation and bicorrelation portmanteau test statistics of Hinich and Patterson (1996) are used, and the autocorrelations and bicorrelations are tested out to the fifth lag. Similarly, there are also a number of possible ways to estimate the parameters related to autocorrelation and bicorrelation within a time series. To obtain these values, the following regression model was fitted to the data:

$$y_t = \phi_0 + \sum_{i=1}^{5} \phi_i y_{t-i} + \sum_{i=1}^{4} \sum_{j=i+1}^{5} \phi_{i,j} y_{t-i} y_{t-j} + \varepsilon_t ,$$

or, in matrix notation,

$$\underline{y} = X\underline{\phi} + \underline{\varepsilon} ,$$

where X is a matrix of constants, lagged values of y, and cross-products of lagged values of y. The values of the parameters of this model are recursively estimated via ordinary least squares to obtain, after each successive observation:

$$\hat{\underline{\phi}} = (X'X)^{-1} X' \underline{y}$$

$$s^2 = \frac{\underline{y}' \left[I - X (X'X)^{-1} X' \right] \underline{y}}{T - p} .$$

$$\hat{\text{var}}\left(\hat{\underline{\phi}}\right) = s^2 (X'X)^{-1}$$

The 16 elements of $\hat{\underline{\phi}}$ then provide estimates of the unique contribution of each specific source of serial dependency within the first five lags (similar in concept to partial autocorrelations), while the diagonal elements of $\hat{\text{var}}\left(\hat{\underline{\phi}}\right)$ provide the inputs necessary to estimate confidence intervals for these parameter estimates.

Plots of the recursively estimated portmanteau test statistics and of a sampling of recursive regression parameter estimates for the two simulated autoregressive data series are shown in Figures 5.7 through 5.10. The plots in Figures 5.7 show the recursive test statistics for autocorrelation and bicorrelation for the strongly autocorrelated simulated returns, while the plots in Figures 5.8 show recursive estimates for various parameters of serial dependency for this series, including the first-order autocorrelation (ϕ_1, or Phi(1)) and two randomly selected parameters of bicorrelation within these simulated returns($\phi_{1,2}$, or Phi(1,2), and $\phi_{4,5}$, or Phi(4,5)). These plots provide a textbook example of the type of behavior one would expect to see within the plots of recursive parameter estimates for a time series with a stable dependency structure. In each case, the parameter estimates initially exhibit a large amount of volatility but then settle down fairly quickly to approximately the true value of the parameters they are estimating. The estimated bicorrelations, for example, converge on their true values of zero, exhibiting fluctuations that grow progressively smaller as time goes by, all the while remaining within the progressively narrower 95% confidence bands around zero. The estimated first-order autocorrelation similarly converges toward its true value of 0.3 and then fluctuates more and more narrowly around this value. In so doing, the estimates quickly intersect the upper 95% confidence band, at which point they are 1.96 standard errors above zero, and the t-statistic computed from these figures would be marginally significant at a 5% level. Additional observations stabilize the parameter estimate at 0.3, while the standard errors, hence the 95% confidence bands, decline in magnitude toward zero. Thus, recursive t-statistics based on the recursive parameter estimates and recursive standard errors become progressively larger and more significant (i.e., their p-values become progressively smaller) as more observations are added to the estimates.

These tendencies are reflected in the recursive plots of the portmanteau test statistics in Figures 5.7. The top plot shows the recursive portmanteau test statistics for autocorrelation (out to lag 5). Just as a the t-statistics for autocorrelation at specific lags would quickly become significant and continue to become progressively larger as more observations are added, the portmanteau test statistics also quickly reach and surpass the 0.5% test significance threshold shown in the plot and then continue to grow in magnitude as more observations are added. Conversely, just as the bicorrelation parameter estimates remained within their confidence limits, the bicorrelation portmanteau test statistics remain below their test thresholds. So, to summarize, stable parameters whose values are equal to zero lead to portmanteau test statistics whose values do not stray far from zero, while stable parameters whose values are non-zero lead to progressively larger portmanteau test statistics.

For the less strongly autocorrelated simulated returns (Simulated AR Series 2), the lessons are similar, although the potential complicating effects of random variation within the data are also illustrated. As shown in the plots of Figures 5.10, the recursive parameter estimates exhibit a great deal of initial instability before finally tapering down to approximately the true values of the parameters they are estimating. But, in each of these cases, the instability exhibited seems to be greater than that for the parameter estimates for the more strongly autocorrelated series (Simulated AR Series 1). For the bicorrelation estimates shown, while the recursive estimates for Phi(4,5) remain within 1.96 standard errors of zero, the recursive estimates for Phi(1,3) actually skirt the upper confidence limit for quite some time before returning to a lower level within the confidence limits. However, the bicorrelations as a group display magnitudes very close to zero, as is clearly illustrated by the recursive bicorrelation test statistic values displayed in Figures 5.9.

The recursive estimates of first-order autocorrelation taper down toward the true value of 0.14 for the underlying parameter, but the initial instability in this case includes a prolonged dip in the value of the estimated parameters until about 900 observations have been included in the estimations. Nevertheless, the recursive autocorrelation test statistics display a pattern similar to that of the Simulated AR Series 1; namely, the recursive test statistics demonstrate a gradual but steady rise in value, finally surpassing the 0.5% test threshold after the 782nd observation has been included in the recursion and then continuing to become increasingly more significant as more observations are included in the analysis. The magnitudes for these recursive test statistics remain well below those for the first simulated series, but this is merely a reflection of the lower autocorrelation levels inherent in the second series relative to the first.

Taiex Daily Returns

For the daily and weekly Taiex returns, on the other hand, the picture is vastly different (see Figures 5.11 through 5.15). Rather than parameter values that taper down toward a constant level and portmanteau test statistics that either fail to stray very far from zero or else gradually increase as more observations are included, each of these return series instead displays large swings in value, often switching from being strongly significant to being close to zero, or vice versa, within the span of relatively few observations, even after thousands of observations have already been included in the estimations.

With regard to autocorrelation within the daily returns, the time path of recursive estimates for first-order autocorrelation within these returns has already been discussed above, in Section 5.4. The time path of the recursive autocorrelation portmanteau test statistics, shown in Figures 5.11, bears a clear resemblance to that of the first-order autocorrelation, appearing to be similarly influenced by interactions between volatility and changes in price limits over time. Of course, as the results of the previous section demonstrated, this does not seem to be the whole story. During the time period before the strictest price limits were imposed, after a brief jump followed by a slight decline, the autocorrelation test statistics exhibit a gradual but steady increase similar to that displayed by the second, less strongly autocorrelated, simulated time series. This implies the existence of persistent, low-level autocorrelation within the daily Taiex returns throughout this time period. It is possible that this autocorrelation persists throughout the entire time series, but it is overshadowed during the latter half of the time frame by the additional autocorrelation that is apparently induced by the price limits.

In comparison to the autocorrelation dependency structure, the bicorrelation dependency structure exhibits a degree of instability that is much more dramatic. Furthermore, contrary to the implications of the previous section, it is clear that whether or not significant test results are obtained for bicorrelation is dependent upon the specific sample period chosen. There are a small number of time intervals, usually short-lived, during which the recursive, or cumulative, test statistics fall below the 0.5% test threshold level of 25.188, so that if the ending date for a sample period starting on January 6, 1982, happened to fall within one of these intervals the test for nonlinearity would fail to detect any significant bicorrelation within the data.

If the sample period included only the first year of data, for example, then the bicorrelation portmanteau test statistic would not yield significant results. But once the recursive test statistics first cross the 0.5% test threshold of 25.188 on March 16, 1983, the subsequent cumulative test statistics remain significant until the 1,582nd observation, for April 20, 1987, is finally added to the calculations. Following the inclusion of this observation, the test statistics fall into insignificant territory for a week, before returning once again to significant levels. However, even throughout the 1,180 observations during which the recursive test statistics first become and then remain significant, these recursive test statistics show widely and dramatically varying levels of significance, a pattern clearly different from either of the two basic patterns of steady ascent or random fluctuations near zero displayed by the test statistics for the two simulated data series.

As of March 1983, after finally accumulating enough evidence, so to speak, to firmly conclude that there are nonlinear dependencies within the daily Taiex returns, the bicorrelation test statistics continue their rapid ascent in value up to a peak value of just over 100 (specifically, 100.123) on May 26, 1983. However, this is followed over the next three days by a decline in the values of the recursive test statistics to a level around 80. Given this dramatic decline, it is important to remember that these test statistics are estimated recursively, so that a given day's test statistic includes all of the information included within the previous day's test statistic, augmented by the information of a single day, with that additional day's evidence receiving a weight equal to that of each of the preceding days. In this specific case, the value of the test statistic after the first 400 day's worth of data was 100.123. If the activity within the next few days exhibited nonlinear activity similar to the average of that over the previous 400 days, then the bicorrelation test statistic should have continued on its dramatic ascent. If, on the other hand, the activity within the next few days exhibited no nonlinear dependencies, then, when averaged across all the hundreds of previous observations, these few additional observations would serve only to slightly dampen the value of the test statistics. Instead, the test statistics decline dramatically from a high of 100.123 on May 26 all the way down to 83.784 on May 31, a decline in value of 16.3% over four trading days, driven by the activity within only 1% of the observations.

This implies that the activity during these four days embodies neither nonlinear dependencies similar to those of the previous 400 days nor a lack of nonlinear dependencies altogether. Instead, the activity within these four brief days must entail very strong nonlinear dependencies working in the opposite direction from, hence partially canceling out, those nonlinear dependencies that are prominent, on average, within the preceding data. Then in the days subsequent to this dramatic movement, the descent in the values of the test statistics ceases almost as quickly as it began, and the level of the test statistics appears to settle down temporarily to a new, lower plateau. Such a pattern, of major reversals or shifts in the magnitude of the test statistics with the addition of very few additional observations, even after thousands of observations have already been accumulated, is seen throughout the subsequent recursive bicorrelation portmanteau test statistic data, clearly demonstrating the existence of numerous episodes of transient nonlinear serial dependence within the daily Taiex return data.

Unfortunately, many of these episodes of highly nonlinear activity are too short, with many lasting only a few days, to allow for nonlinearity to be tested within these intervals. However, a somewhat longer sample that averages over a number of such episodes can still be used to illustrate the existence of significant nonlinear dependencies appearing within one interval that reverse the effects of the significant dependencies that appeared during a previous interval, so that test statistics for the full period, which average across all of these sets of dependencies, are less significant than those of either subperiod.

Following the decline in the recursive bicorrelation portmanteau test statistics from their first major peak down to a level of around 80 beginning in June, 1983, the recursive test statistics remain fairly steady throughout the following nine months, after which they experience a quick decline to a new, lower value in the low 60's. After resting at this level for another three months or so, the test statistics experience another, much more dramatic, decline over a four-day period until they reach a low of 35.242 on May 30, 1984, which is the 295th observation after the peak value of 100.123 that occurred just over a year before. However, testing these 295 subsequent observations by themselves yields a bicorrelation test statistic of 39.433 (for which the p-value is 0.00002), which is highly significant and of even greater magnitude than the full sample test statistic (35.242) for the same ending date of May 30, 1984. Thus, despite the fact that the activity during these 295 observations coincided with a 65% decline in the magnitude of the bicorrelation test statistics, this decline is clearly not caused by a simple "washing out" or dilution of early highly nonlinear activity by subsequent data that does not exhibit such dependencies. Rather, it must be the case that at least some of the nonlinear dependencies within these subsequent 295 observations actually reversed the effects of some of the dependencies exhibited by the returns within the earlier 400 days' worth of returns, leaving a much lower net level of dependencies within the data when averaged out across all 695 of these early observations.

To reiterate, such results clearly demonstrate the existence of changes within the nonlinear serial dependency structure over time. Moreover, the many major reversals or shifts in the magnitudes of the test statistics (as well as in those of the estimated bicorrelation parameters) indicate that many of these changes in the dependency structure take place within a span of only a few days. This clearly demonstrates the existence of numerous episodes of very strong but transient dependencies within the daily Taiex returns. And in a number of cases, the effects of these transient dependencies are sufficiently strong even to push the overall test statistics down to magnitudes at which they are no longer significant. For example, the nonlinear dependencies embodied in the five days' worth of returns from July 7, 1989 to July 13, 1989 are sufficiently strong to decrease the value of the recursive bicorrelation test statistics by 40%, from 26.15 ($p = 0.0035$) down to 15.79 ($p = 0.106$), and this substantial decline in magnitude came despite the fact that a full 2,156 observations had already been accumulated in the former test statistic before these additional five observations were included.

Fortunately for the overall test results presented in the preceding chapter, however, after a final trough in the recursive test statistics of 15.11 on May 21, 1990 the subsequent observations lead to a major increase in the value of the test statistics over the next five-and-a-half months. These test statistics then reach a highly significant final peak value of 159.4 on November 15, 1990. For the returns of the days following this peak value, as both the test statistics and the parameter estimates illustrate, the dependency structure underlying these daily returns appears to stabilize at a very significant level and remain relatively stable for the final two years of the sample period. As a consequence, the return series ends up with significant test statistics for the full sample period. But contrary to the implications of Section 5.5, although nonlinear dependencies do seem to play a role in the return dynamics throughout most of the sample period, there do not appear to be any underlying low-level dependencies within the data whose values and magnitudes remain constant throughout the entire sample. Rather, the entire nonlinear dependency structure underlying these returns seems to shift in direction and magnitude over time, sometimes very quickly and sometimes more gradually, and the test statistics for any given period simply reflect the average of the directions and magnitudes of the nonlinear dependencies within that time interval.

Taiex Weekly Returns

With only about a sixth (538 versus 3,142) of the observations over the same time period as the daily return series, the weekly Taiex returns do not generate recursive test statistics with as many major shifts and reversals as those of the daily returns (see Figures 5.14 and 5.15). Nonetheless, there is still ample evidence of instability within the dependency structures of the weekly returns. Interestingly, as was the case for the daily sampled returns, the recursive statistics for the weekly sampled returns exhibit a peak in value very early in the series in April, 1983, and another, much larger peak near the middle of the series, in the latter half of 1987.

For the autocorrelation test statistics, the earlier peak of 23.68, which pushes the test statistics up to significant levels, is succeeded the following week by a test statistic of only 10.13, an insignificant value 57% lower than that of the previous week. The subsequent autocorrelation test statistics then settle down at insignificant levels throughout the remainder of the first half of the data series before once again ascending in value toward their second, and largest, peak of 56.95 as of the week ending on September 30, 1987, after which 278 observations have been included in the calculations. This peak value is followed by a quick reversal, leading to a 60% decline in the test statistics down to 22.69 over the next three weeks. Subsequently, however, the recursive autocorrelation test statistics tend to exhibit less dramatic moves, fluctuating seemingly randomly within significant territory until the last full week of 1990, during which the test statistic finally drops down to a level where it is no longer significant. Afterwards, the test statistics remain at insignificant levels throughout the remainder of the data. As with the daily returns, the dependency structure seems to stabilize during the final two years of the sample.

The timing of the major changes in the nonlinear serial dependency structure is similar to that of the changes in the linear serial dependency structure, though the levels of bicorrelation tend to remain relatively higher than the levels of autocorrelation, and reversals following increases in bicorrelation levels occur, if at all, much more gradually than those of autocorrelation levels. The early peak in average bicorrelation levels in April 1983, rather than being substantially and quickly reversed as it is for autocorrelation, is followed instead by bicorrelation levels that fluctuate within a relatively narrow band and remain significant throughout the remainder of the first half of the data series, until the bicorrelation levels start rising dramatically toward their highest peak of 334.52 on January 13, 1988. This peak illustrates the influence of the second major episode of transient nonlinear dependencies within the weekly data. Unlike the quick reversal that is experienced by the autocorrelation levels following this mid-data peak, however, the bicorrelation levels decline much more gradually, continuing a fairly steady but more moderate decline until the final nadir in bicorrelation levels of 45.50 is reached on December 26, 1990. Notably, this is also the same date as of which the autocorrelation levels drop down below the 0.5% test threshold to remain fairly steady but insignificant throughout the remainder of the data. Likewise, the bicorrelation levels also remain fairly stable, though at a significant magnitude and with a slight upward drift, for the remainder of the data.

