Chapter 6

Linear Filtering and Taiwan Stock Return Nonlinearity

6.1. Introduction

The results of the previous chapter demonstrate that the serial dependencies within Taiwanese stock returns that are reflected in the significant autocorrelation and nonlinearity test results of Chapter Four are not constant; rather, they shift in direction and magnitude over time, with a number of brief episodes of very strong dependencies accounting for much of the magnitude of the full sample results. Hinich and Patterson (1996) find similar results for U.S. securities. These results notwithstanding, numerous researchers, such as Hsieh (1992), have found that GARCH-type models seem to be able to account for or capture the full-sample nonlinear serial dependencies found within a number of financial time series.

So, for the sake of comparison, the primary focus for this chapter and Chapter Seven returns to the full-sample test results and the effects of a few varieties of linear and nonlinear time series models on these results. The present chapter focuses on modeling the linear dependencies within the data, while the next chapter focuses on the nonlinear serial dependencies, modeling these jointly with the observed linear dependencies.

There are a number of reasons for devoting a separate chapter to examining the linear dependencies. The first of these is to show that the significant test results for nonlinearity obtained in Chapter Four are in fact attributable to nonlinear dependencies within the data (whether stable or not) and are not being affected by linear relationships and dependencies within the data. Furthermore, the residuals obtained by filtering out the linear dependencies from the data can provide clues about the best way to model the nonlinear dependencies within the data, such as the proper order for a GARCH model, which can be obtained from the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the residuals from a linear model (cf., Bollerslev (1988)). A final major reason for separately modeling the linear dependencies before jointly modeling both the linear and nonlinear dependencies is to allow for comparisons between the two sets of results, thereby highlighting the effects of nonlinearity on the empirical results for linear effects within the data (such as autocorrelation and day-of-the-week effects) and illustrating the importance of tackling both types of dependencies simultaneously.

Stocks and Indices Examined

One of the primary time series to be examined in this chapter is the daily Taiex returns series. For comparative purposes, the daily returns from five other stock market indices will also be examined. These other indices include the Dow-Jones Industrial Average for the New York Stock Exchange and the Financial Times 30 Stock Price Index for the London Stock Exchange, as well as three indices from Asia, the Nikkei 225 Stock Average Price Index for the Tokyo Stock Exchange, the Hang Seng Index for the Hong Kong Stock Exchange, and the Singapore Straits Times Industrials Index for the Singapore Stock Exchange. All of these indices are sampled over the period from January 5, 1982, through February 26, 1993. However, despite using the same sample period for all six indices, such factors as Saturday trading and different holiday schedules lead to different sample sizes for each of the indices. The following table gives the sample size for each series of index returns, along with the abbreviation used to denote each series in subsequent sections.

Index	Abbreviation	No. of Observations
Taiwan Stock Exchange Weighted Stock Index	Taiex	3142
Dow-Jones Industrial Average	DJIA	2810
Financial Times 30 Stock Price Index	FT-30	2800
Nikkei 225 Stock Average Price Index	Nikkei	2991
Hang Seng Index	HSI	2750
Singapore Straits Times Industrial Price Index	STI	2755

In addition to examining the daily index returns, it is also useful to study the returns for individual stocks underlying the index. Unfortunately, given the sheer number of stocks trading on the Taiwan Stock Exchange that were examined in the previous two chapters, it would be impossible to examine all of these stocks in this chapter. Instead, a subsample of twelve stocks was randomly drawn from among the stocks for which there were at least 800 days' worth of return observations. The twelve stocks selected, their stock identification numbers, and the number of observations available for each are listed in the table below.

Stock	Stock ID No.	No. of Observations
Chia Hsin Cement	1103	2579
Eagle Food	1209	2572
Carnival Textile	1417	850
Chu Wa Wool	1439	850
Tah Tong Textile	1441	900
Ta Nun Chemicals	1706	2563
Hsin Chu Glass	1801	2555
Wan Yu Paper	1908	2580
Chun Yuan Steel	2010	856
Nan Kang Rubber Tire	2101	2580
Cal-Comp. Electronics, Inc.	2312	892
Evergreen Marine	2603	1504

Although all of these stocks face Saturday trading and the same holiday schedule, they nonetheless entail different numbers of observations due to differences in when they first started trading on the exchange. For the longest series, whose trading began well before the start of the sample period, the earliest day of trading activity available was January 6, 1984. For the shortest series, the first day for which a return was available was January 5, 1990. The final day of returns for all of the series of stock returns was December 29, 1992.

6.2. Preliminary Analysis

Before modeling any linear dependencies within these six index series and twelve stock series, the first step to be taken is to perform some preliminary data analysis to get a better view of some of the important statistical features of these series of returns. The results of this analysis are summarized in Table 6.1.

Among the indices, the most volatile were those associated with the Asian "Tigers," Taiwan, Hong Kong, and Singapore. Of these, the Taiex and the Hang Seng Index were especially volatile. But despite the fact that the sample period included a massive bubble followed by a 90% decline in the value of the index, the Taiex nevertheless saw the highest level of average daily returns among the indices. Of course, this high average is accompanied by the highest standard deviation of returns of any of the indices. The Hang Seng Index, meanwhile, exhibited the second highest levels for both of these measures. Interestingly, the index with the third highest level of average daily returns, the FT-30, also had the lowest standard deviation of returns among all of the indices. Thus, it appears to dominate, from a risk-return perspective, not only the Nikkei and Singapore STI indices, whose average returns were far below those of the other indices, but also the Dow-Jones Industrial Average, even though this latter index displayed the second lowest levels of standard deviation among all the indices.

But given the aggregate nature of indices, even those exhibiting the highest levels of volatility are typically less volatile than individual stocks, and this is the case for the relationship between the Taiex returns and those of the individual Taiwanese stocks examined here. The standard deviations of the returns on these stocks are very high, on average about 70% higher than the standard deviation of the Taiex returns. However, in spite of these high standard deviations, which would suggest high ex-ante expected returns, most of the stocks exhibited negative returns over the sample period. This is at least partially a consequence of the fact that a number of these stocks first became listed when the market was well on its way toward achieving "bubble" status. Nonetheless, for better or worse, individual stocks could still buck the market trends, and Evergreen Marine, for example, which is part of the Evergreen transportation conglomerate whose green "Evergreen" trailers are seen on highways throughout America, managed to achieve positive average returns, despite the fact that it first traded during September, 1987.

Moving beyond the basic mean and standard deviation measurements to higher-order moments, the six indices and the twelve stocks all exhibit some degree of negative or left skewness, a reflection of the fact that the most extreme movements in the markets tend to be negative. Probably the most prominent example of this is the "Crash of '87," which saw one-day declines ranging from 40.5% for the Hang Seng Index to 12.4% for the Financial Times 30 Index, down to a price-limited 4.8% decline for the Taiex. (Actually, the 40.5% decline for the Hang Seng Index was not really a one-day decline, but represented the drop in the market over the week during which the exchange was closed subsequent to October 19, 1987 to allow time for the market to adjust to the new market conditions.) Similarly, all of the individual Taiwan stocks studied also exhibit negative skewness, but, as with the Taiex, the price limits tend to limit the extant left-skewness for these stocks to relatively low levels.

The price limits have a similar effect on the kurtosis levels for the Taiex and the Taiwanese stocks. The distributions of returns for the other indices studied are all highly leptokurtic (i.e., the tails of their return distributions taper out much more slowly than do those of a normal bell curve for the same level of variance), similar to what has been found for most financial time series. The Taiex and the Taiwanese stocks, on the other hand, face truncation of their returns due to the effects of the price limits, with the result that they exhibit much lower levels of kurtosis, with half of the stocks exhibiting less kurtosis even than the normal distribution.

Combining the facts that a normal distribution has zero skewness and zero excess kurtosis allows these two statistics to be combined into a test for normality, such as the Bera-Jarque skewness-kurtosis test. Not surprisingly, given the left-skewness and excess kurtosis demonstrated within these series of returns, the Bera-Jarque skewness-kurtosis test rejects normality at a level of less than 1% for all of the indices and all but two of the stocks. The bispectrum test for Gaussianity, on the other hand, rejects normality for all eighteen sets of returns, with p-values of less than 0.0005 in all eighteen cases.