Lucky Cement Company

Before concluding this section and returning to the use of Hinich and Patterson's windowed testing procedure to examine the stability of serial dependencies within individual stocks listed on the Taiwan Stock Exchange, the returns for an arbitrarily selected stock, the Lucky Cement Company (Stock 1108), will be examined via recursive estimation and testing to determine whether the serial dependencies within such individual stock returns exhibit behavior similar to that of the daily index returns. The results for this stock, for which there are 730 observations, from June 7, 1990, to December 29, 1992, are shown in Figures 5.16 and 5.17.

A cursory glance at these plots reveals a dependency structure that seems to be much more stable than that of the index returns. However, it must be remembered that the time period for these stock returns is not the same as that of the index returns. Instead, Lucky Cement's results should be compared to the results for the last two-and-a-half years for the Taiex returns. Once these time frames are correctly lined up, the results appear much more similar. For both autocorrelations and bicorrelations, the early estimates quickly become significant (note that the initial test statistics are not calculated until 54 observations have been accumulated). However, early peaks in the level of these dependencies are soon followed by unstable and generally declining levels of serial dependencies.

Finally, after about nine months of data have been accumulated, and as is the case for the same period for the index returns, the values of the parameters of autocorrelation and bicorrelation appear to stabilize at levels that are (at least marginally) significant, where they remain throughout the rest of the data. For the index returns, this final stabilization occurs after thousands of observations have already been accumulated, so it does not drive much of a change in the overall levels of the portmanteau test statistics. For the much shorter series of Lucky Cement returns, on the other hand, the dependency structures appear to stabilize after only about 200 observations have been accumulated (taking the nadir in general bicorrelation levels of 23.93 on the 199^{th} observation, for February 23, 1991, as the starting point for such stabilization). Thus, the significant, stabilized dependencies have a much greater impact on the subsequent cumulative portmanteau test statistics for Lucky Cement than they do for the index returns. Consequently, for the period coinciding with this prolonged stabilization within the parameter values, the time paths for these portmanteau test statistics more closely resemble those for the autocorrelation test statistics of the simulated autocorrelated series.

But, to reiterate, the time paths for the recursive test statistics and parameter values for Lucky Cement seem to reflect changes in the serial dependency structure similar to those that occur within the index data. The visual differences between the two sets of data seem to be merely a consequence of the fact that the Lucky Cement returns start at such a late date relative to the Taiex data. But the recursive test statistics and parameter estimates for the daily (as well as the weekly) Taiex return data clearly indicate that the dependency structures within these returns are in fact shifting over time, with numerous episodes of very strong but transient dependencies (especially nonlinear dependencies) within these returns, as were detected by the windowed test procedure. Presumably, as seems to be the case for Lucky Cement, the same would also hold true for the various other stocks trading on the Taiwan Stock Exchange, and significant windows for such returns from windowed testing would reflect such episodes of transient dependence.

5.7. Episodes of Transient Dependence and the Returns of Individual TSE Stocks

The evidence of the previous sections of this chapter demonstrates that the serial dependencies within the daily and weekly returns of the Taiwan stock index are not stable. Rather, they shift over time and are characterized by numerous brief episodes of very strong but transient dependencies. While the strongest appearances of such transient dependencies do not by themselves appear to be driving any of the full sample results, they do reflect the underlying instability in the serial dependency structure. The evidence within the immediately preceding section, moreover, indicates that the daily stock returns of a sample stock, the Lucky Cement Company, exhibit patterns of shifting serial dependency structures similar to those of the daily index returns.

The next logical question to ask is whether the remaining stocks trading on the Taiwan Stock Exchange also appear to exhibit instabilities within their serial dependency structures similar to those of the index returns. But now that the conclusions of the windowed testing procedure have been verified by the results of the recursive estimation and testing, we can return to the use of Hinich and Patterson's windowed testing procedure to examine the individual stock returns. Not only is this procedure much less computationally intense than recursive estimation and testing, but it also has the added advantage of being able to provide a number of summary statistics, such as the percentage of significant windows, for ready comparison of results across stocks and between the index and individual stocks. In applying this procedure to the individual stock returns, in order to most clearly differentiate these returns from random walk data and to focus on the episodes during which serial dependencies appear most prominently, the test threshold for each window is set very low, at 0.005. Also, 1% clipping of the data is employed to control for the effects of any anomalous observations, which are more likely to appear within the returns of individual stocks than within index returns.

A summary of the results from this procedure, categorized by industry, are presented in Table 5.3. The first two columns of this table give the identification number and number of observations for each stock, while the third and fourth columns present, for comparison, the bispectrum test results from the previous chapter. Finally, the last three columns present a summary of results from the windowed testing, including the total number of (overlapping) windows of data, the number of these windows that test significant at an 0.005 level for either autocorrelation or bicorrelation, and, comparing these two figures, the percentage of windows that exhibit significant serial dependencies (of either variety). The similarity of these results to those for the Taiex daily returns (see Table 5.1) are immediately clear. Despite the fact that the vast majority of these stocks exhibit very strong nonlinear dependencies within their returns (and very strong serial dependencies as well, though these results from Table 4.2 are not repeated in this chapter), such strong underlying dependencies only manifest themselves within a very small number of windows.

While the daily Taiex returns entailed 115 windows of returns, the total number of windows for individual stocks ranged from 1, for stocks that started trading just before the end of the sample period, to 94, for stocks that traded across the full sample period for stocks, from January 6, 1984 through December 29, 1992. Across all of the stocks included in the sample, the average of the percentage of these windows that is significant is a relatively low 16.8%, while the median is even lower, at 13.8%. For eight of the stocks, none of the windows exhibit significant dependencies, despite the fact that for half of these eight stocks the bispectrum tests for nonlinearity are significant at levels of 0.0005 or less (of the four remaining of these eight stocks, there were too few observations to run the bispectrum test for two of the stocks, while the p-values for the other two stocks were 0.189 and 0.019, respectively). Four stocks, on the other hand, had significant results for 100% of their windows. In all four of these cases, however, the stocks had started trading just before the end of the sample and only had one window's worth of observations. Furthermore, the period during which these stocks traded coincides with a period, illustrated for the Lucky Cement Company in the preceding section, during which the market exhibited linear and nonlinear dependencies that were both significant and fairly stable over an extended period of time. Thus, the 100% significant results for these four cases are consistent with the results for the index returns.

Looking at the results across industries, the averages of the percentages of significant windows range from 11.3% for the Shipping industry (2600) to 41.9% for the Glass industry (1800). This latter industry, though, contains only six stocks, two of which had only one window's worth of data, with that single window being significant in both cases. The concomitant percentage of significant windows of 100% for each of these two stocks inflates the average figure for this industry; using the median rather than the average for this industry yields a much lower figure of 18.2%.

In general, therefore, the windowed test results for the individual stock returns look quite similar to those for the daily Taiex returns. Thus, it is reasonable to assume that the pattern of shifting dependency structures over time marked by numerous brief episodes of very strong, transient dependencies that is observed within the index returns is also at work within the returns for the individual stocks trading on the Taiwan Stock Exchange.

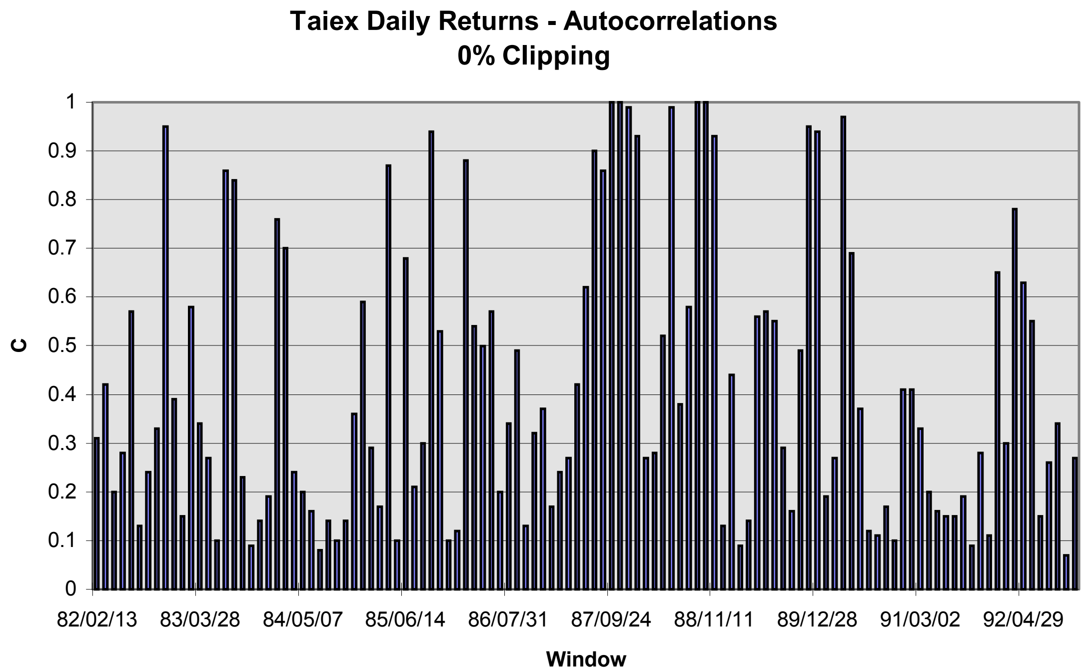
5.8. Conclusions on the Temporal Stability of the Serial Dependency Structure Within Taiex and Taiwan Stock Returns

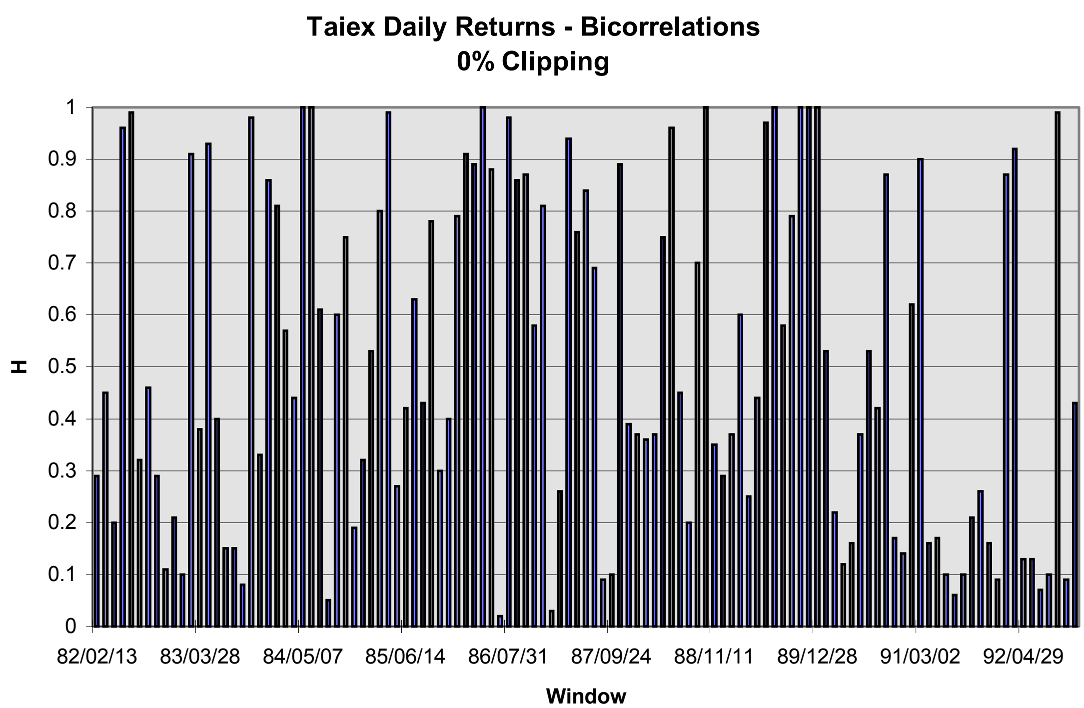
The results of Chapter Four showed that serial dependencies, in terms of both autocorrelation and more complicated nonlinear dependencies, play a significant role in the return dynamics not only for the Taiwan Stock Exchange Weighted Stock Index but also for most of the stocks trading on the Taiwan Stock Exchange. As complicated a picture as that presents for efforts to model or predict such returns, the results of this chapter suggest an even more complicated picture. Such modeling efforts typically assume, and require, that the serial dependency structure underlying the data remains constant over time.

Unfortunately, just as Hinich and Patterson (1996) found for a number of U.S. stocks, the results of this chapter indicate that, not only for the Taiex but also for most of the individual stocks trading on the Taiwan Stock Exchange, the serial dependency structures underlying these returns are not stable. Instead, they exhibit substantial shifts and reversals over time that on numerous occasions take the form of brief episodes of especially strong but transient dependencies. The appearances of such episodes, which are sometimes as brief as four or five days, are reflected in the significant results for a small number of subsample windows. Furthermore, these brief episodes, embodying the strongest serial dependencies within the time series, exert a very strong influence on the full sample results, accounting for up to half of the magnitude of these results.

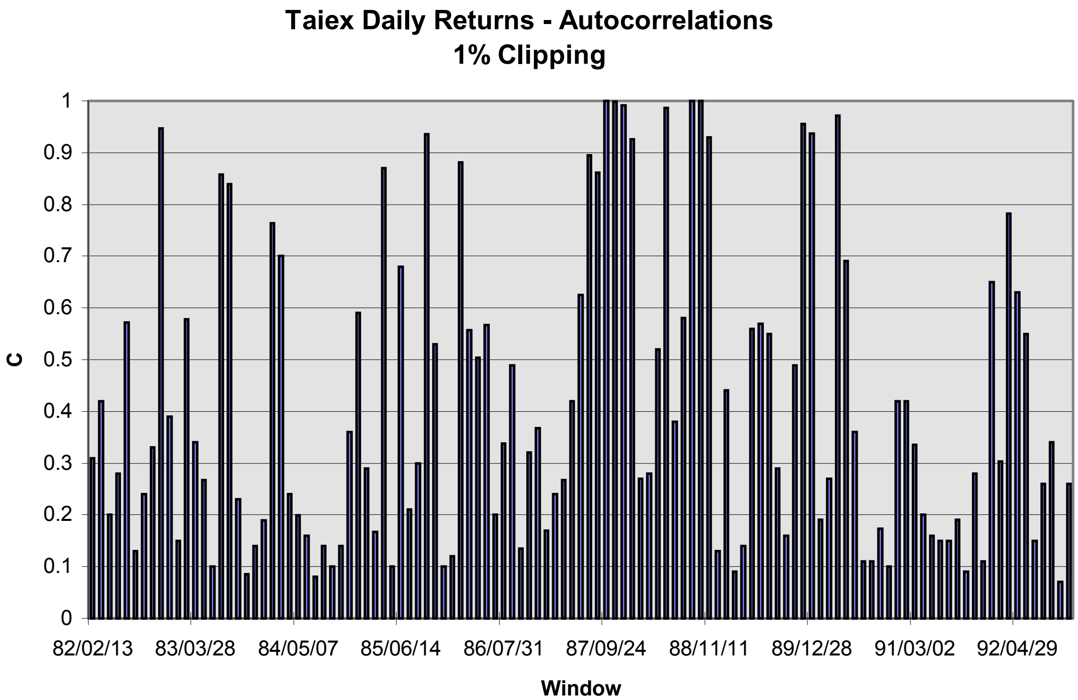
However, despite contributing the largest proportion to the magnitude of the full sample test results, these episodes do not completely drive the significance of such results, which are still highly significant even after the magnitudes of the test statistics are reduced by half. But, especially for the nonlinear dependencies, these episodes do reflect the underlying instability that seems to exist in the serial dependency structure, which exhibits numerous shifts of magnitude and direction throughout the length of these return data series. Some of these shifts lead to very strong serial dependencies, while others lead to insignificant levels of dependence.

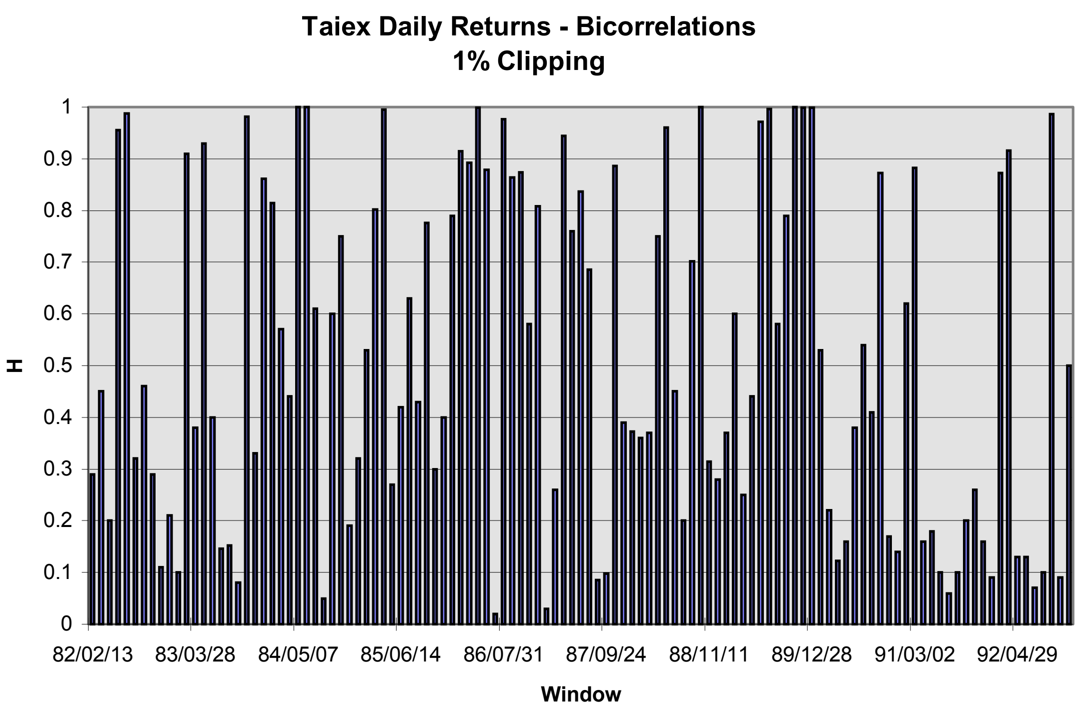
Consequently, and especially for the nonlinear dependencies, the significant test statistics for the full sample seem to reflect, not the existence of any serial dependencies that are constant throughout the data set, but rather serial dependencies whose values are changing throughout the data set but which, on average, are significant. Thus, the significant portmanteau test statistics obtained in Chapter Four were, to a certain extent, "the luck of the draw," and a different sample period could have led to very different conclusions.



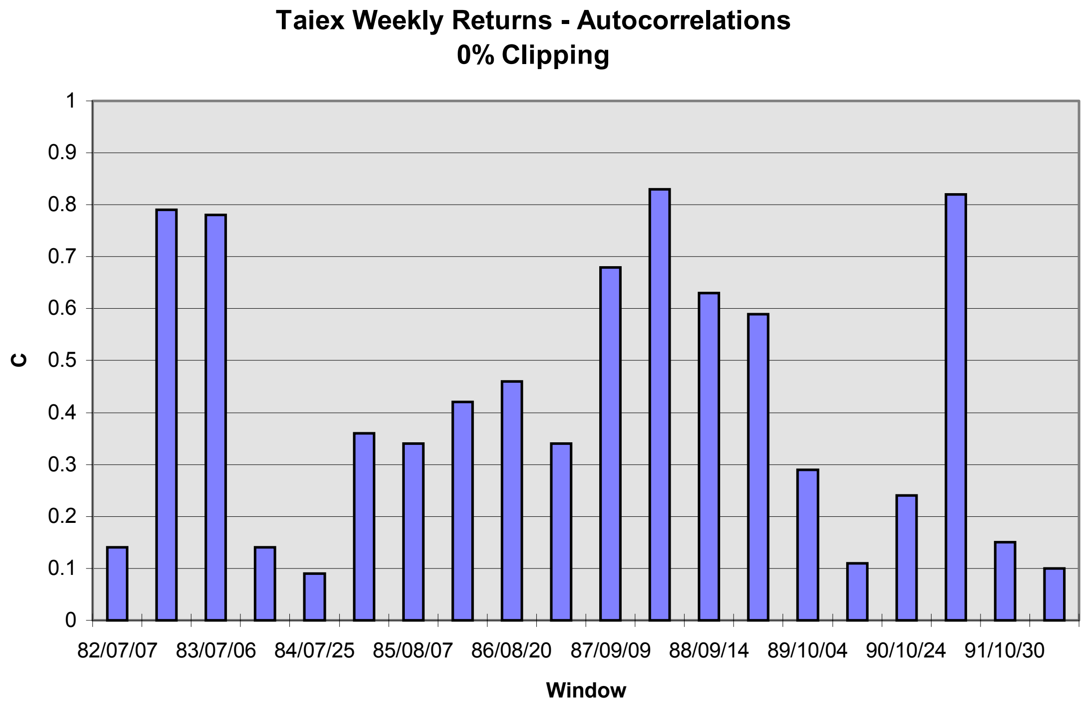


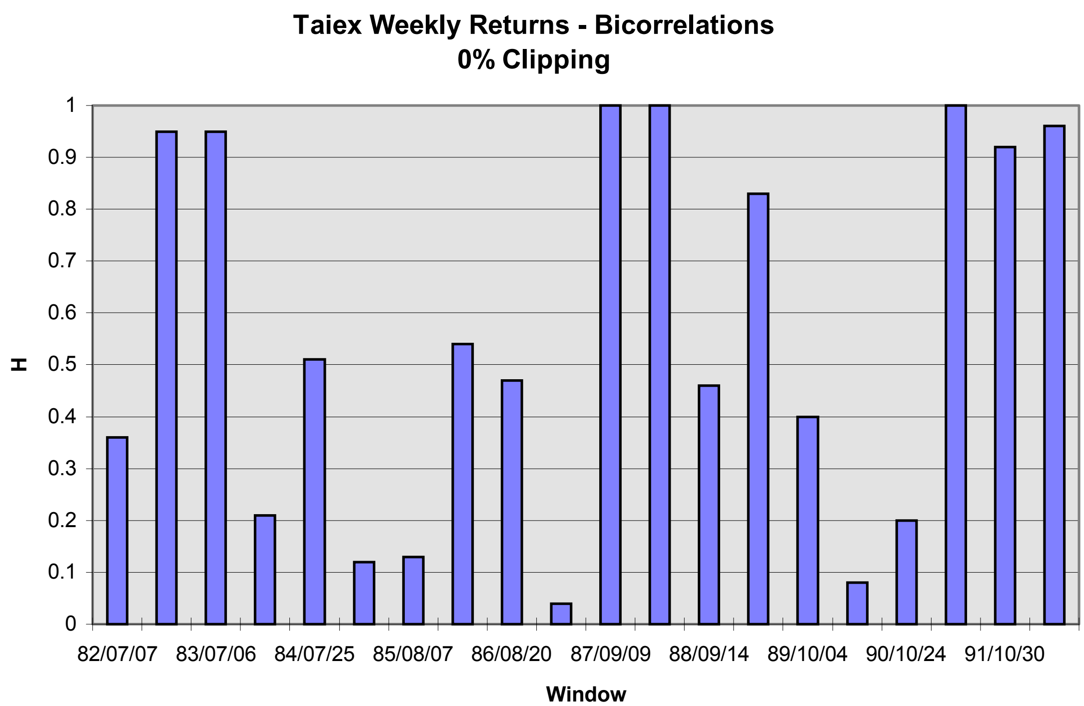
Figures 5.1
Windowed Test Results for Taiex Daily Returns with No Data Clipping



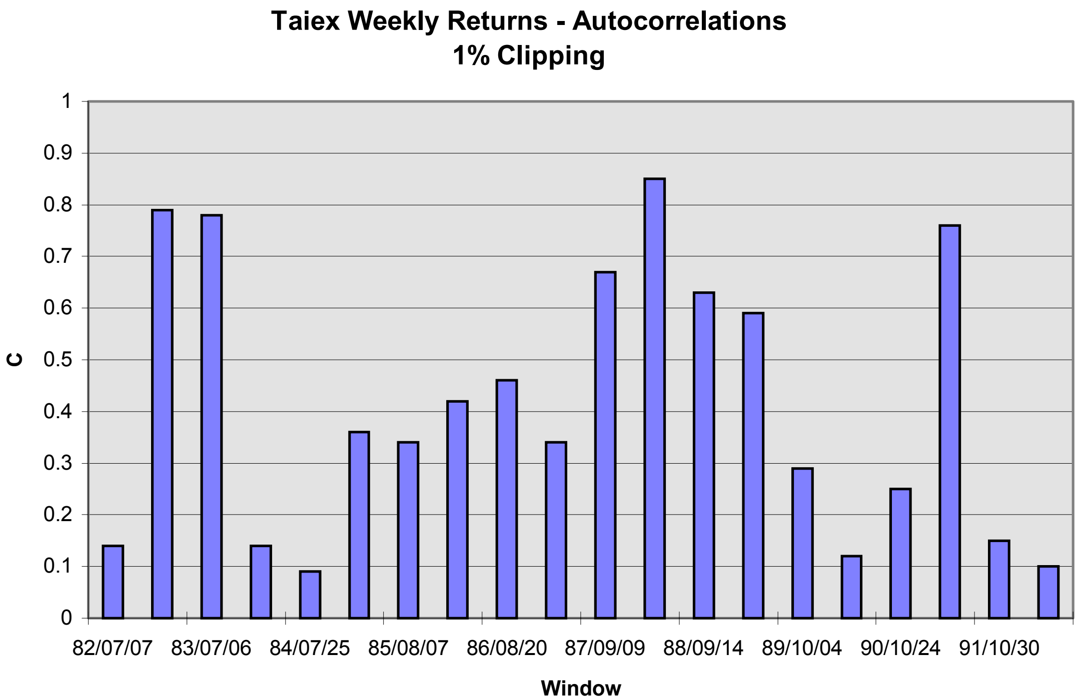


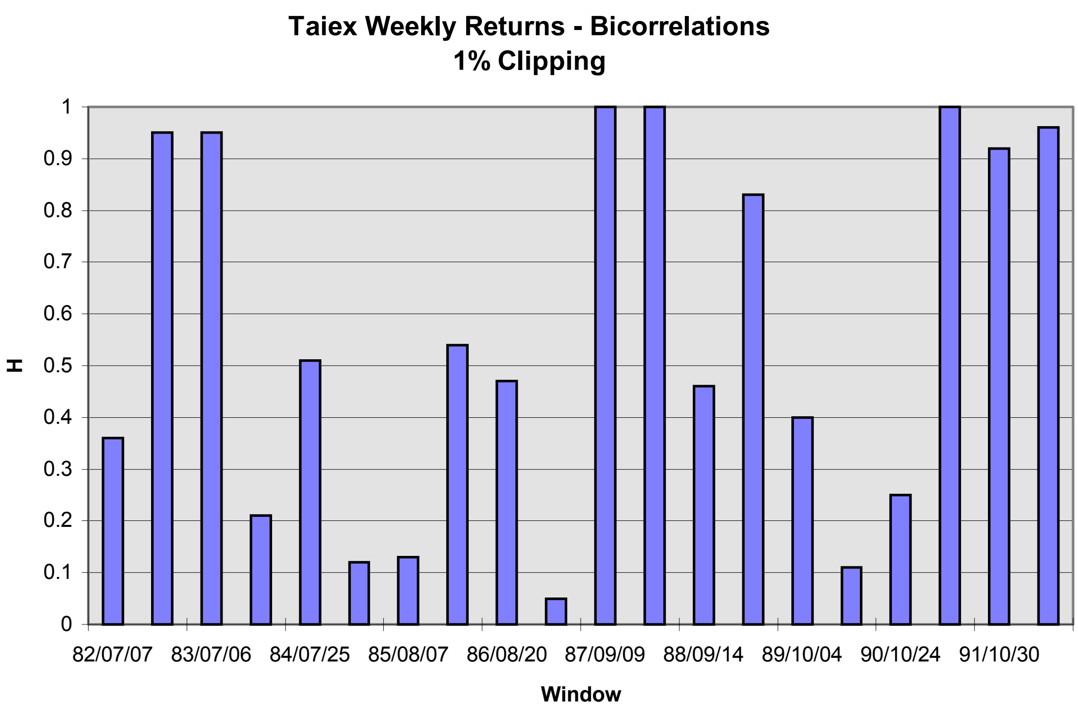
Figures 5.2
Windowed Test Results for Taiex Daily Returns with 1% Data Clipping



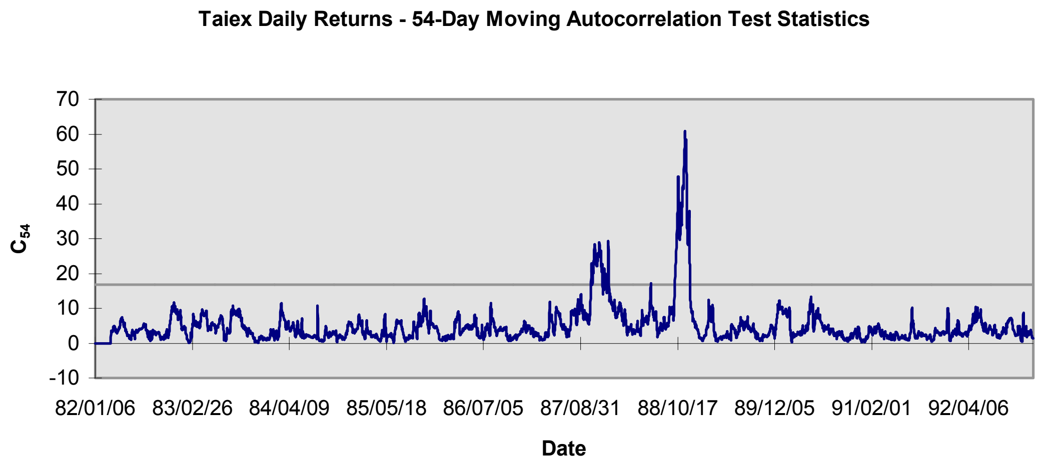


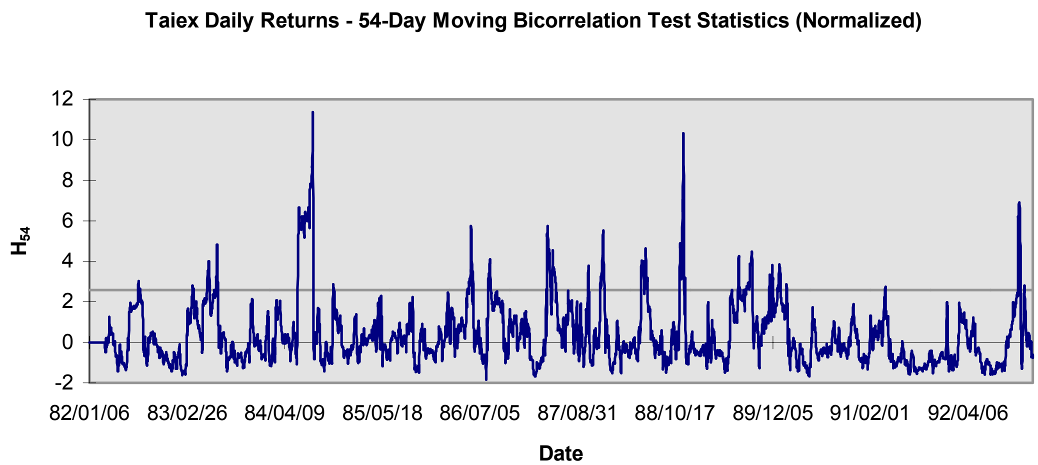
Figures 5.3
Windowed Test Results for Taiex Weekly Returns with No Data Clipping