Thus, none of the sets of returns follows a Gaussian random walk, since none of them is normally distributed. But do they nonetheless follow a random walk, albeit with non-normal increments? The tests for serial dependencies within these returns provide clear evidence that the answer is no. The Box-Pierce Q-statistics are highly significant for all six indices and all twelve stocks, indicating that each of these sets of returns exhibits significant autocorrelation. Furthermore, in addition to these linear dependencies, and as would be expected given the results of Chapter Four, each of these sets of returns also exhibits significant nonlinear serial dependencies of one form or another. The bispectrum test for linearity, which is not very powerful against GARCH effects, is highly significant for all the indices and all but one of the stocks, Chu Wa Wool (stock 1439). However, the McLeod and Li test, which is more sensitive to GARCH effects but can also be used in the detection of bilinearity, is highly significant for all eighteen sets of returns, including that of Chu Wa Wool.

Interestingly, though, these two sets of test results reveal some possible differences in the return generating processes across these eighteen series. Chu Wa Wool, for example, exhibits highly significant nonlinearity as measured by the McLeod and Li test but not as measured by the bispectrum test. The Hang Seng Index and Wan Yu Paper (stock 1908) returns, on the other hand, yield relatively low test scores for the McLeod and Li test but generate very large test statistics for the bispectrum test for linearity. These findings would suggest that conditionally heteroskedastic models, for example, would perform better for the Chu Wa Wool returns than for the Hang Seng or Wan Yu Paper returns.

However, there is a caveat to these results. As with the returns examined in Chapter Five, Hinich and Patterson's windowed test procedure reveals that the dependency structures underlying these index and stock returns may not be stable across time. In order to increase the power of this procedure to detect significant dependencies, a wider window, 125 days versus 54 days, and a higher test threshold, 0.01 versus 0.005, were used for the test procedure in this chapter than were used in the previous chapter. Nonetheless, even with this increased power, and in spite of the highly significant test statistics for the full sample, only a relatively small proportion of individual windows exhibited significant test statistics. For the index returns, an average of 38.22% of the windows exhibited significant nonlinear dependencies in the form of bicorrelation, while an average of only 13.23% of the windows exhibited significant autocorrelation. The results were similar for the individual stocks. For these, an average of 35.95% of the windows displayed significant bicorrelation while only about a quarter of the windows, on average, displayed significant autocorrelation. These results must be kept in mind throughout the following sections, during which stable dependency structures are implicitly assumed.

6.3. Optimal Linear Filtering and Residual Nonlinear Dependencies

The next step in the analysis for this chapter is the modeling of the linear dependencies within these six index return and twelve individual stock return data sets. The goals of this step are to examine the inferences that these linear models yield and to determine the effects, if any, that such linear pre-filtering has on the nonlinearity test results.

In developing these linear models, the most important of the linear dependencies to account for are the serial linear dependencies, i.e., the autocorrelations. For the sake of parsimony, to avoid what one author referred to as "filtering the hell out of the data," the autocorrelations that are modeled will be restricted to the first seven lags for the stock, Taiex, and Nikkei returns and the first six lags for the other sets of index returns. This would include all of the returns for an entire week prior to a given day's return and, at least according to the results from Chapter Five for the daily Taiex returns, would capture most of the significant autocorrelation within these returns. In addition to the autocorrelation terms, because numerous studies have found evidence of day-of-the-week effects within financial time series, dummy variables will also be included in the model to account for and filter out any structural shifts in the level of returns caused by such effects. Thus, the basic dynamic linear regression model that will be fit to the six series of index returns and twelve series of stock returns is:

$$r_t = \phi_0 + \phi_{Mon.} d_{Mon.} + \phi_{Tues.} d_{Tues.} + \phi_{Wed.} d_{Wed.} + \phi_{Fri.} d_{Fri.} (+\phi_{Sat.} d_{Sat.}) + \sum_{i=1}^{6(or\,7)} \phi_{t-i} r_{t-i} + \varepsilon_t ,$$

where $d_{\text{"Day-of-the-Week"}}$ is a dummy variable, with a value of either zero or one, denoting the day of the week on which a given return occurs (the default day, against which the others are compared, is Thursday). The final model that is fitted to each of the series of returns includes all of the day-of-the-week effects shown above but is edited to include only the specific autocorrelation effects that are significant at a level of 0.05 or less.

A summary of the inferences yielded by this model is presented in Table 6.2, while the full results for the model are presented in Table 6.3. Four of the indices, the FT-30, the Nikkei, the Hang Seng, and the Singapore STI, appear to exhibit significant day-of-the-week effects, including a negative Monday effect in all four cases. The DJIA and the Taiex, on the other hand, do not appear to exhibit any such effects, nor do most of the individual Taiwanese stocks. But contrary to the random walk hypothesis, all of the sets of returns, including all of the sets of index returns as well as all of the sets of individual stock returns, exhibit significant autocorrelations. Among these, the autocorrelations of the Taiex returns and the individual stock returns tend to have the greatest magnitudes, probably as a consequence of the price limits, and the returns of stock 2101 appear to be especially recalcitrant, requiring all of the first five lags to be fit in order to produce a series that is "whitened" out to lag six. Nonetheless, all of the series save for the Hang Seng returns exhibit significant autocorrelation at multiple lags.

Using these models to filter out the autocorrelation and day-of-the-week effects from these eighteen sets of returns, however, appears to have little effect on the descriptive statistics and serial dependency test statistics for these data series. The skewness and kurtosis statistics remain little changed, and the concomitant skewness-kurtosis tests for normality continue to reject normality for all of the indices as well as most of the individual stocks. Moreover, the bispectrum test for Gaussianity continues to strongly reject normality for all of the sets of residuals, including those for which the skewness-kurtosis test failed to reject normality.

Furthermore, the bispectrum test for linearity is highly significant, once again, for all of the index residuals and all but the Chu Wa Wool individual stock return residuals. Furthermore, while the linear models are successful, as measured by the Box-Pierce Q-statistics, in filtering out the autocorrelation from these sets of returns, the McLeod and Li test statistics reveal that the squared residuals, from all eighteen sets of returns, still exhibit highly significant levels of autocorrelation. Thus, as indicated by these two sets of results, the nonlinear dependencies within the data seem to be little affected by the removal of the linear dependencies.

The converse is not necessarily true, however, and ignoring the evident sources of model misspecification found above could have a dramatic impact on both the inferences that are made regarding the linear dependencies and estimated magnitudes of the effects of these dependencies. The lack of normality, by itself, can be very serious in terms of its effect on estimation results and, in the very least, calls into question the validity of the t-statistics that were used to determine which model parameters were significant. The evident nonlinearity, furthermore, can affect the results in a variety of ways. Significant bispectrum test results for nonlinearity are more likely to be indicative of mean nonlinearity, while the significant McLeod and Li tests could be driven by a variety of types of nonlinearity, including both bilinearity (a type of mean nonlinearity) and dynamic heteroskedasticity. The former possibility can result in an "omitted variables bias" affecting all of the parameters included in the model, while the latter possibility would suggest that some variation of weighted least squares rather than OLS is necessary to obtain parameter estimates with good statistical properties.

Assuming that the significant McLeod and Li test statistics are being driven by dynamic heteroskedasticity in the form of GARCH effects, then one possible "variation of weighted least squares" estimation that would be suggested is the fitting of a model for which the sequence of error terms ε_t^2 is subject to a Normal GARCH(p,q) process:

$$\varepsilon_t \sim N(0, h_t)$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

In order to determine the orders p and q for such a process, Bollerslev (1988) showed that this GARCH variance formulation can be rewritten in the form of a linear ARMA model for ε_t^2:

$$\varepsilon_t^2 = \omega + [\alpha(L) + \beta(L)]\varepsilon_t^2 - \beta(L)(\varepsilon_t^2 - h_t) + (\varepsilon_t^2 - h_t),$$

for which $(\varepsilon_t^2 - h_t)$ would be a white noise process. As this analogy suggests, the autocorrelation and partial autocorrelation functions for ε_t^2 can then be used to determine the orders for p and q. In most cases, however, the orders $p=q=1$ are found to suffice.

The autocorrelation and partial autocorrelation functions for the squared residual series for our index and stock data are shown in Figures 6.2. For most of these series, both the ACF and the PACF taper off only very slowly, indicating positive, non-zero values for both p and q. In many of these cases, however, the basic GARCH(1,1) specification, with $p=q=1$, would appear to suffice. In a few cases, though, the PACF appears to cut off quickly enough so that a strict ARCH model, with p equal to zero, would be adequate to describe the data. Most notably, for the FT-30 residuals the PACF cuts off after the first lag while the ACF tapers down exponentially, indicating that an ARCH(1) model may be appropriate. For the Singapore residuals, on the other hand, while the ACF clearly tapers down exponentially, the PACF could be described either as cutting off after the second lag, suggesting an ARCH(2) specification, or as tapering down sinusoidally after the first lag, in which case a GARCH(1,1) model would appear to be more appropriate.