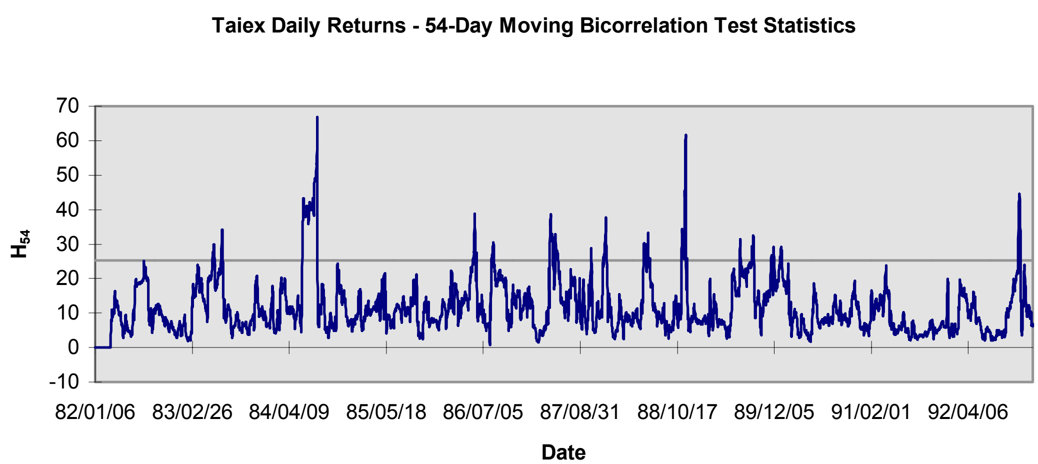




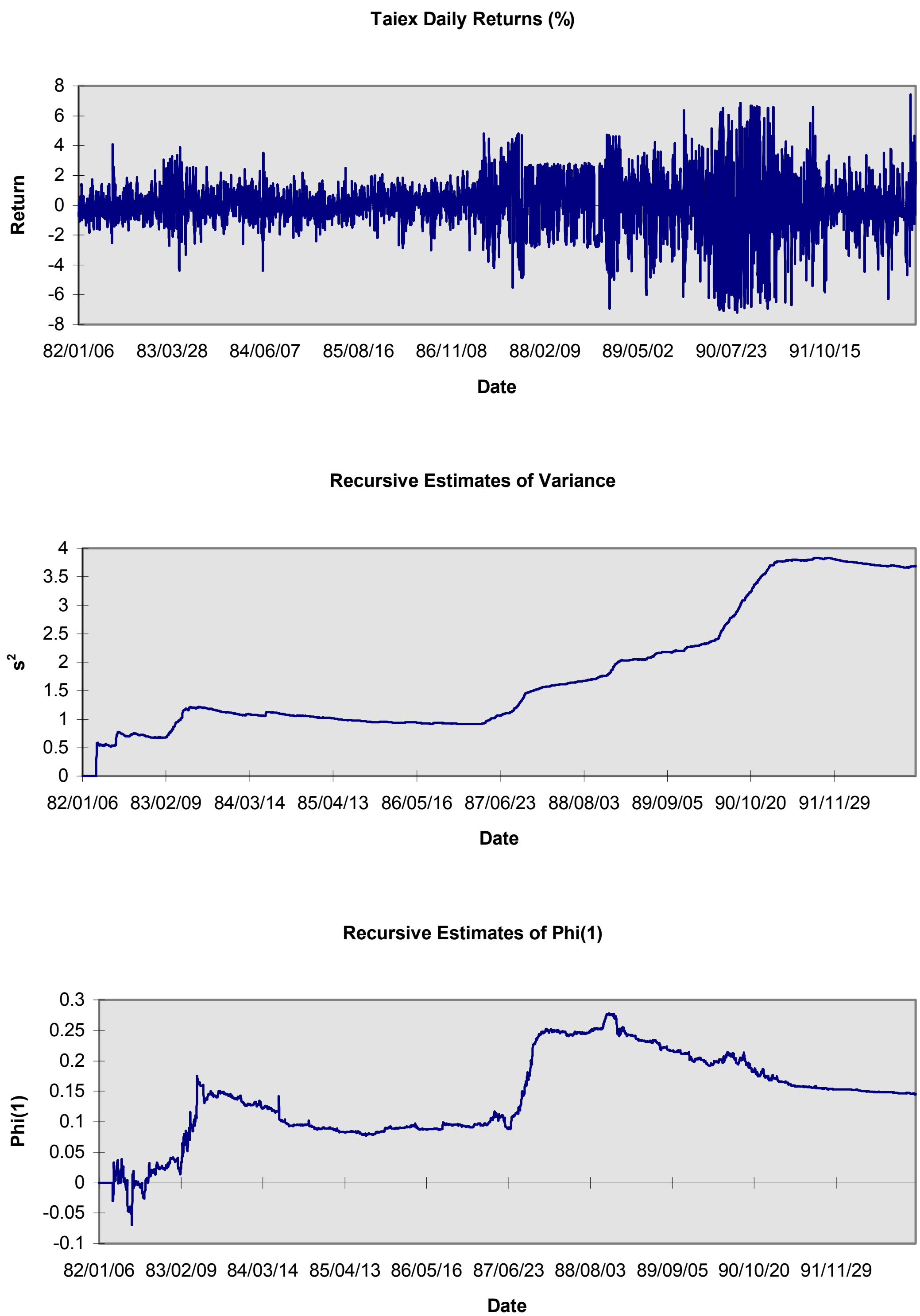
Figures 5.4
Windowed Test Results for Taiex Weekly Returns with 1% Data Clipping



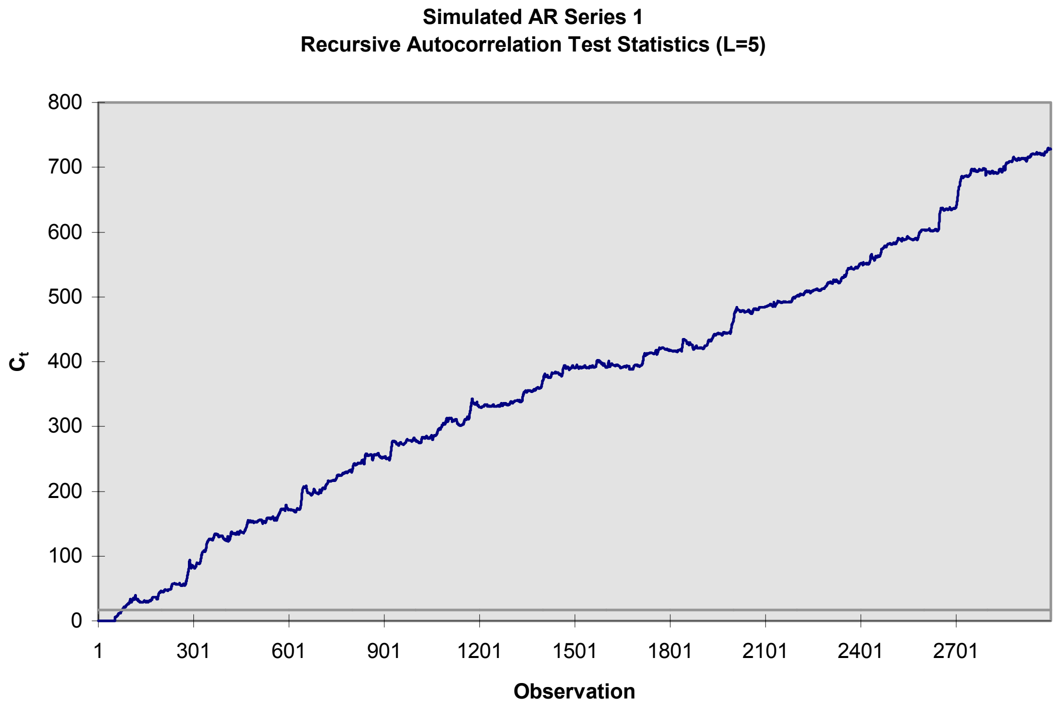


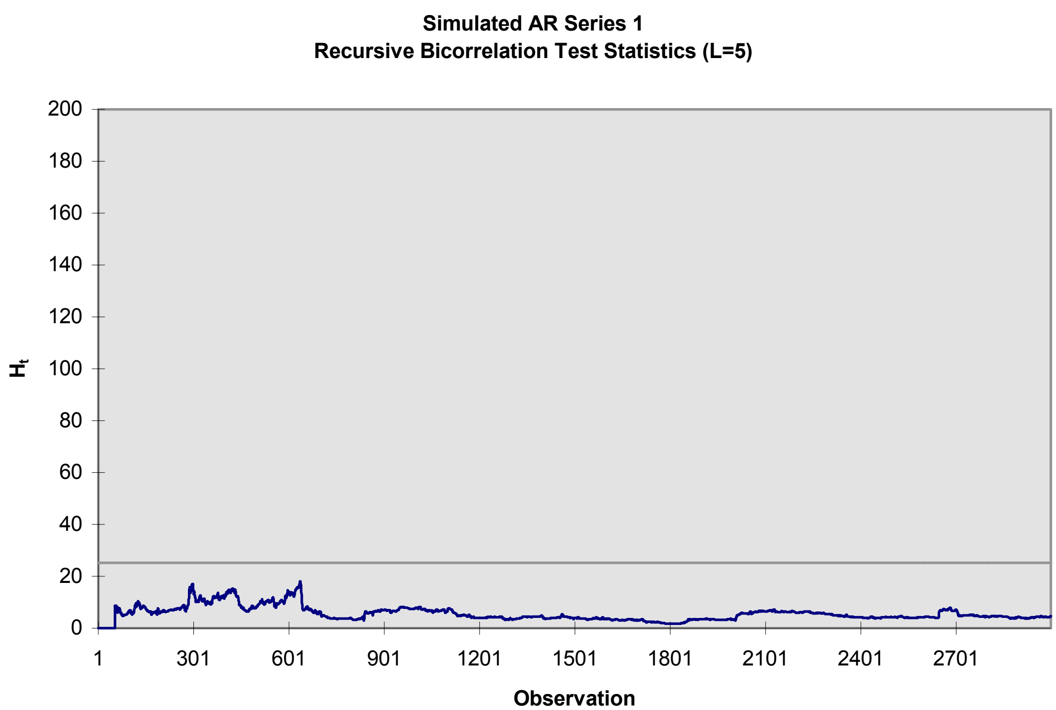


Figures 5.5
Taiex Daily Return Moving Autocorrelation and Bicorrelation Test Statistics

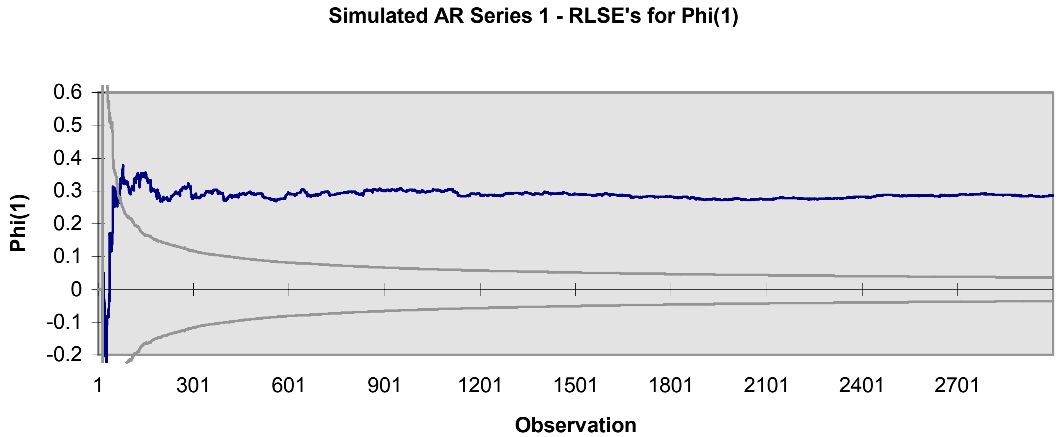


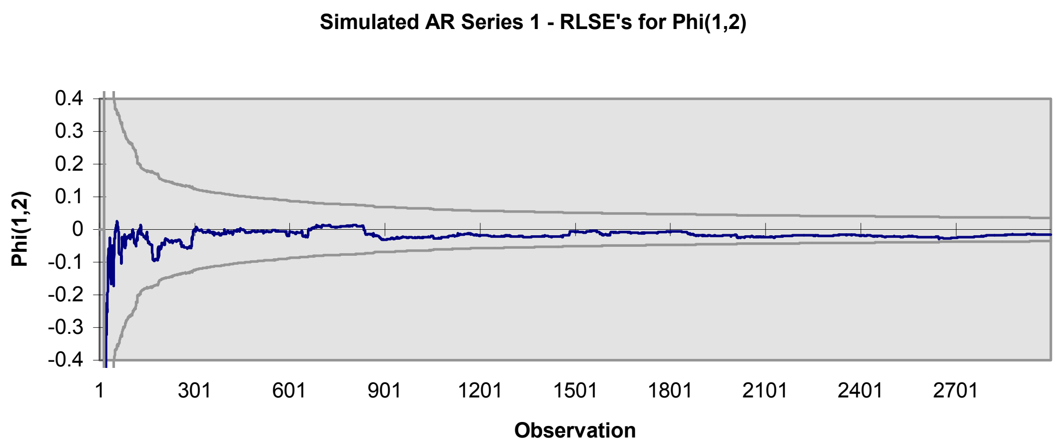
Figures 5.6
Taiex Daily Returns - Variance vs. 1st Order Autocorrelation