However, returning to the windowed test results, the plots for which are presented in Figures 6.3, nonstationarity still appears to be a potential problem. As would be expected (or at least hoped), the number of windows exhibiting significant autocorrelation is lower for the linear model residuals than for the raw returns, leaving a relatively low average of 8.00% of the windows exhibiting significant autocorrelation for the index residuals and 10.71% among the stock residuals. An examination of the window plots reveals, however, that the linear models appear to be fitting the linear dependencies within the strongest windows from the raw returns. Thus, fitting such models entails as much of a shifting of autocorrelation from stronger windows to weaker windows as of a general removal of autocorrelation from the data. Fitting such models has little effect of the bicorrelation structure, however, and the proportion and location of significant bicorrelation windows remain fairly constant, with only about a third of the windows exhibiting significant bicorrelation.

Finally, because of the importance of the squared residual ACF and PACF in identifying the orders for a GARCH model specification, the stability of the autocorrelation structure for these squared residuals was also examined. And as with the autocorrelations and bicorrelations for the original, non-squared data, the squared residuals for each of the stocks and indices appear to exhibit wildly varying levels of autocorrelation over time (see the bottom row of plots for Figures 6.3). And despite the typically extremely high values of the $Q_{xx}(6)$ statistics for the full samples, only a relatively small minority of windows exhibit autocorrelation levels among the squared residuals that are significant at even a 0.01 level. For the indices, the average percentage of significant windows is 23.10%, or less than one-in-four, while the average percentage for the individual stocks is only slightly higher, at 28.16%. Furthermore, an examination of the plots of squared residual autocorrelation levels across windows reveals that these autocorrelation levels vary dramatically over time. Consequently, there appears to be a substantial amount of variability underlying the ACF's and PACF's examined above in regard to determining the optimal GARCH specification. Even under ideal conditions, the ACF and PACF can indicate multiple possible model specifications. The current results regarding the apparent transience of these functions only serve to multiply this uncertainty, casting doubts upon the appropriateness of any specific GARCH specification obtained from an examination of these functions.

6.4. Linear Filtering and Changes in Price Limit Regimes

One of the key findings of the previous chapter was of the relationship between changes in the level of autocorrelation within Taiwanese stock returns and changes in the price limit regimes imposed on the Taiwan Stock Exchange. The previous section ignored this relationship, so before concluding this chapter, two brief attempts will be made to remove the effects of the price limits from the model residuals before performing the various tests for nonlinearity and model misspecification on them.

The first approach entails trying to incorporate the effects of the price limits directly into the linear model that is fitted to the Taiex returns and those of the stocks in the subsample that have a long enough sample period to have been affected by the changes in the price limits. The second approach involves trying to filter the effects of the price limits out of the returns prior to fitting the linear model to the data. In the first case, the original series of returns is used, but an adjustment is made to the model. For the second case, on the other hand, the original model is used, but an adjustment is made to the returns to which the model is fit.

Excess Autocorrelation Approach

As was found in the previous chapter, the level of first-order autocorrelation within the Taiex returns changes across the different price-limit regimes, with the highest levels of first-order autocorrelation occurring during the period for which the price limits were their strictest, at 3%. As the price limits were subsequently relaxed, the level of first-order autocorrelation fell. So, one way to attempt to control for the effects of the price limits entails trying to directly model these changes in autocorrelation that are driven by the price-limit changes. The general model used to capture these effects is as follows:

$$r_t = \phi_0 + \phi_M d_M + \phi_T d_T + \phi_W d_W + \phi_F d_F + \phi_S d_S + \sum_{i=2}^{4} \phi_{PLR(i)} d_{PLR(i)} r_{t-1} + \sum_{i=1}^{7} \phi_{t-i} r_{t-i} + \varepsilon_t ,$$

where the variables in the first summation are designed to capture the effects on first-order autocorrelation of the final three price-limit regimes during the sample period.

Although the relevant histograms are not shown, this model does seem to be able mitigate some of the distribution truncation effects of the price limits. Beyond that, however, as the results shown in Table 6.4 indicate, this "excess-autocorrelation" model seems to have little systematic effect even on the test results it is designed to influence the most directly, namely the windowed test results for autocorrelation. So, perhaps not surprisingly, the use of this model also does not seem to have much of an effect on any of the remaining test statistics, and nonlinearity remains a key problem in terms of model specification. But the results of this model provide further evidence that the extant nonlinearity is not an artifact of any of the linear dependencies within these sets of returns or of any of the price limits to which they are subject.

Linear Pre-Filtering Approach

The second approach to controlling for the effects of the price limits, rather than adjusting the model to account for effects of the price limits, attempts instead to pre-filter the original returns to create a new data series that serves as a proxy for what the original series might have looked like in the absence of the price limits. In order to do this, the time interval over which the returns were calculated for each day was chosen to be long enough to span any truncation and induced autocorrelation effects caused by the daily price limits. In other words, rather than calculating the one-day return for each day, a multiple day return was calculated as of each daily price observation. There did not seem to be much of a truncation effect within the weekly Taiex returns examined in Chapter Four, so one-week, or six-day, returns probably cover a sufficiently long period to be free of the direct impact of the price limits.

Thus, the initial step in the linear pre-filtering process was, for each daily observation, to calculate the six-day returns for the six-day period up to and including that given day. In other words, the following sequence of returns was calculated:

$$r_t^6 = \ln p_t - \ln p_{t-6} = \sum_{i=1}^{6} r_{t-i+1},$$
$$t = 7,8,\ldots,T$$

But while this preliminary series would escape the truncation effects of the price limits, it faces a new problem. Because each observation within this series entails a substantial amount of data, namely five days' worth of single daily returns, that is shared with the preceding and succeeding observations, this series is in effect an integrated series; more specifically, it follows an ARIMA(1,1,(6)) process. Thus, the ARIMA(1,1,(6)) elements must next be filtered out before the final, proxy series of returns could be obtained.

The I(1) elements is removed by taking the first differences within the series, leaving the following:

$$\begin{aligned} r_t^6 - r_{t-1}^6 &= (\ln p_t - \ln p_{t-6}) - (\ln p_{t-1} - \ln p_{t-7}) \\ &= (\ln p_t - \ln p_{t-1}) - (\ln p_{t-6} - \ln p_{t-7}) \\ &= r_t - r_{t-6} \end{aligned}$$

Thus, the first-differenced series is simply the difference between a given day's daily return and the daily return for the sixth previous day. To remove the ARMA(1,(6)) elements, an ARMA(1,(6)) model such as follows,

$$(r_t - r_{t-6}) - \phi_1(r_{t-1} - r_{t-7}) = \theta_0 - \theta_1\varepsilon_{t-1} + \varepsilon_t,$$

is estimated and fitted to the differenced series, and it is the series of residuals from this ARMA model, $\hat{\varepsilon}_t = r_t^{\Pr oxy}$, that finally serves as the proxy for what the original set of returns may have looked like in the absence of the price limits. The original model from Section 6.3,

$$r_t = \phi_0 + \phi_{Mon.}d_{Mon.} + \phi_{Tues.}d_{Tues.} + \phi_{Wed.}d_{Wed.} + \phi_{Fri.}d_{Fri.} + \phi_{Sat.}d_{Sat.} + \sum_{i=1}^{7}\phi_{t-i}r_{t-i} + \varepsilon_t,$$

is then fit to this proxy series of returns, r_t^{Proxy}, to obtain the final results, presented in Table 6.5.