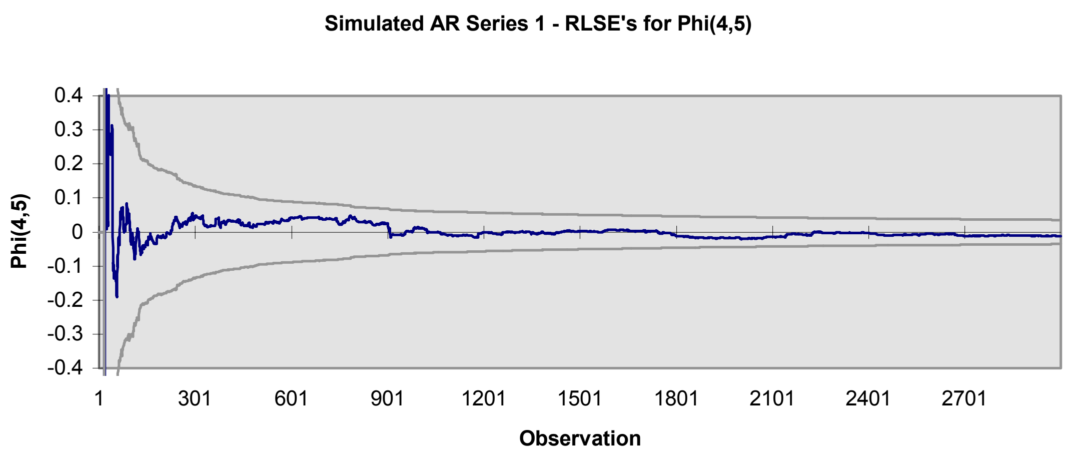




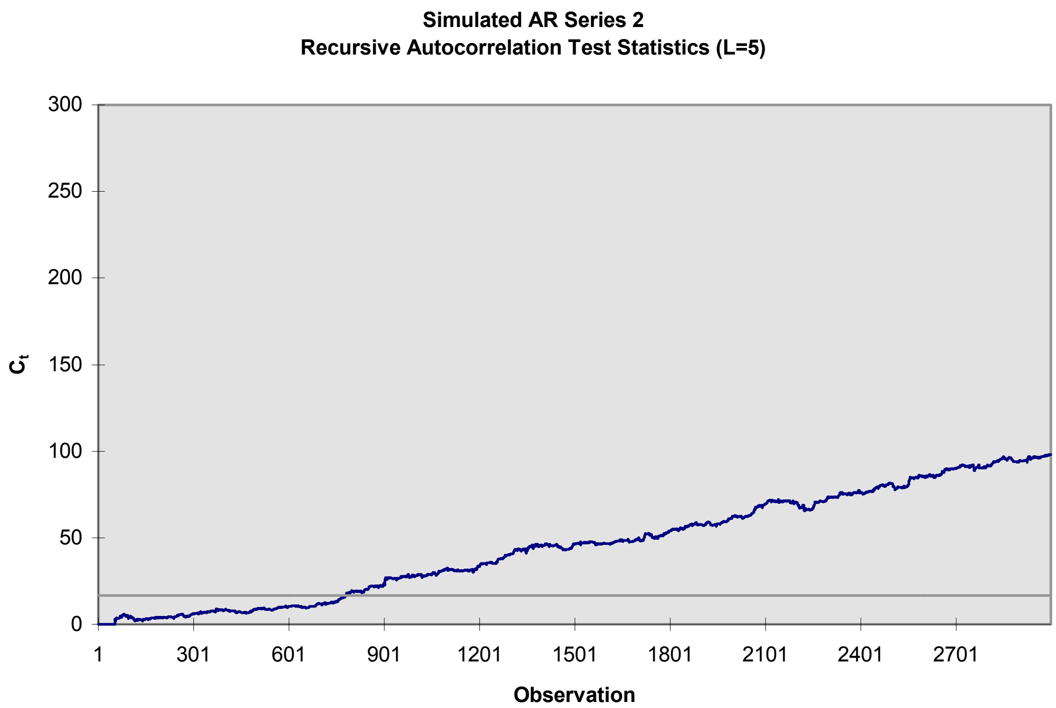
Figures 5.7
Simulated AR Series 1 - Recursive Autocorrelation and Bicorrelation Test Statistics

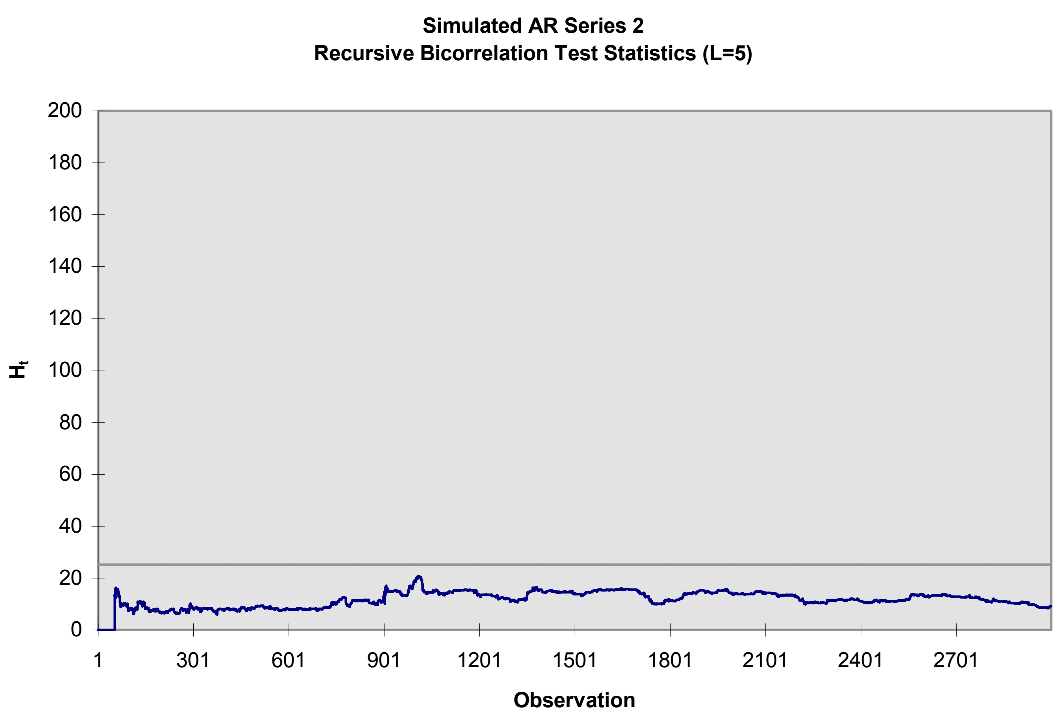




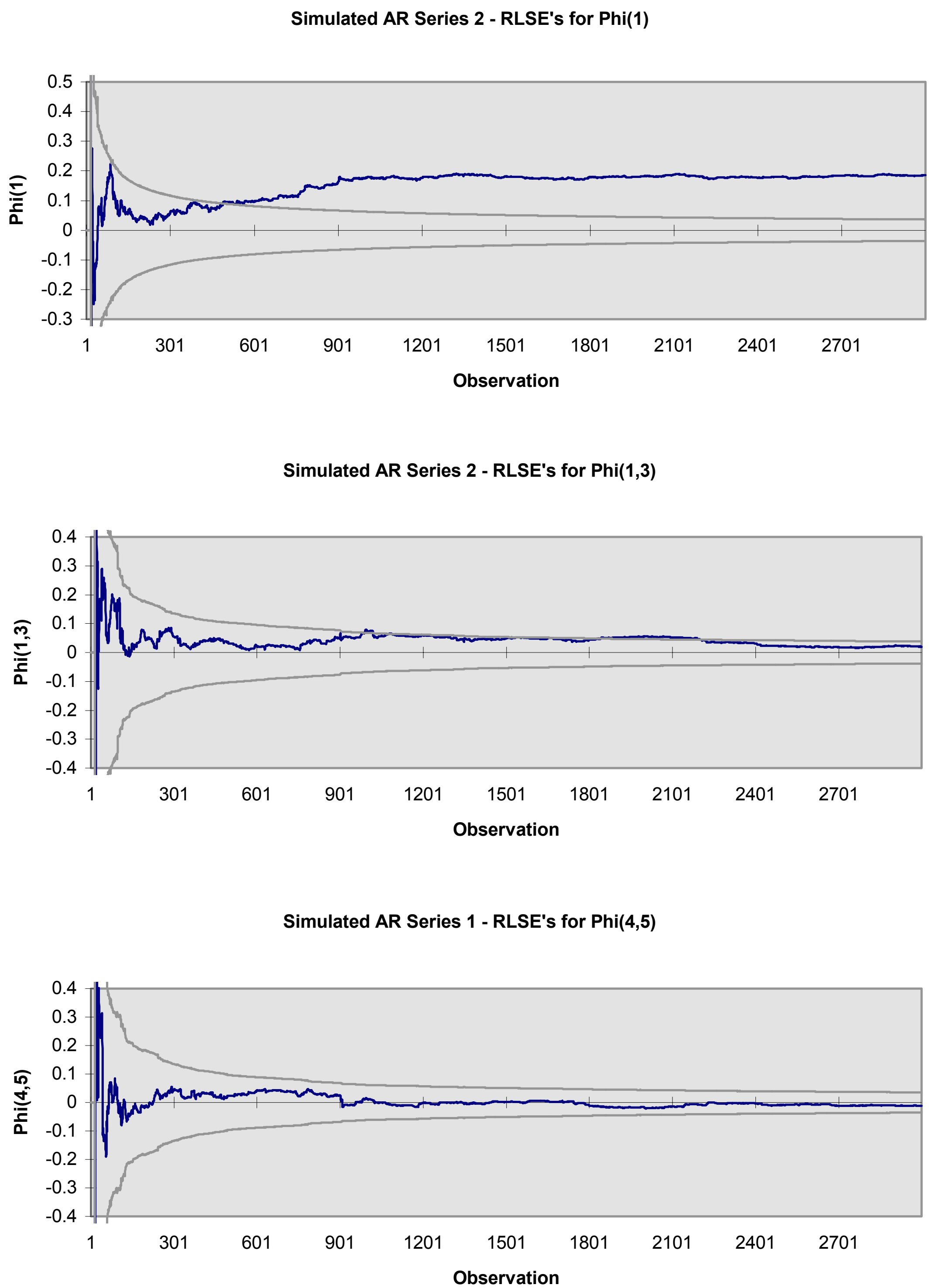


Figures 5.8
Recursive Parameter Estimates for Simulated AR Series 1

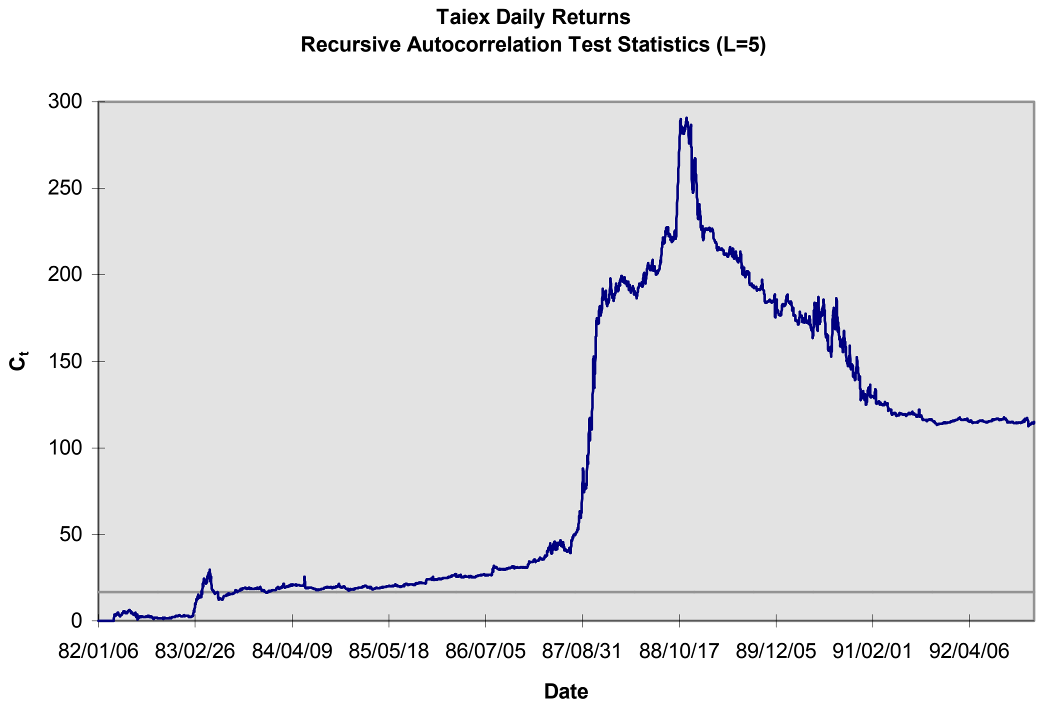


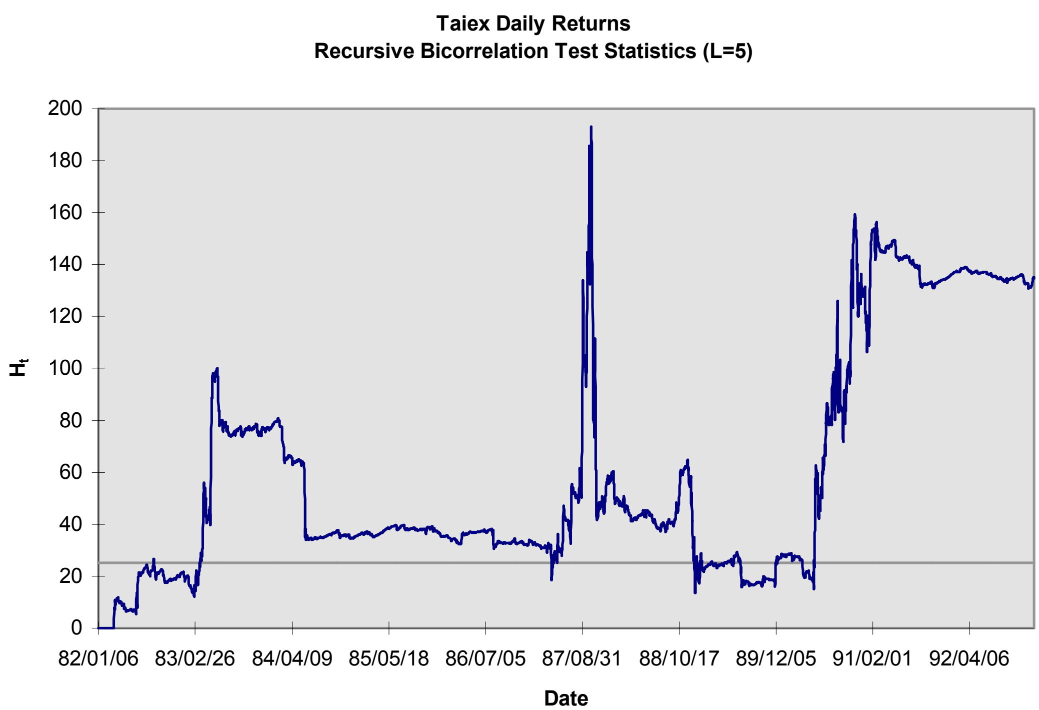


Figures 5.9
Simulated AR Series 2 - Recursive Autocorrelation and Bicorrelation Test Statistics



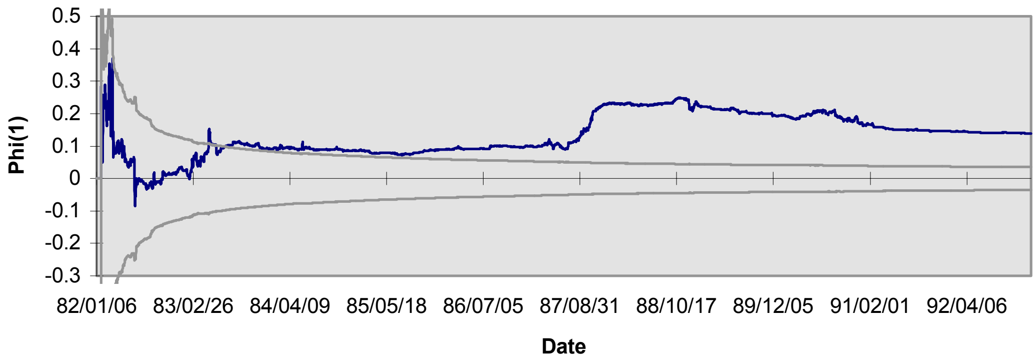
Figures 5.10
Recursive Parameter Estimates for Simulated AR Series 2



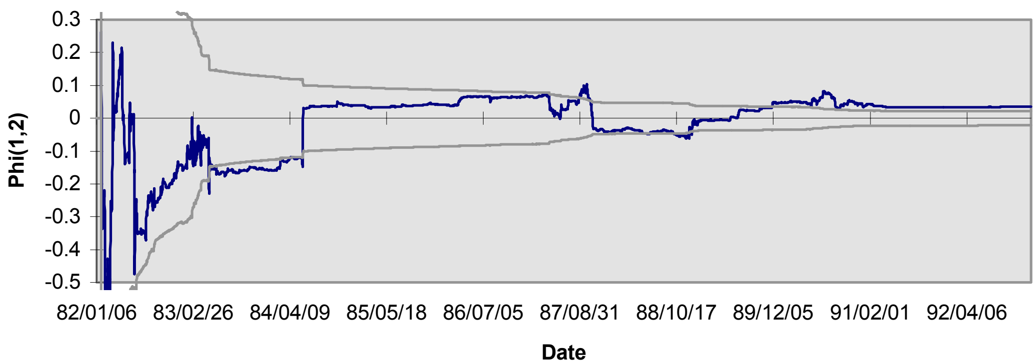


Figures 5.11
Taiex Daily Returns - Recursive Autocorrelation and Bicorrelation Test Statistics

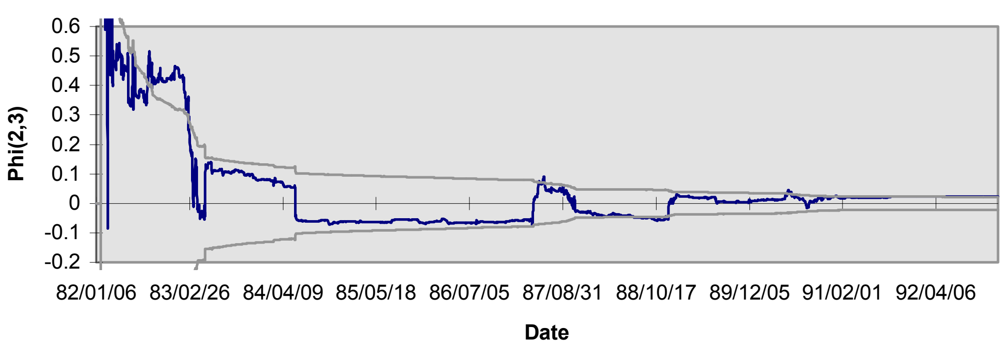
Taiex Daily Returns - RLSE's for Phi(1)



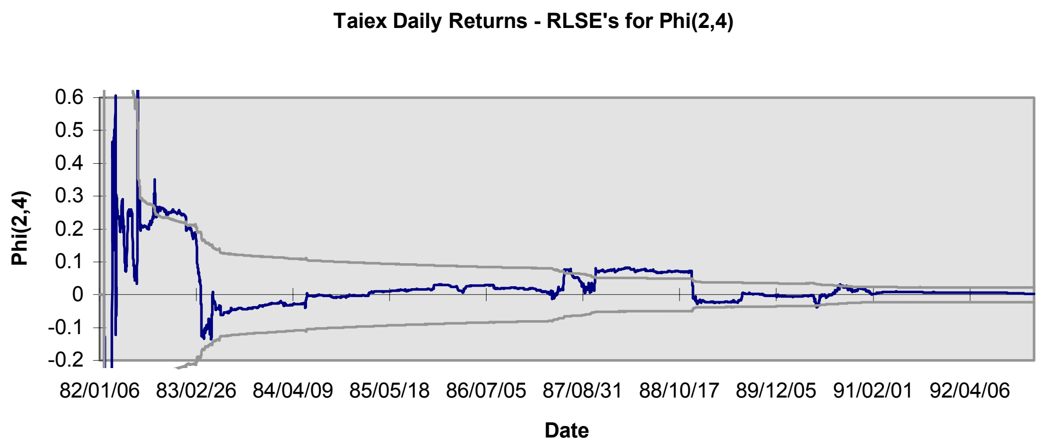
Taiex Daily Returns - RLSE's for Phi(1,2)

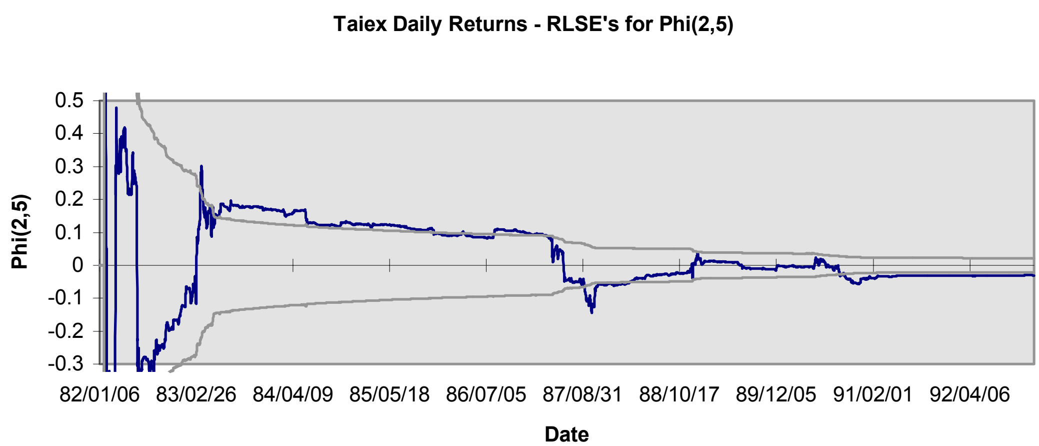


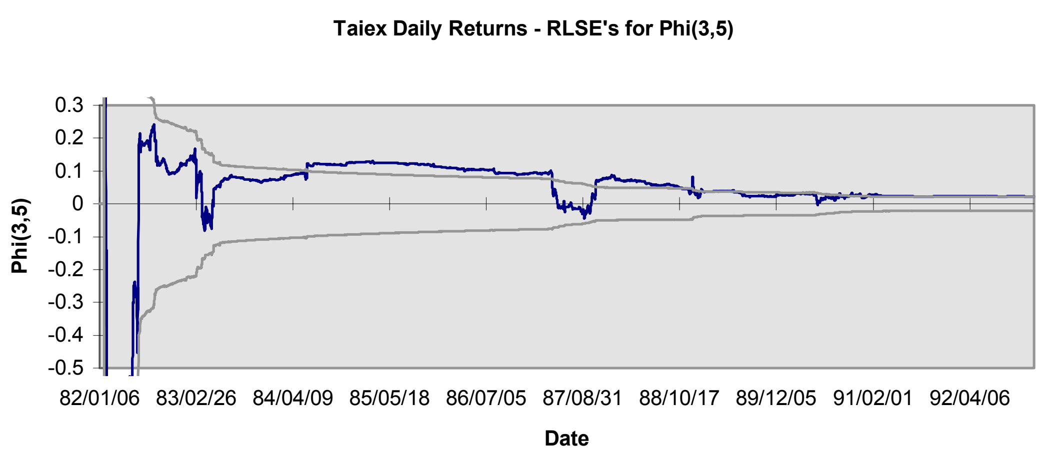
Taiex Daily Returns - RLSE's for Phi(2,3)



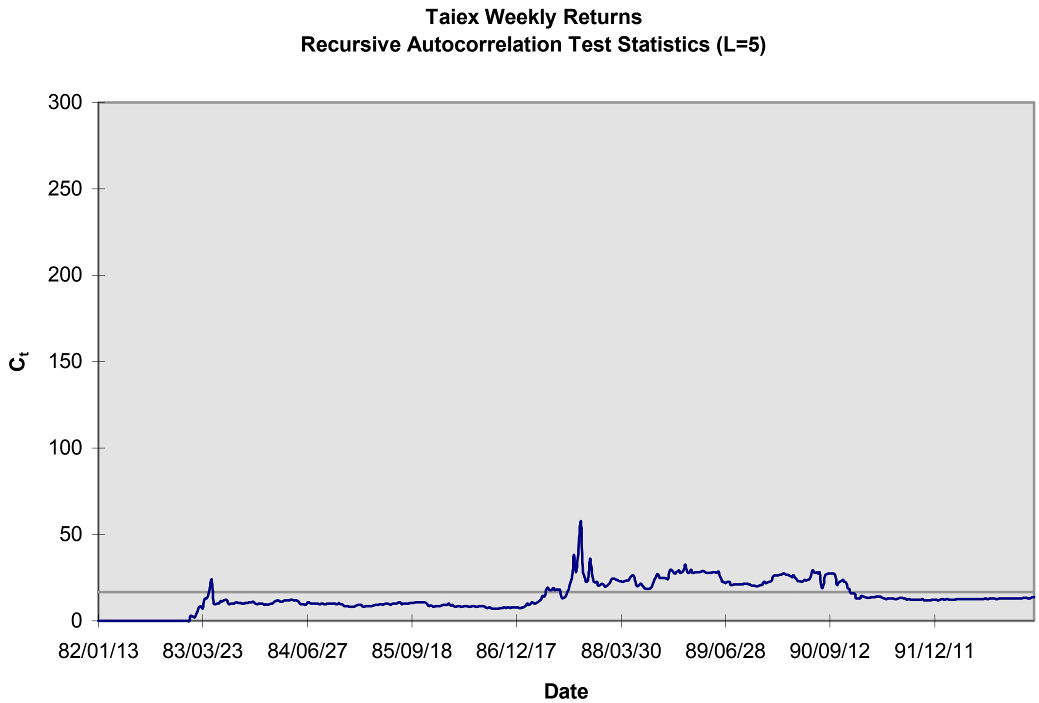
Figures 5.12
Recursive Parameter Estimates for Taiex Daily Returns

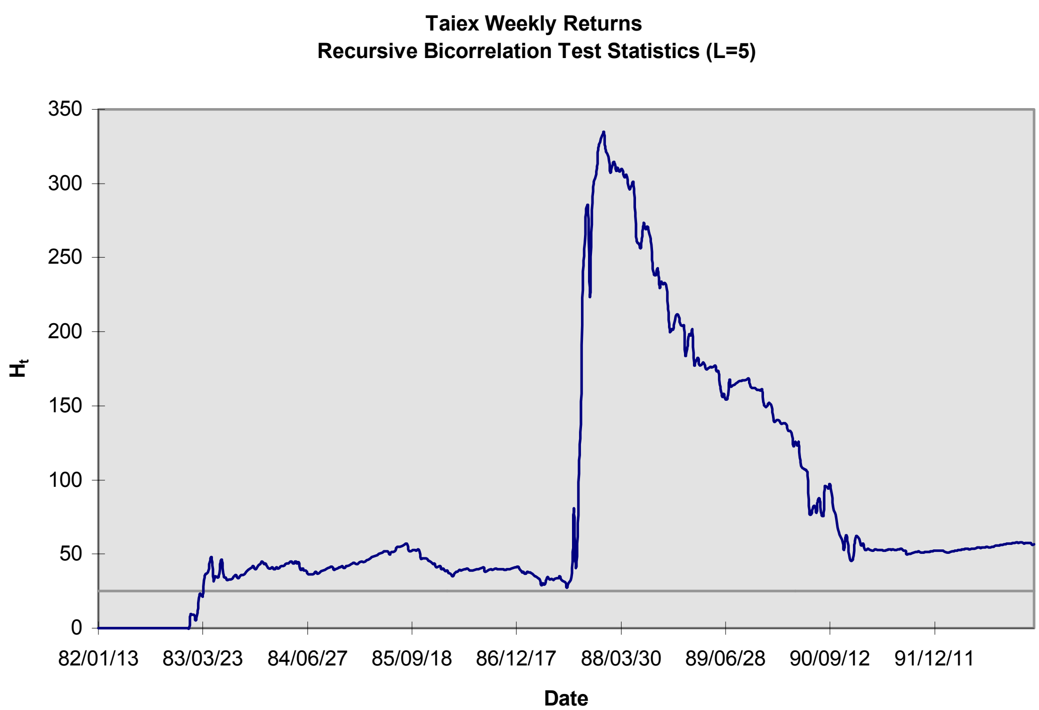






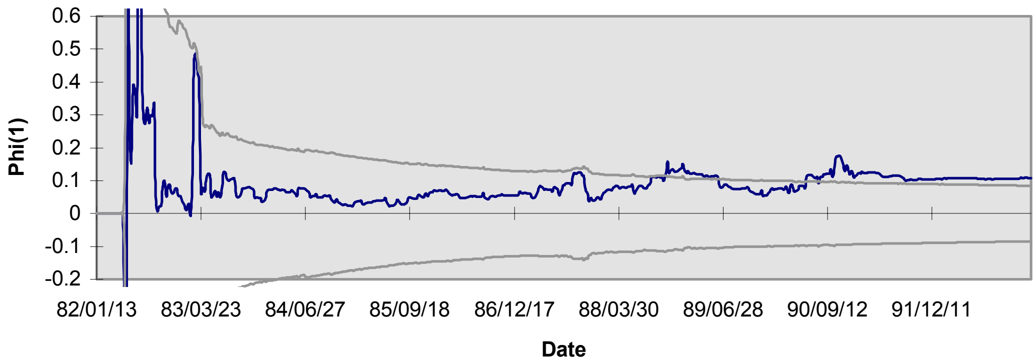
Figures 5.13
Recursive Parameter Estimates for Taiex Daily Returns



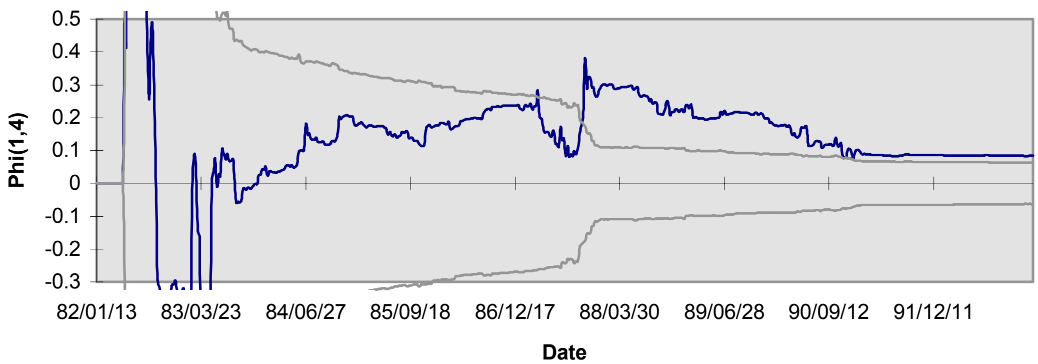


Figures 5.14
Weekly Taiex Returns - Recursive Autocorrelation and Bicorrelation Test Statistics

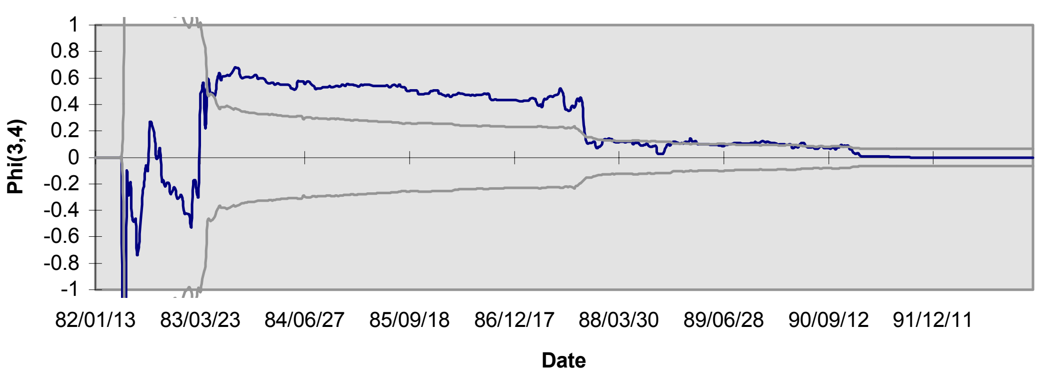
Weekly Taiex Returns - RLSE's for Phi(1)