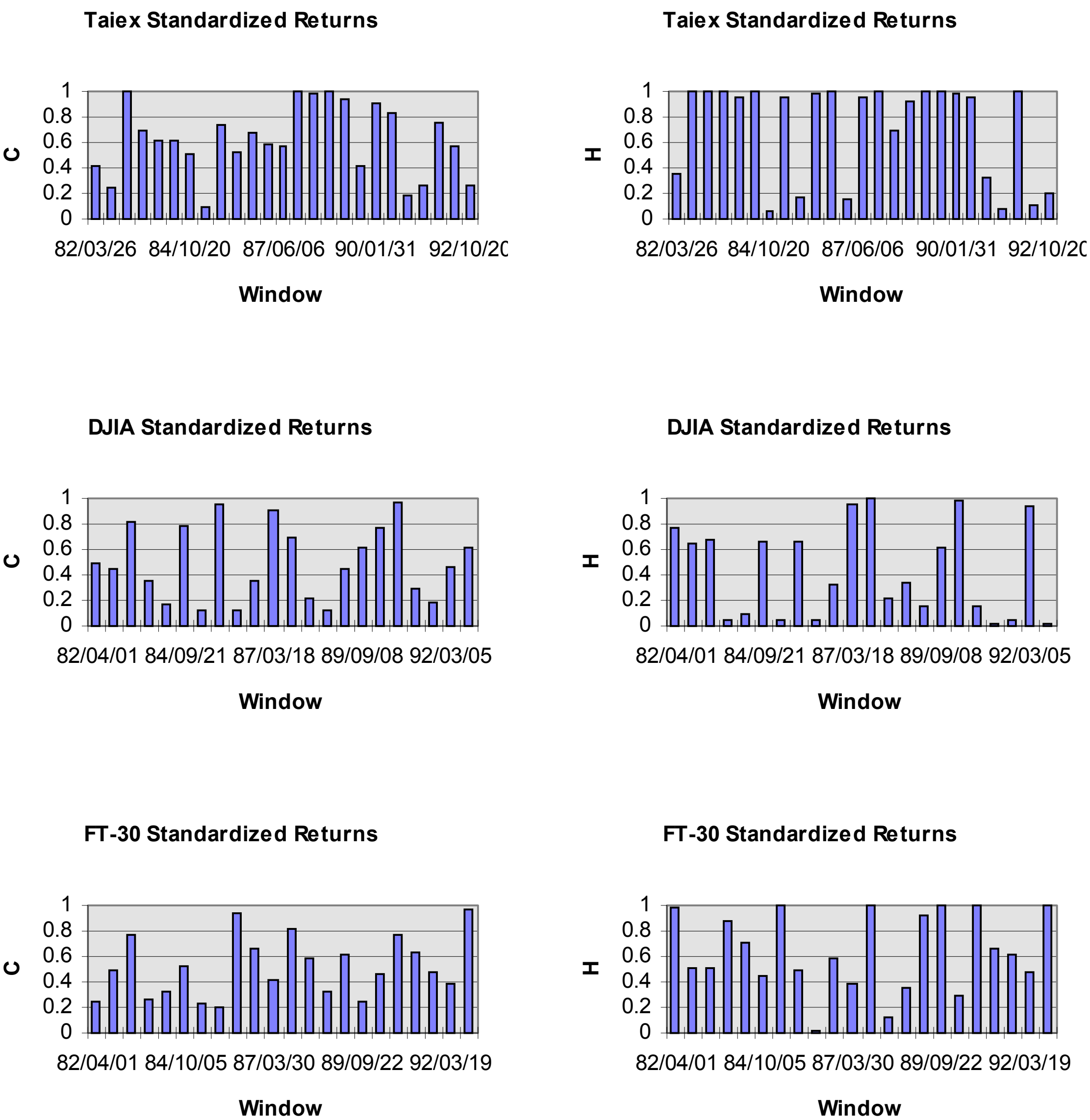
Once again, as with the excess autocorrelation approach, this approach generates a time series for which the truncation effects of the price limits appear to have been largely removed. But, beyond that, and beyond a not unexpected shifting of the specific lags of returns for which autocorrelation appears to be significant, this pre-filtering approach to controlling for the effects of the price limits seems to have little systematic effect on the model and test results.

6.5. Conclusions

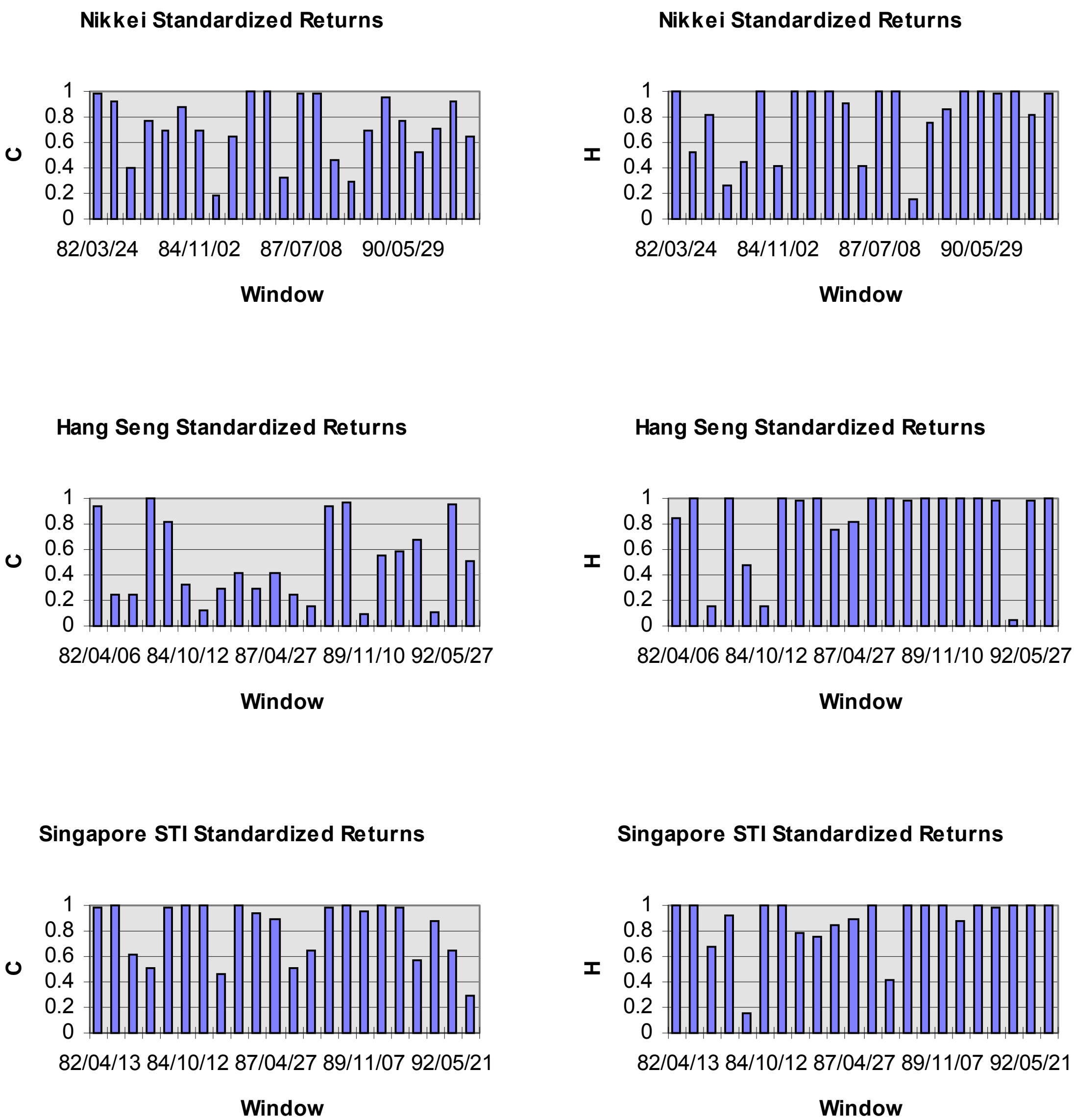
The returns for six stock indices and twelve Taiwanese stocks were examined in this chapter. All of these sets of returns appear to exhibit significant autocorrelation, and many of the indices appear to exhibit significant day-of-the-week effects, including a negative Monday effect. However, controlling for these linear dependencies appears to have no effect of the nonlinearity and nonstationarity results that are found for the raw returns.

Furthermore, these test results indicate that, in addition to being non-normally distributed, the residuals from these models also exhibit highly significant levels of nonlinearity, similar to those of the original returns, as well as a substantial amount of time-variability among both the linear and nonlinear serial dependencies. Such results clearly indicate that the linear models fit are misspecified, so that any inferences drawn from them are questionable. The results of the McLeod and Li tests suggest that GARCH-type models might provide a better specification, and the ACF's and PACF's of the squared residuals from the fitted linear models suggest possible specifications for the orders for such models. Unfortunately, windowed autocorrelation tests on these squared residuals reveal that their parameterizations are also subject to substantial levels of time-variability. This finding introduces greater uncertainty into the process; not only into the specific interpretations of the ACF's and PACF's and the application of this information, but also into the search for well-specified models in general.