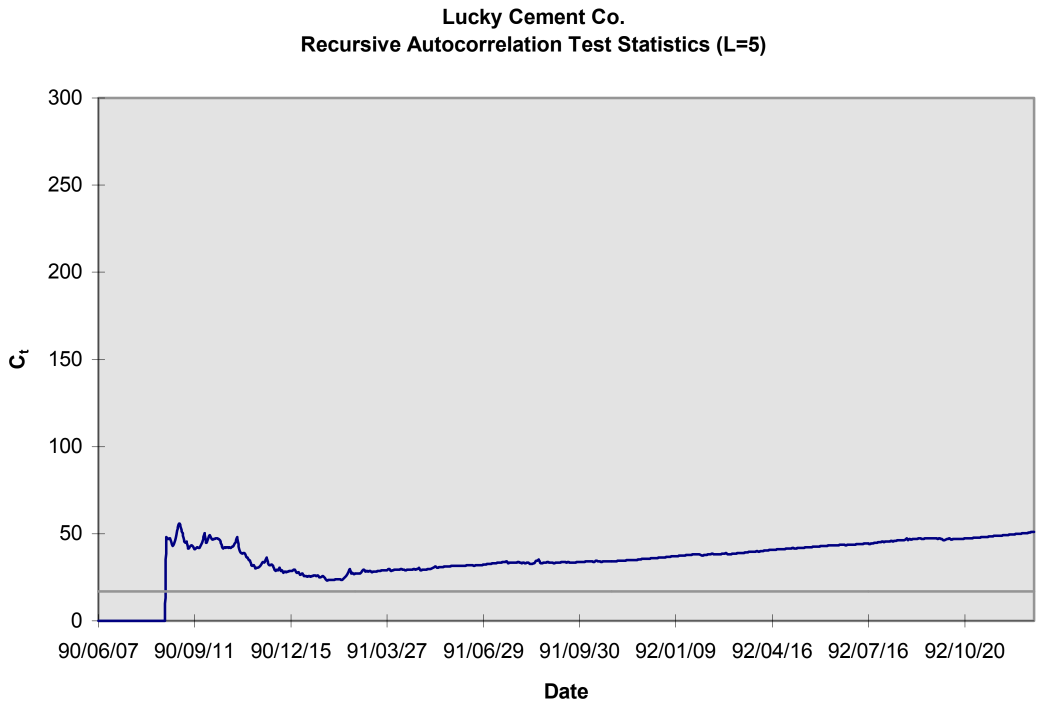
Weekly Taiex Returns - RLSE's for Phi(1,4)

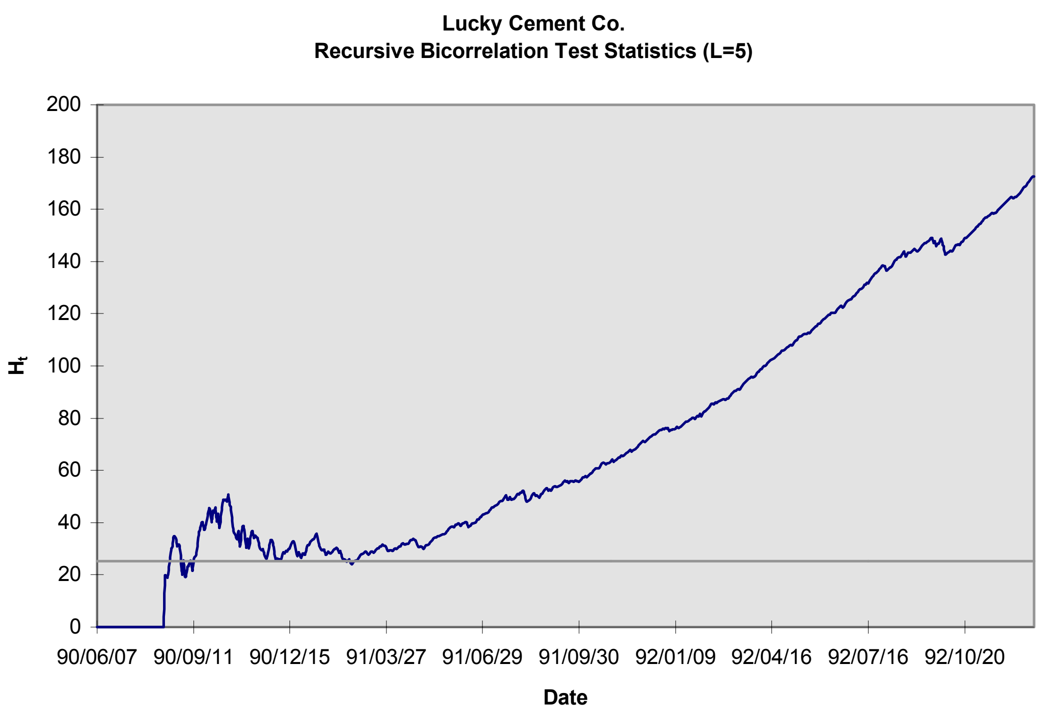


Weekly Taiex Returns - RLSE's for Phi(3,4)

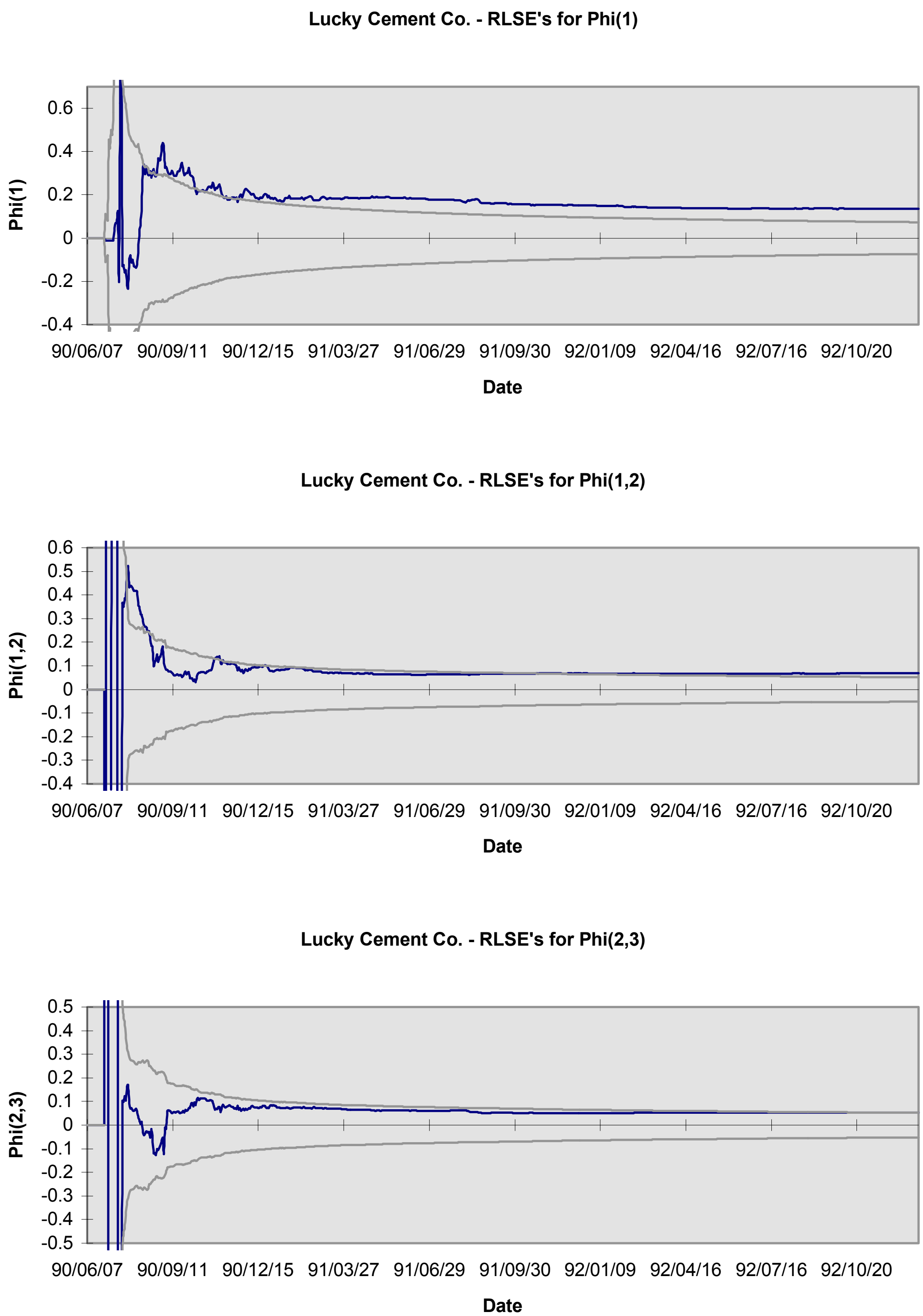


Figures 5.15
Recursive Parameter Estimates for Weekly Taiex Returns





Figures 5.16
Lucky Cement Co. - Recursive Autocorrelation and Bicorrelation Test Statistics



Figures 5.17
Recursive Parameter Estimates for Lucky Cement Co.

Table 5.1
Results of Windowed Testing for Taiex Data

Return Data	**Daily**				**Weekly**			
	Original		**Clipped**		**Original**		**Clipped**	
No. of observations	3142		3142		538		538	
C_T (L=N$^{.4}$)	186.41		185.50		21.19		23.26	
(p-value)	(0.000)		(0.000)		(0.048)		(0.026)	
H_T (L=N$^{.4}$)	124.65		121.07		33.00		25.87	
(p-value)	(0.000)		(0.000)		(0.000)		(0.000)	
C_T (L=5)	115.03		115.61		13.76		14.96	
(p-value)	(0.000)		(0.000)		(0.017)		(0.011)	
H_T (L=5)	24.94		23.65		9.29		8.84	
(p-value)	(0.000)		(0.000)		(0.000)		(0.000)	
Windowed tests:	**Non-O/L**	**O/L**	**Non-O/L**	**O/L**	**Non-O/L**	**O/L**	**Non-O/L**	**O/L**
Window size	54	54	54	54	50	50	50	50
# of windows	58	115	58	115	10	20	10	20
Inter-window statistics:								
Corr(C,H)	-0.053	0.194	-0.054	0.194	0.481	0.616	0.467	0.589
Corr(C,Var)	0.207	0.133	0.210	0.134	0.234	0.264	0.255	0.291
Corr(H,Var)	-0.109	-0.050	-0.110	-0.051	0.241	0.335	0.278	0.375
th=.005 ($\alpha\approx$0.01)								
% Significant C	3.45%	3.48%	3.45%	3.48%	0%	0%	0%	0%
% Significant H	5.17%	6.96%	5.17%	6.96%	10.00%	15.00%	10.00%	15.00%
Total # Significant	5	11	5	11	1	3	1	3
Total % Significant	8.62%	9.57%	8.62%	9.57%	10.00%	15.00%	10.00%	15.00%
th=.01 ($\alpha\approx$0.02)								
% Significant C	5.17%	4.35%	5.17%	4.35%	0%	0%	0%	0%
% Significant H	6.90%	7.83%	6.90%	7.83%	10.00%	15.00%	10.00%	15.00%
Total # Significant	7	13	7	13	1	3	1	3
Total % Significant	12.07%	11.30%	12.07%	11.30%	10.00%	15.00%	10.00%	15.00%
th=.05 ($\alpha\approx$0.10)								
% Significant C	5.17%	6.96%	5.17%	6.96%	0%	0%	0%	0%
% Significant H	15.52%	13.91%	15.52%	13.91%	10.00%	25.00%	20.00%	30.00%
Total # Significant	12	21	12	21	1	5	2	6
Total % Significant	20.69%	18.26%	20.69%	18.26%	10.00%	25.00%	20.00%	30.00%
th=.10 ($\alpha\approx$0.19)								
% Significant C	10.34%	11.30%	10.34%	11.30%	0%	0%	0%	0%
% Significant H	15.52%	18.26%	15.52%	18.26%	30.00%	35.00%	30.00%	35.00%
Total # Significant	14	30	14	30	3	7	3	7
Total % Significant	24.14%	26.09%	24.14%	26.09%	30.00%	35.00%	30.00%	35.00%
th=.20 ($\alpha\approx$0.36)								
% Significant C	15.52%	16.52%	15.52%	16.52%	0%	10.00%	0%	5.00%
% Significant H	29.31%	29.57%	29.31%	29.57%	30.00%	40.00%	30.00%	40.00%
Total # Significant	24	46	24	46	3	8	3	8
Total % Significant	41.38%	40.00%	41.38%	40.00%	30.00%	40.00%	30.00%	40.00%

Table 5.2
Effects of Removing Significant Data Windows

Daily Taiex Returns - Test results after removing significant autocorrelation windows:

Test threshold for windows removed	Windows removed (out of 58)	Obs.	C_T	p-value	H_T	p-value
Full Data Set	0	3142	115.026	3.55E-23	24.940	0.000
0.005	2	3034	73.868	1.60E-14	28.983	0.000
0.010	3	2980	68.793	1.83E-13	30.854	0.000
0.050	3	2980	68.793	1.83E-13	30.854	0.000
0.100	6	2818	64.603	1.35E-12	32.403	0.000
0.200	9	2656	54.295	1.82E-10	30.745	0.000

Daily Taiex Returns - Test results after removing significant bicorrelation windows:

Test threshold for windows removed	Windows removed (out of 58)	Obs.	C_T	p-value	H_T	p-value
Full Data Set	0	3142	115.026	3.55E-23	24.940	0.000
0.005	3	2980	109.331	5.67E-22	24.873	0.000
0.010	4	2926	107.201	1.60E-21	24.270	0.000
0.050	9	2656	102.485	1.58E-20	22.037	0.000
0.100	9	2656	102.485	1.58E-20	22.037	0.000
0.200	17	2224	114.999	3.59E-23	12.109	0.000

Weekly Taiex Returns - Test results after removing significant bicorrelation windows:

Test threshold for windows removed	Windows removed (out of 10)	Obs.	C_T	p-value	H_T	p-value
Full Data Set	0	538	13.764	0.017	9.292	0.000
0.005	1	488	8.403	0.135	7.465	4.21E-14
0.010	1	488	8.403	0.135	7.465	4.21E-14
0.050	1	488	8.403	0.135	7.465	4.21E-14
0.100	3	388	9.775	0.082	5.941	1.42E-09
0.200	3	388	9.775	0.082	5.941	1.42E-09

Note: A p-value of "0.000" denotes a p-value of less than 1×10^{-24}.