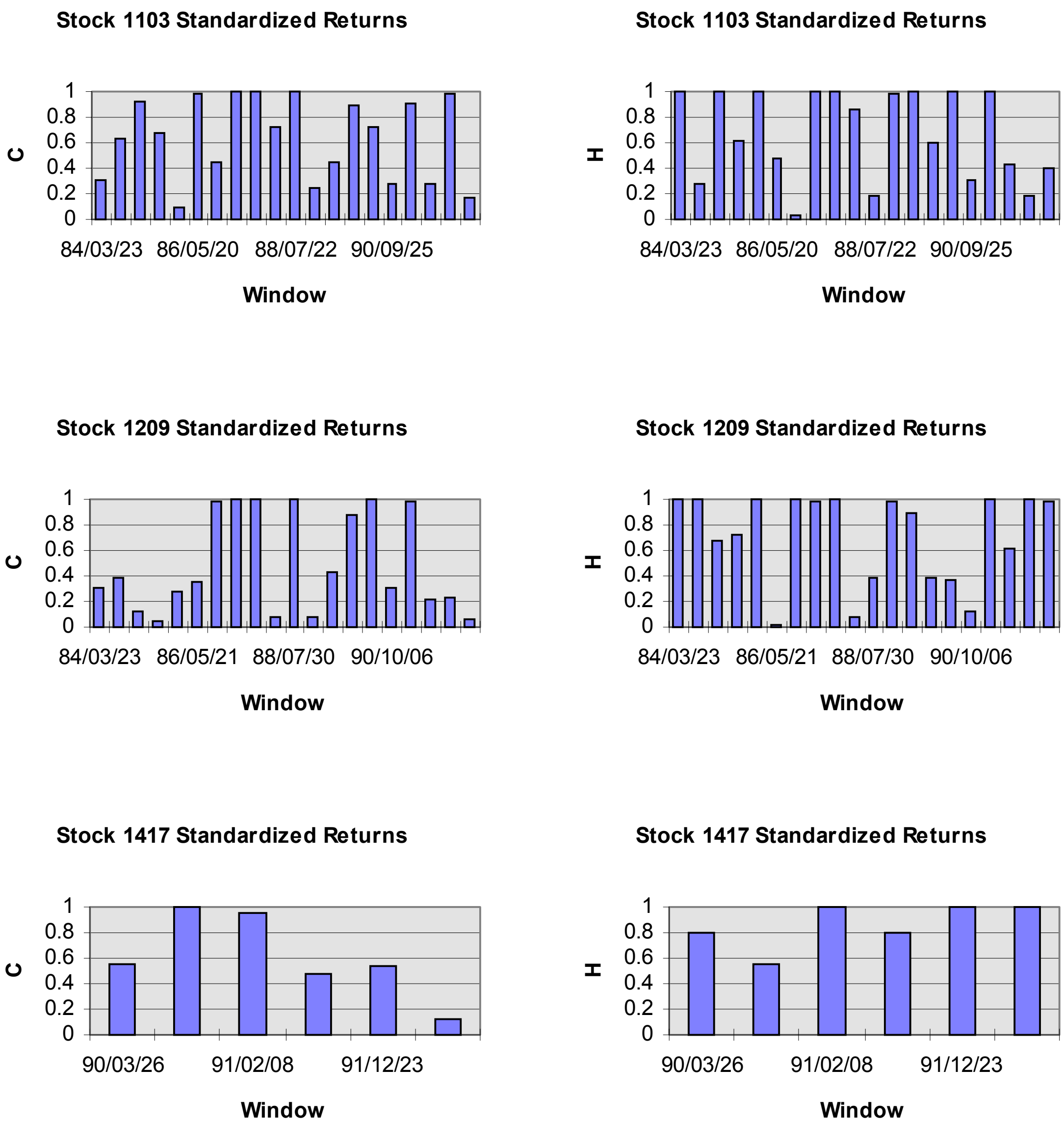
Finally, efforts were made to control for the effects of the price limits on the return dynamics for Taiwanese returns series . While such efforts did appear to ameliorate some of the distributional truncation effects of the price limits, they did not seem to have any systematic influence on any of the test results or their interpretations.



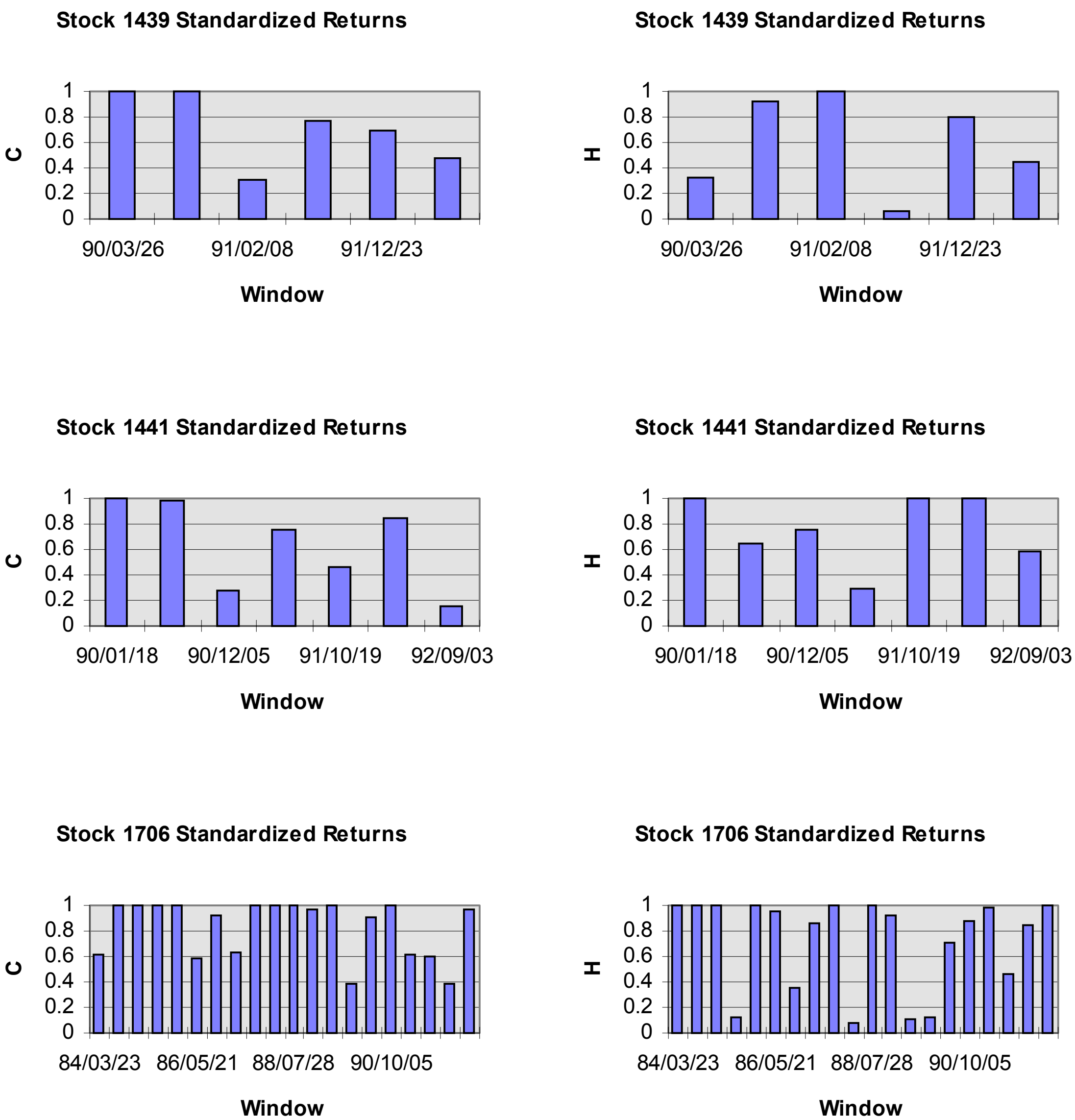
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns



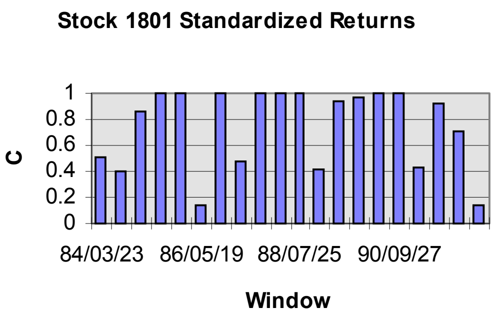
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns (Cont.)