Table 5.3
Results of Bispectrum and Windowed Stability Tests

Cement Industry (1100) - 9 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1101	2577	47.63	16.76	94	16	17.0%
1102	2580	40.43	14.99	94	14	14.9%
1103	2579	33.24	13.90	94	12	12.8%
1104	2578	30.87	17.37	94	8	8.5%
1105	2579	27.52	13.42	94	14	14.9%
1107	1429	15.78	10.64	84	28	33.3%
1108	730	20.32	9.06	51	2	3.9%
1109	302	12.61	2.70	26	2	7.7%
1106	2311	8.74	5.77	10	4	40.0%
Average	1962.778	26.349	11.623	71.222	11.111	17.0%
% Sig.		100.0%	100.0%			

Food Industry (1200) - 25 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1201	2574	33.69	17.82	94	12	12.8%
1203	2574	36.66	12.18	94	14	14.9%
1207	2580	34.12	11.82	94	15	16.0%
1209	2572	31.35	9.65	94	16	17.0%
1210	2580	23.49	17.04	94	9	9.6%
1215	850	14.36	4.84	30	3	10.0%
1216	850	18.25	10.30	30	2	6.7%
1217	850	12.96	4.78	30	5	16.7%
1217A	301	11.89	1.62	10	1	10.0%
1218	850	12.58	13.54	30	2	6.7%
1218A	27	n.a.	n.a.	n.a.	n.a.	n.a.
1219	591	11.81	7.70	20	4	20.0%
1220	315	6.57	4.20	10	1	10.0%
1221	312	6.11	0.88	10	0	0.0%
1202	2579	17.99	17.51	94	8	8.5%
1206	1811	12.29	11.15	66	15	22.7%
1211	2578	21.66	8.83	94	11	11.7%
1212	2579	30.05	13.65	94	12	12.8%
1213	850	7.93	6.94	30	7	23.3%
1214	850	12.16	13.47	30	3	10.0%
1222	226	12.83	1.42	7	3	42.9%
1204E	1328	4.31	4.3	48	15	31.3%
1208E	2458	14.41	10.04	90	24	26.7%
1223	144	5.2	2.31	4	2	50.0%
1224	69	n.a.	n.a.	1	0	0.0%
Average	1443.565	17.073	8.956	52.043	8.000	17.0%
% Sig.		100.0%	87.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Plastics Industry (1300) - 18 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1301	2580	33.63	17.93	94	15	16.0%
1303	2580	35.08	14.62	94	12	12.8%
1304	2580	34.22	13.26	94	12	12.8%
1305	2580	32.97	14.13	94	12	12.8%
1307	2029	26.32	13.06	74	7	9.5%
1308	1867	17.21	9.99	68	10	14.7%
1309	1861	20.70	7.41	67	10	14.9%
1310	1543	14.87	14.35	56	4	7.1%
1311	1194	11.24	8.39	43	6	14.0%
1312	1144	14.73	15.46	41	4	9.8%
1312A	1144	9.68	6.49	41	8	19.5%
1313	1075	11.40	7.31	38	5	13.2%
1314	419	22.07	14.76	14	2	14.3%
1315	184	4.02	3.37	5	1	20.0%
1302	1866	14.81	11.41	68	36	52.9%
1306	2230	12.96	10.28	81	22	27.2%
1316	58	n.a.	n.a.	1	1	100.0%
1317	8	n.a.	n.a.	n.a.	n.a.	n.a.
Average	1584.353	19.744	11.389	57.235	9.824	21.9%
% Sig.		100.0%	100.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Textile Industry (1400) - 42 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1402	2580	23.17	13.50	94	10	10.6%
1407	2577	19.39	16.85	94	8	8.5%
1407A	1299	5.30	3.53	47	11	23.4%
1408	2580	18.51	19.00	94	10	10.6%
1409	2580	23.04	11.49	94	10	10.6%
1410	2542	21.89	9.20	93	20	21.5%
1414	850	9.91	6.83	30	2	6.7%
1416	850	7.88	5.94	30	3	10.0%
1417	850	13.78	3.82	30	2	6.7%
1420	2579	20.51	17.87	94	9	9.6%
1423	2559	31.42	17.95	93	11	11.8%
1426	2512	21.38	20.42	92	12	13.0%
1432	2580	21.65	15.16	94	10	10.6%
1433	2286	27.37	16.40	83	13	15.7%
1434	2003	21.51	13.22	73	13	17.8%
1435	1428	12.70	10.14	51	4	7.8%
1436	1352	6.82	6.95	49	5	10.2%
1438	1149	7.20	7.13	41	5	12.2%
1439	850	3.75	1.13	30	5	16.7%
1440	919	9.31	4.29	33	3	9.1%
1441	900	8.03	4.51	32	2	6.3%
1443	767	7.22	5.56	27	1	3.7%
1444	680	11.86	15.98	24	0	0.0%
1446	342	2.30	1.73	11	3	27.3%
1447	263	22.79	6.06	8	3	37.5%
1448	211	4.75	3.31	6	0	0.0%
1449	187	2.22	1.90	5	1	20.0%
1401	2555	17.78	17.99	93	18	19.4%
1413	850	5.10	1.19	30	1	3.3%
1418	850	9.65	10.18	30	1	3.3%
1419	2342	30.97	7.50	85	21	24.7%
1422	2528	16.90	16.84	92	18	19.6%
1425	2577	24.54	16.32	94	15	16.0%
1431	2580	22.89	15.34	94	23	24.5%
1437	1176	4.71	5.27	42	5	11.9%
1442	885	4.79	2.68	31	2	6.5%
1445	541	3.47	0.83	19	3	15.8%
1405	1523	2.21	0.75	55	25	45.5%
1424E	1209	6.59	2.07	43	9	20.9%
1429	1877	17.75	10.12	68	16	23.5%
1430	1297	12.00	9.50	47	15	31.9%
1450	64	n.a.	n.a.	1	0	0.0%
Average	1503.071	13.781	9.182	54.190	8.286	14.4%
% Sig.		100.0%	90.2%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Electrical Machinery Industry (1500) - 12 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1502	2580	25.06	24.27	94	7	7.4%
1503	2577	30.35	10.67	94	13	13.8%
1504	2579	34.26	10.17	94	15	16.0%
1506	2579	33.61	15.72	94	19	20.2%
1507	890	12.62	5.02	31	3	9.7%
1510	180	5.48	3.15	5	1	20.0%
1501	1212	15.92	13.16	43	20	46.5%
1508	592	11.59	7.94	20	4	20.0%
1509	312	5.06	4.51	10	3	30.0%
1505	872	7.16	7.63	31	11	35.5%
1505E	847	8.96	6.96	30	7	23.3%
1511	28	n.a.	n.a.	n.a.	n.a.	n.a.
Average	1383.636	17.279	9.927	49.636	9.364	22.0%
% Sig.		100.0%	100.0%			

Electrical Appliances, Wire, & Cable Industry (1600) - 11 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1601	2559	45.15	15.66	93	9	9.7%
1602	2580	29.50	16.09	94	6	6.4%
1603	2580	31.34	10.39	94	18	19.1%
1604	2580	20.85	20.88	94	8	8.5%
1605	2580	28.29	15.60	94	10	10.6%
1606	2580	38.26	12.67	94	11	11.7%
1608	1277	12.68	7.71	46	8	17.4%
1609	1152	11.96	10.70	41	2	4.9%
1610	853	13.52	12.38	30	1	3.3%
1611	840	12.11	8.38	30	3	10.0%
1607	2453	14.78	11.11	89	21	23.6%
Average	2003.091	23.495	12.870	72.636	8.818	11.4%
% Sig.		100.0%	100.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Chemical Industry (1700) - 14 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1701	2576	32.03	10.55	94	18	19.1%
1702	2580	32.57	11.78	94	10	10.6%
1704	2580	29.55	14.14	94	8	8.5%
1705	2579	30.63	7.95	94	13	13.8%
1708	1871	18.94	11.02	68	13	19.1%
1709	1844	20.62	21.19	67	8	11.9%
1710	1481	16.52	14.55	53	12	22.6%
1711	1140	15.47	8.82	41	4	9.8%
1712	862	9.37	7.93	30	4	13.3%
1713	834	6.92	6.17	29	2	6.9%
1714	378	4.59	2.43	13	2	15.4%
1703	2580	23.12	9.24	94	12	12.8%
1707	2530	26.26	9.32	92	11	12.0%
1706	2563	10.57	10.72	93	23	24.7%
Average	1885.571	19.797	10.415	68.286	10.000	14.3%
% Sig.		100.0%	100.0%			

Glass Industry (1800) - 6 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1802	2578	32.05	7.64	94	10	10.6%
1804	1245	9.85	9.18	45	4	8.9%
1805	905	8.56	6.97	32	2	6.3%
1801	2555	10.98	8.82	93	24	25.8%
1806	71	n.a.	n.a.	1	1	100.0%
1807	64	n.a.	n.a.	1	1	100.0%
Average	1236.333	15.360	8.153	44.333	7.000	41.9%
% Sig.		100.0%	100.0			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Pulp & Paper Industry (1900) - 10 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
1902	2580	21.03	18.18	94	11	11.7%
1903	1835	13.17	11.43	66	8	12.1%
1904	2580	27.49	12.45	94	7	7.4%
1905	2580	33.26	11.68	94	14	14.9%
1907	2534	41.20	11.21	92	11	12.0%
1907A	1209	12.52	8.62	43	7	16.3%
1907B	1141	10.22	7.96	41	6	14.6%
1908	2580	25.94	24.08	94	15	16.0%
1909	2032	19.40	17.44	74	12	16.2%
1906E	928	2.97	2.47	33	5	15.2%
Average	1999.900	20.720	12.552	72.500	9.600	13.6%
% Sig.		100.0%	100.0%			

Iron & Steel Industry (2000) - 20 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2002	2150	22.38	12.79	78	21	26.9%
2003	1475	13.45	12.75	53	6	11.3%
2004	1470	14.57	10.11	53	5	9.4%
2005	1458	11.94	12.77	53	5	9.4%
2006	1275	12.24	10.20	46	4	8.7%
2007	1207	9.37	7.69	43	2	4.7%
2007A	784	10.35	8.24	28	4	14.3%
2008	1139	11.88	8.86	41	1	2.4%
2009	905	7.00	4.33	32	5	15.6%
2010	856	10.88	11.45	30	1	3.3%
2012	340	7.03	11.87	11	1	9.1%
2014	249	-0.55	-0.17	8	3	37.5%
2014A	51	n.a.	n.a.	n.a.	n.a.	n.a.
2015	171	2.15	2.07	5	0	0.0%
2011	745	11.62	11.29	26	4	15.4%
2011A	38	n.a.	n.a.	n.a.	n.a.	n.a.
2013	269	4.27	-0.63	8	1	12.5%
2001	2281	16.64	13.13	83	30	36.1%
2016	157	2.25	0.34	4	1	25.0%
2017	45	n.a.	n.a.	n.a.	n.a.	n.a.
Average	995.941	9.851	8.064	35.412	5.529	14.2%
% Sig.		94.1%	82.4%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Rubber Industry (2100) - 8 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2102	2575	22.40	11.78	94	17	18.1%
2103	2578	26.85	15.46	94	10	10.6%
2104	1847	18.45	11.98	67	8	11.9%
2105	1444	13.89	14.84	52	3	5.8%
2106	575	8.37	8.19	20	2	10.0%
2107	238	3.37	1.98	7	5	71.4%
2101	2580	32.47	14.30	94	20	21.3%
2108	49	n.a.	n.a.	n.a.	n.a.	n.a.
Average	1691.000	17.971	11.219	61.143	9.286	21.3%
% Sig.		100.0%	100.0%			

Automobile Industry (2200) - 4 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2201	2580	22.78	13.15	94	14	14.9%
2202	1146	10.42	9.72	41	3	7.3%
2203	1140	9.93	9.15	41	6	14.6%
2204	517	8.76	4.36	18	3	16.7%
Average	1345.750	12.973	9.095	48.500	6.500	13.4%
% Sig.		100.0%	100.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Electronics Industry (2300) - 26 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2301	2579	27.69	12.43	94	14	14.9%
2302	2278	22.47	6.03	83	17	20.5%
2303	2132	18.02	18.16	77	7	9.1%
2303A	46	n.a.	n.a.	n.a.	n.a.	n.a.
2304	1490	12.87	10.34	54	10	18.5%
2305	1193	8.42	7.90	43	2	4.7%
2306	1177	9.85	8.57	42	4	9.5%
2308	1146	9.73	8.60	41	4	9.8%
2309	1142	7.08	6.98	41	3	7.3%
2310	1142	7.35	5.99	41	4	9.8%
2311	981	9.40	7.54	35	8	22.9%
2312	892	8.60	7.70	32	3	9.4%
2313	693	11.05	10.07	24	3	12.5%
2314	680	10.41	3.67	24	2	8.3%
2315	674	11.72	9.63	23	4	17.4%
2316	541	6.91	0.15	19	4	21.1%
2317	439	8.24	4.51	15	1	6.7%
2318	434	5.20	3.11	15	1	6.7%
2319	403	8.45	6.76	13	2	15.4%
2319A	201	4.45	2.32	6	1	16.7%
2321	324	9.33	4.88	11	2	18.2%
2324	251	3.99	5.55	8	1	12.5%
2307	1153	6.37	3.26	41	8	19.5%
2320	377	6.95	4.38	12	0	0.0%
2322	312	5.06	6.73	10	0	0.0%
2323	252	7.03	4.74	8	2	25.0%
Average	915.440	9.866	6.800	32.480	4.280	12.7%
% Sig.		100.0%	96.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Construction Industry (2500) - 13 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2501	2552	27.97	13.21	93	11	11.8%
2504	2580	29.13	12.71	94	13	13.8%
2506	2580	24.03	18.02	94	17	18.1%
2510	958	9.99	8.25	34	2	5.9%
2511	485	18.17	8.38	16	4	25.0%
2512	249	28.31	7.95	8	3	37.5%
2505	2573	21.17	19.23	94	19	20.2%
2509	1262	10.19	9.49	45	11	24.4%
2513	192	9.94	1.25	6	2	33.3%
2503	2522	8.40	6.81	92	23	25.0%
2507	1408	20.67	6.31	51	23	45.1%
2508	2478	25.52	9.72	90	16	17.8%
2514	72	n.a.	n.a.	1	1	100.0%
Average	1531.615	19.458	10.111	55.231	11.154	29.1%
% Sig.		100.0%	91.7%			

Shipping Industry (2600) - 8 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2603	1504	11.84	9.93	54	8	14.8%
2604	1143	12.04	9.22	41	1	2.4%
2605	867	10.28	5.05	31	3	9.7%
2606	585	11.86	6.54	20	2	10.0%
2607	580	8.63	3.37	20	2	10.0%
2608	575	2.89	2.63	20	2	10.0%
2609	201	7.97	2.83	6	1	16.7%
2601	2580	32.03	14.25	94	16	17.0%
Average	1004.375	12.193	6.728	35.750	4.375	11.3%
% Sig.		100.0%	100.0%			

Hospitality Industry (2700) - 6 Stocks

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2704	2579	24.76	13.06	94	12	12.8%
2706	433	6.85	5.13	15	1	6.7%
2701	2049	19.63	14.22	74	10	13.5%
2702	1477	13.28	14.97	53	8	13.1%
2703	2579	18.96	18.53	94	17	18.1%
2705	1141	5.20	5.64	41	6	14.6%
Average	1709.667	14.780	11.925	61.833	9.000	13.1%
% Sig.		100.0%	100.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Banking & Insurance Industry (2800) - 16 Stocks

		Bispectrum Test (Z-Statistics)		**Windowed Stability Test Results**		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2801	2560	31.15	13.84	93	11	11.8%
2802	2549	29.22	14.10	93	19	20.4%
2803	2568	25.15	11.88	94	16	17.0%
2804	2580	27.31	18.50	94	11	11.7%
2805	2303	26.52	26.08	84	17	20.2%
2806	2324	22.84	11.58	85	12	14.1%
2807	2491	33.12	11.87	91	13	14.3%
2808	2524	24.95	11.02	92	14	15.2%
2809	2269	24.22	15.51	83	11	13.3%
2810	2478	29.35	16.90	90	12	13.3%
2811	2395	24.85	10.14	87	16	18.4%
2812	2440	24.28	17.34	89	14	15.7%
2813	1780	16.15	14.23	64	14	21.9%
2814	715	8.52	6.29	25	1	4.0%
2815	288	3.63	2.88	9	1	11.1%
2816	188	28.89	5.94	5	1	20.0%
Average	2028.250	23.759	13.006	73.625	11.438	15.2%
% Sig.		100.0%	100.0%			

Department Stores (2900) - 7 Stocks

		Bispectrum Test (Z-Statistics)		**Windowed Stability Test Results**		
Stock No.	**No. of Obs.**	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
2903	2576	27.72	16.43	94	11	11.7%
2905	1217	6.48	6.40	44	1	2.3%
2907	403	7.29	4.27	13	3	23.1%
2901	2540	15.29	11.43	93	15	16.1%
2904	2567	33.22	11.53	94	12	12.8%
2906	853	8.70	7.65	30	3	10.0%
2902E	1309	19.25	14.34	47	16	34.0%
Average	1637.857	16.850	10.293	59.286	8.714	15.7%
% Sig.		100.0%	100.0%			

Table 5.3
Results of Bispectrum and Windowed Stability Tests (Cont.)

Overall Results:

		Bispectrum Test (Z-Statistics)		Windowed Stability Test Results		
	No. of Obs.	**Gaussianity**	**Linearity**	**No. of Windows**	**# Sig. Win.**	**% Sig. Win.**
mean	1508.768	16.658	9.846	55.402	8.321	16.8%
median	1304	13.45	9.72	47	7	13.8%
min	58	-0.55	-0.63	1	0	0.0%
max	2580	47.63	26.08	94	36	100.0%
% Sig.		99.6%	95.0%			
# Sig.		240	229			
# Total		241	241			

Note: the “% Sig.” figuresfor the Bispectrum test results provide the percentages of stocks within a given industry or overall whose relevant test statistics, under the appropriate assumptions, would be considered significant at a 5% level.