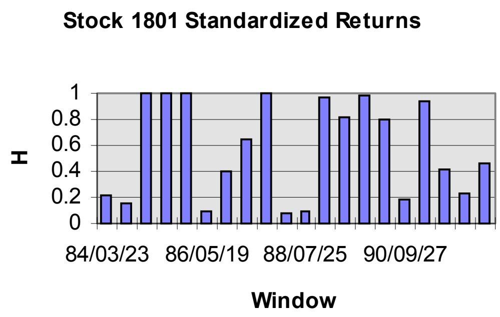


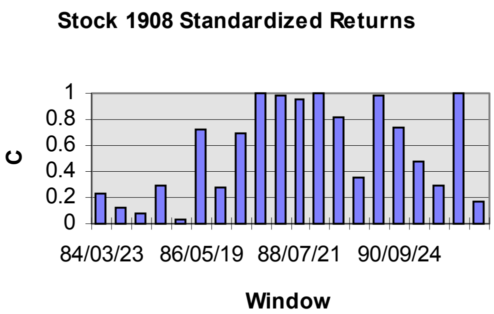
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns (Cont.)

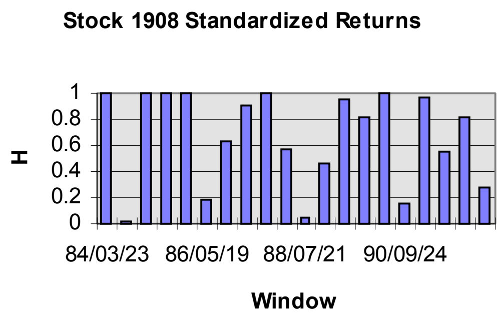


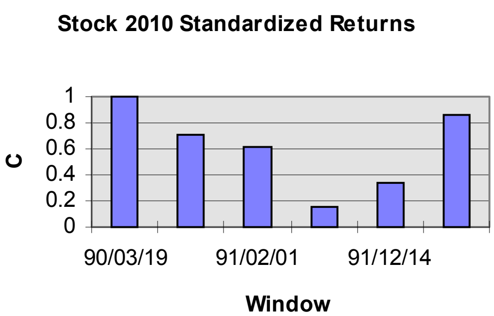
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns (Cont.)

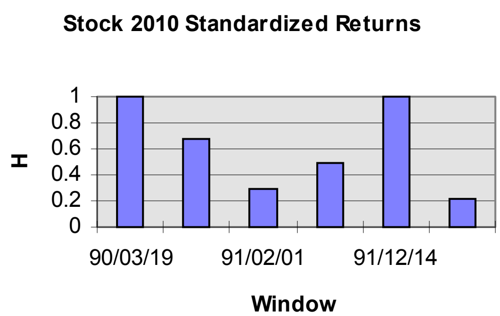




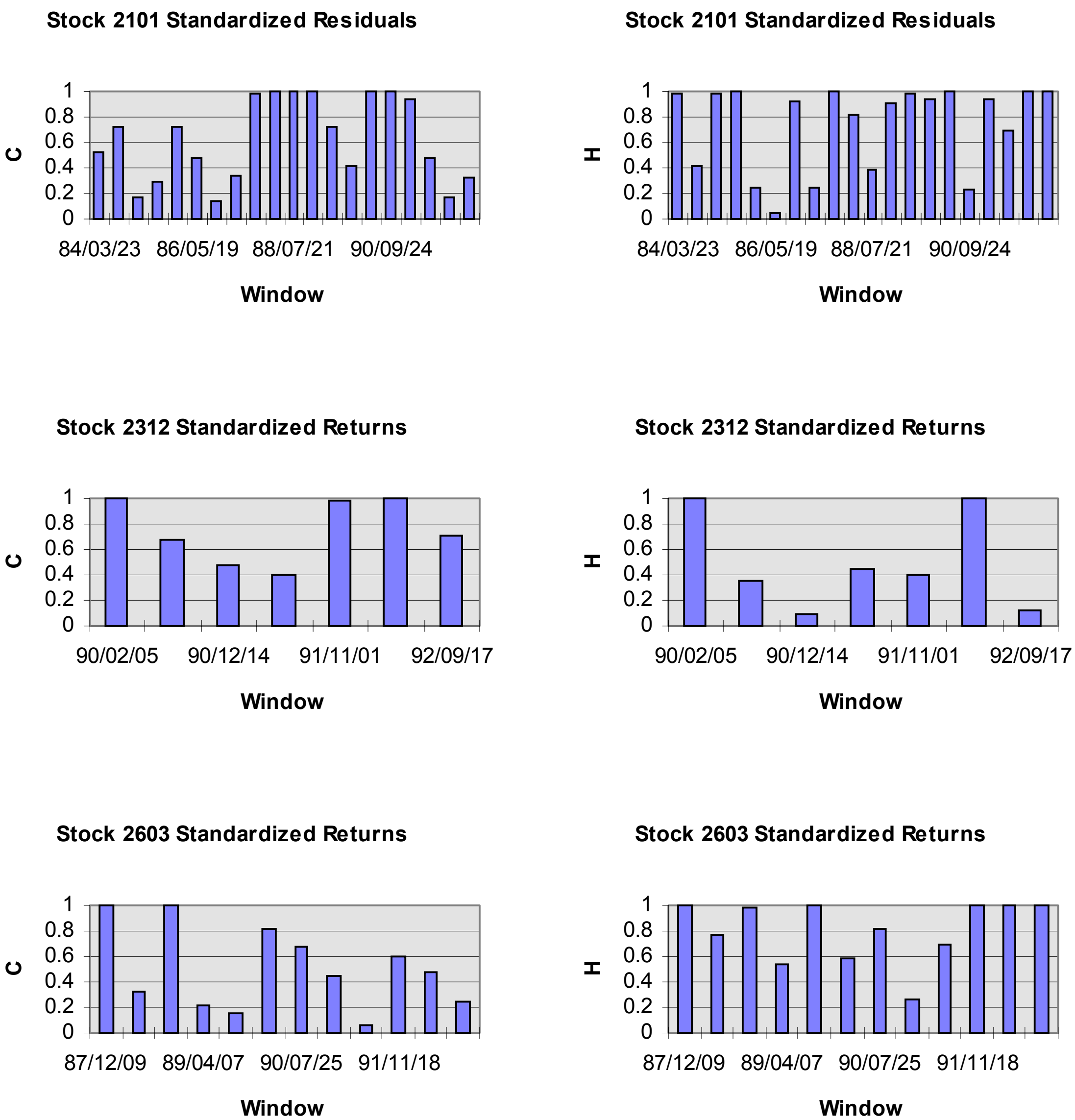




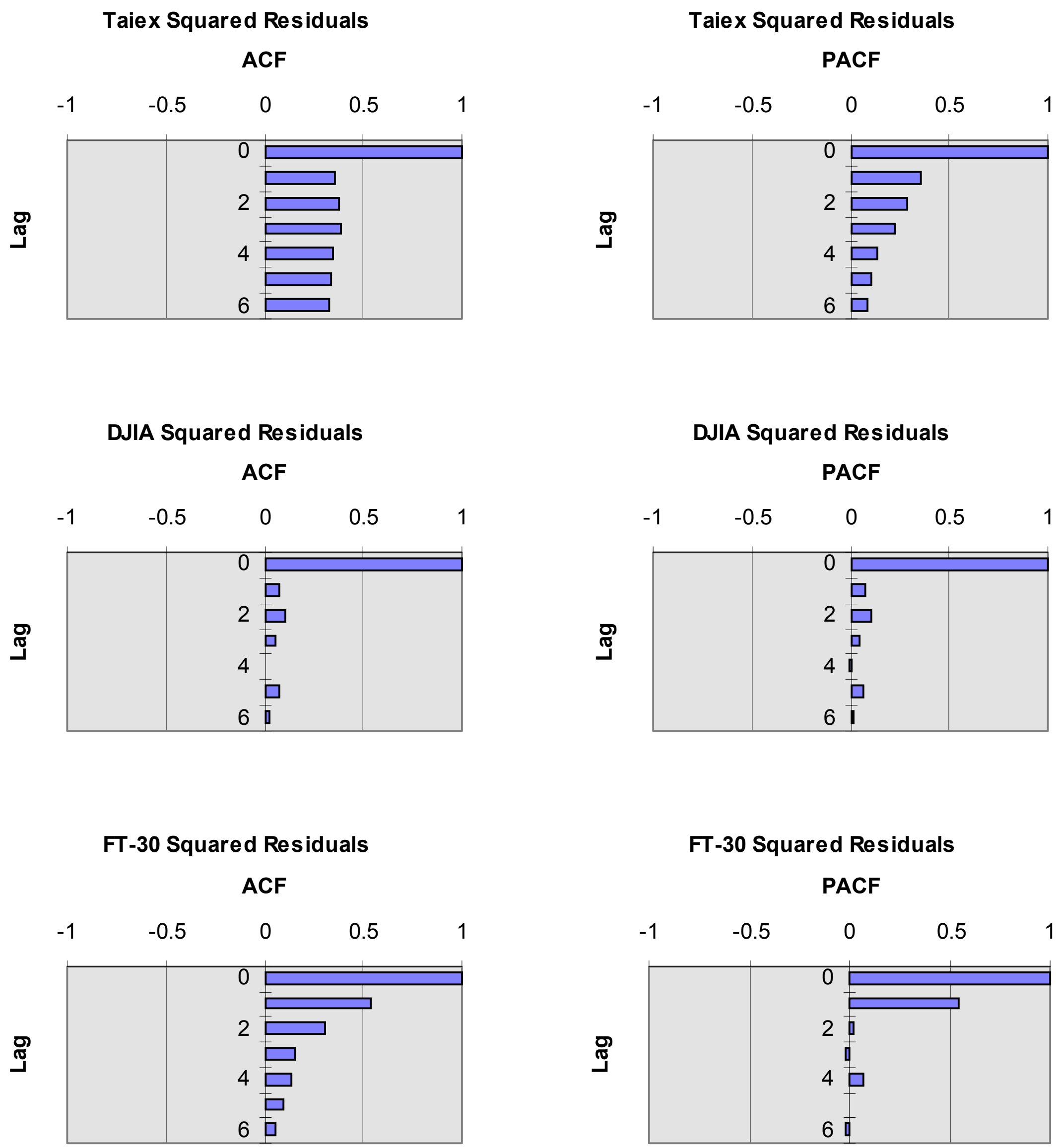




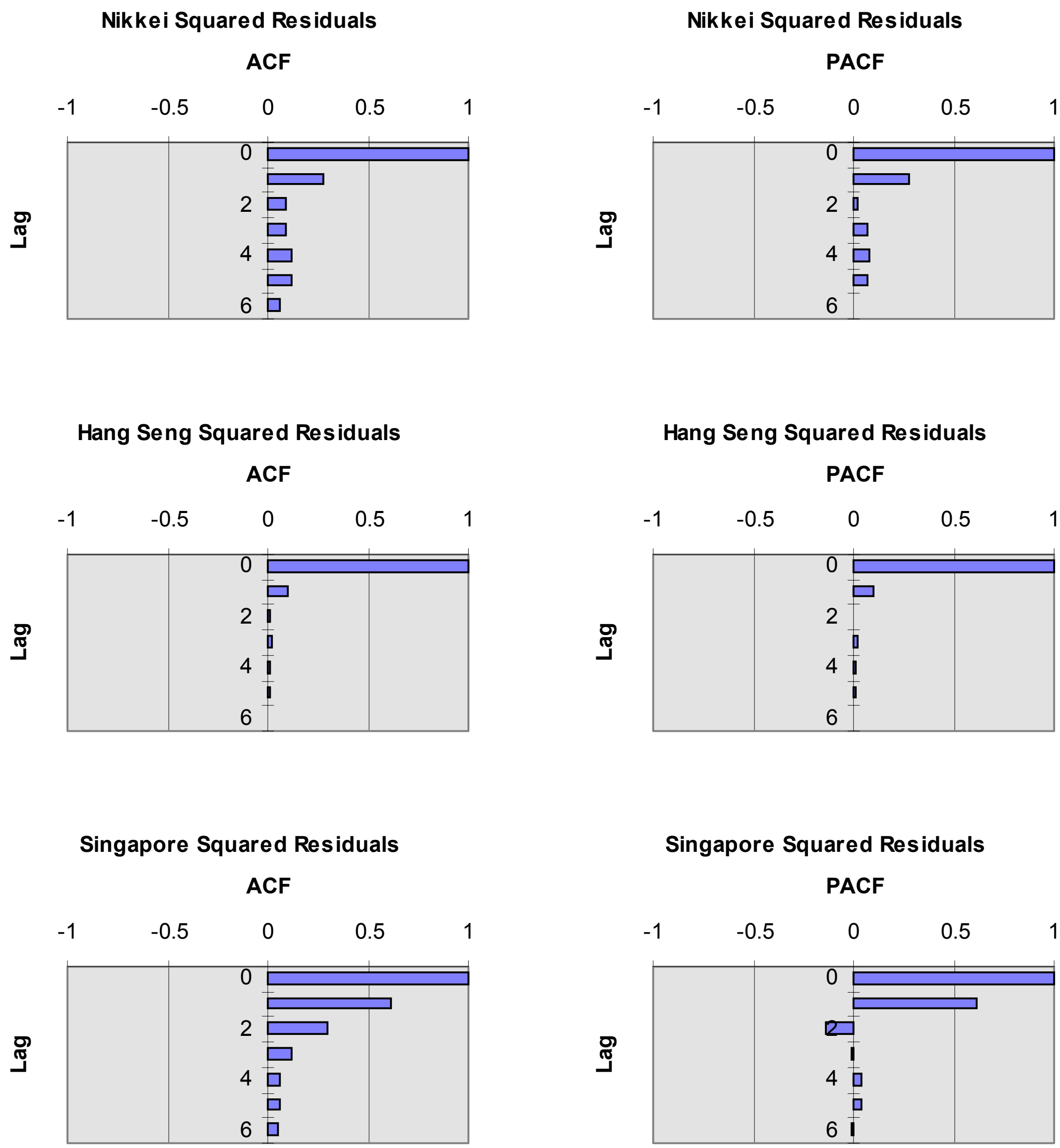
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns (Cont.)



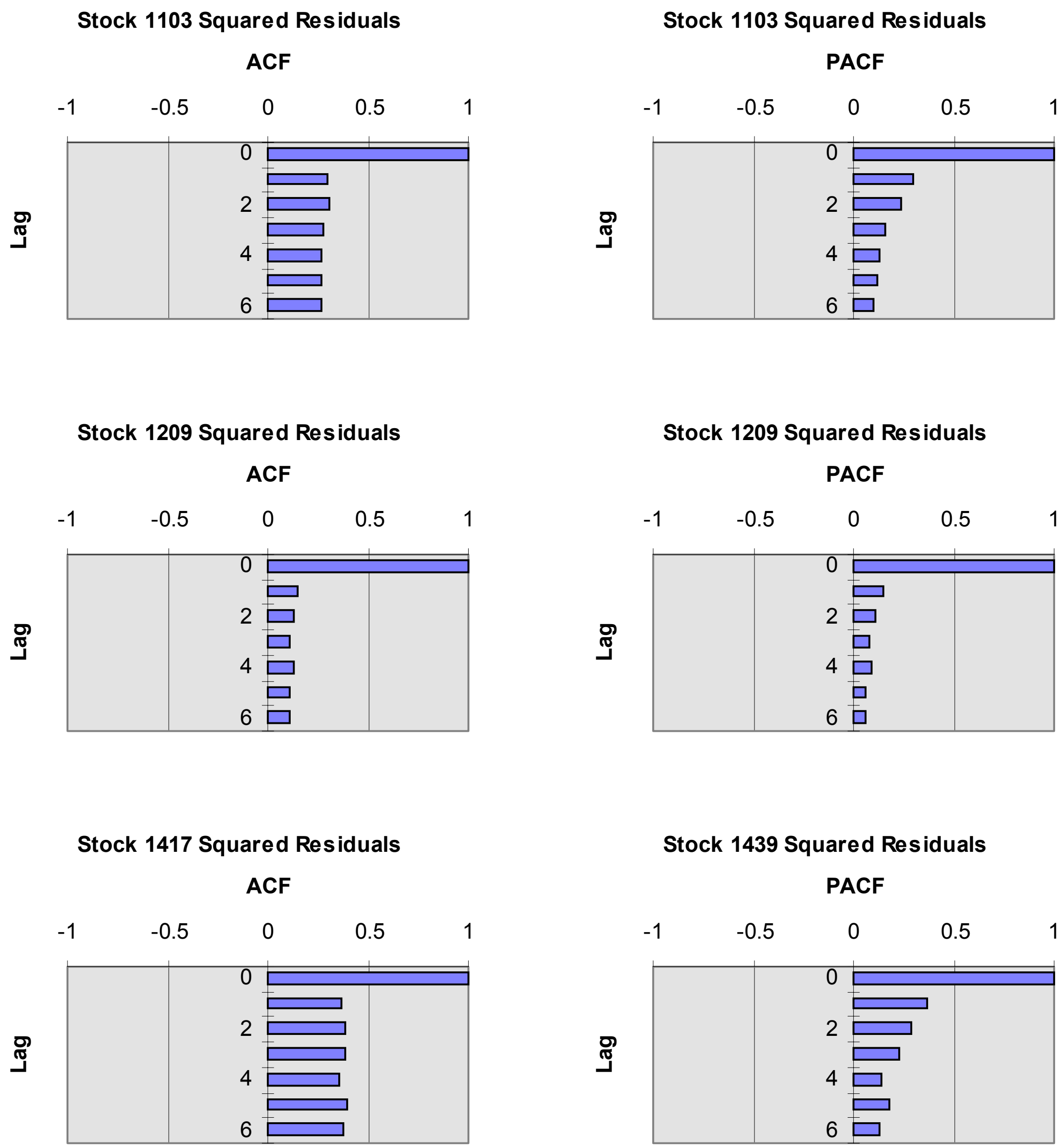
Figures 6.1
Windowed Test Result Significance Levels for Standardized Returns (Cont.)



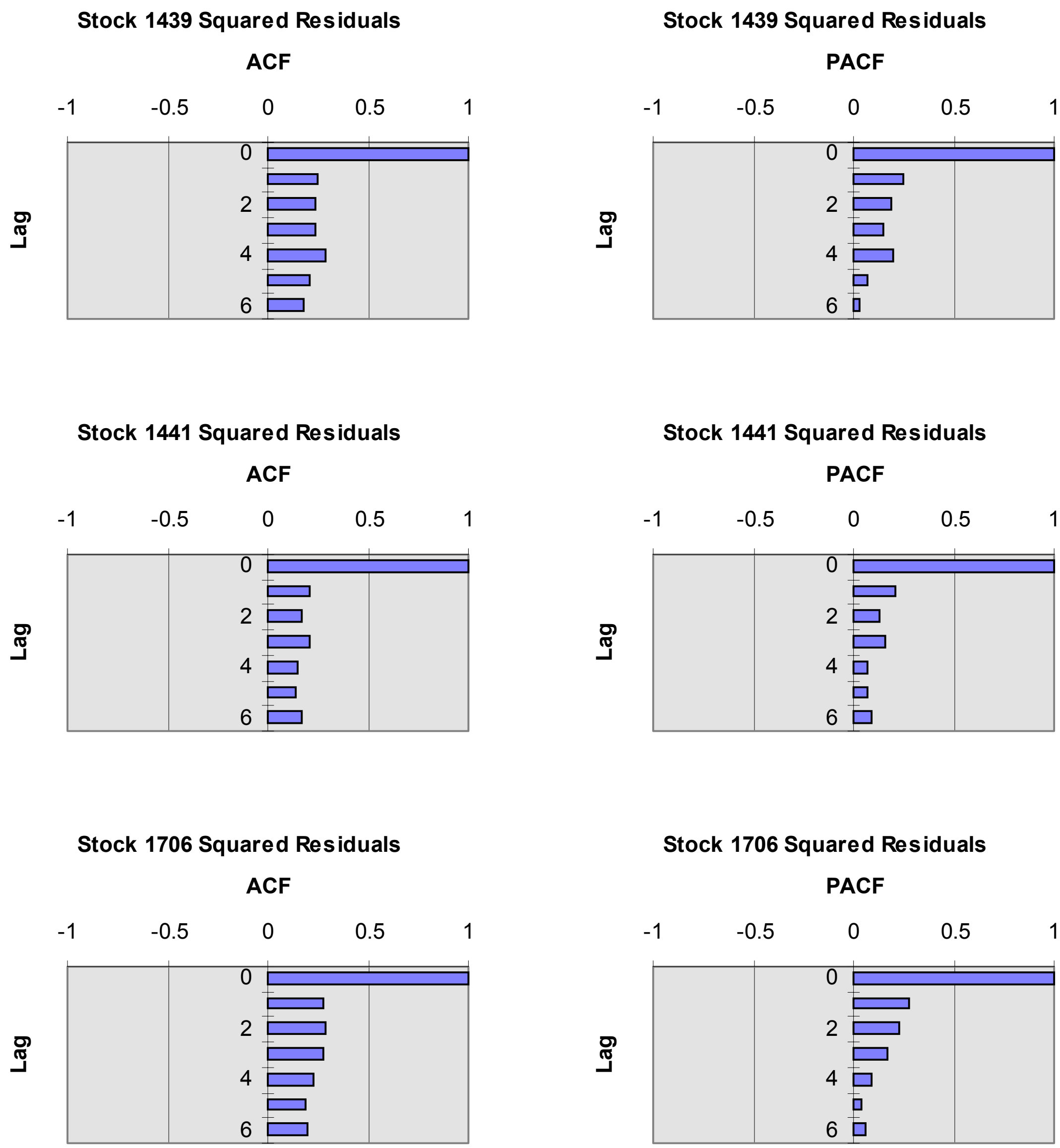
Figures 6.2
Squared Residual ACF's and PACF's



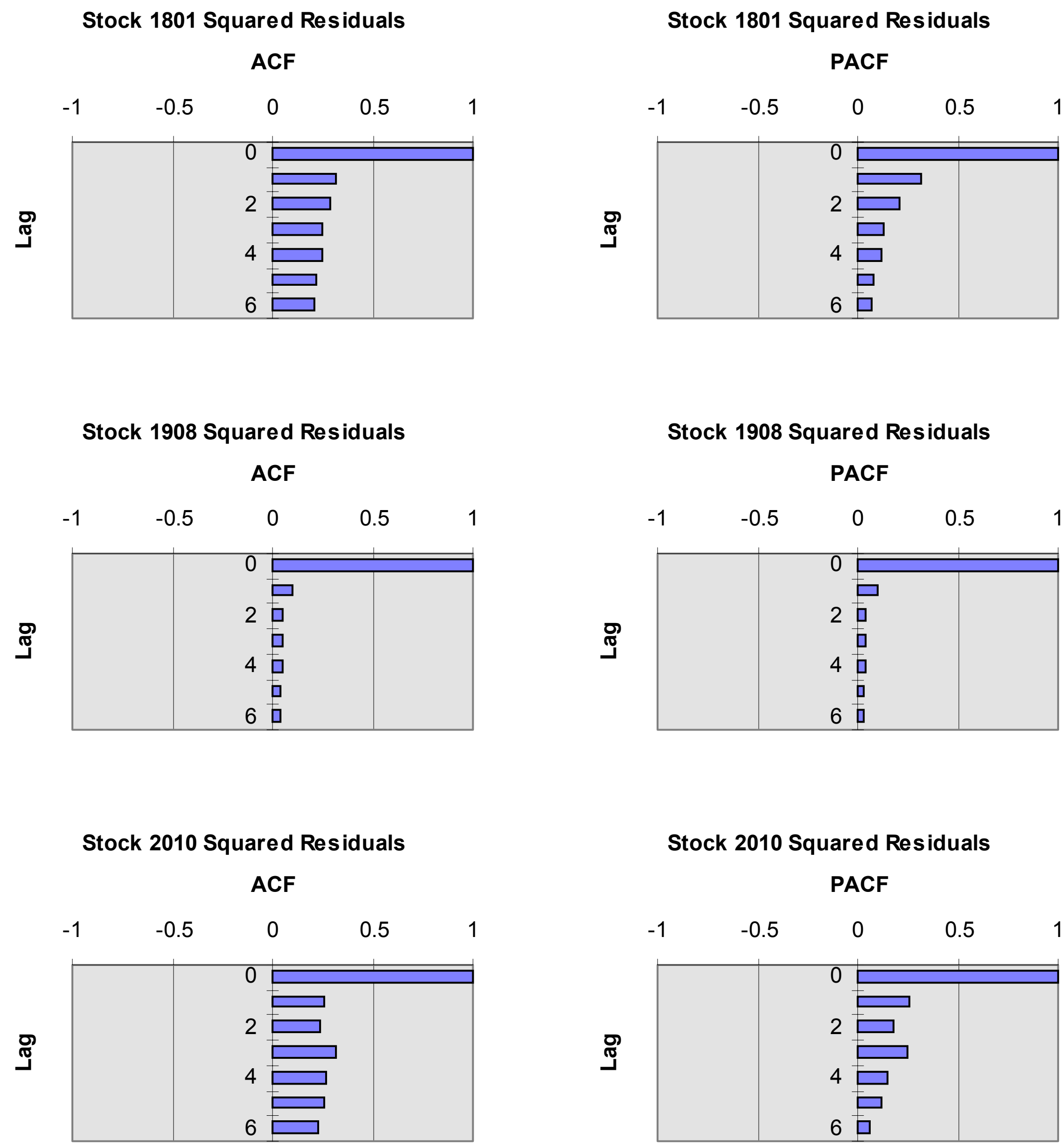
Figures 6.2
Squared Residual ACF's and PACF's (Cont.)



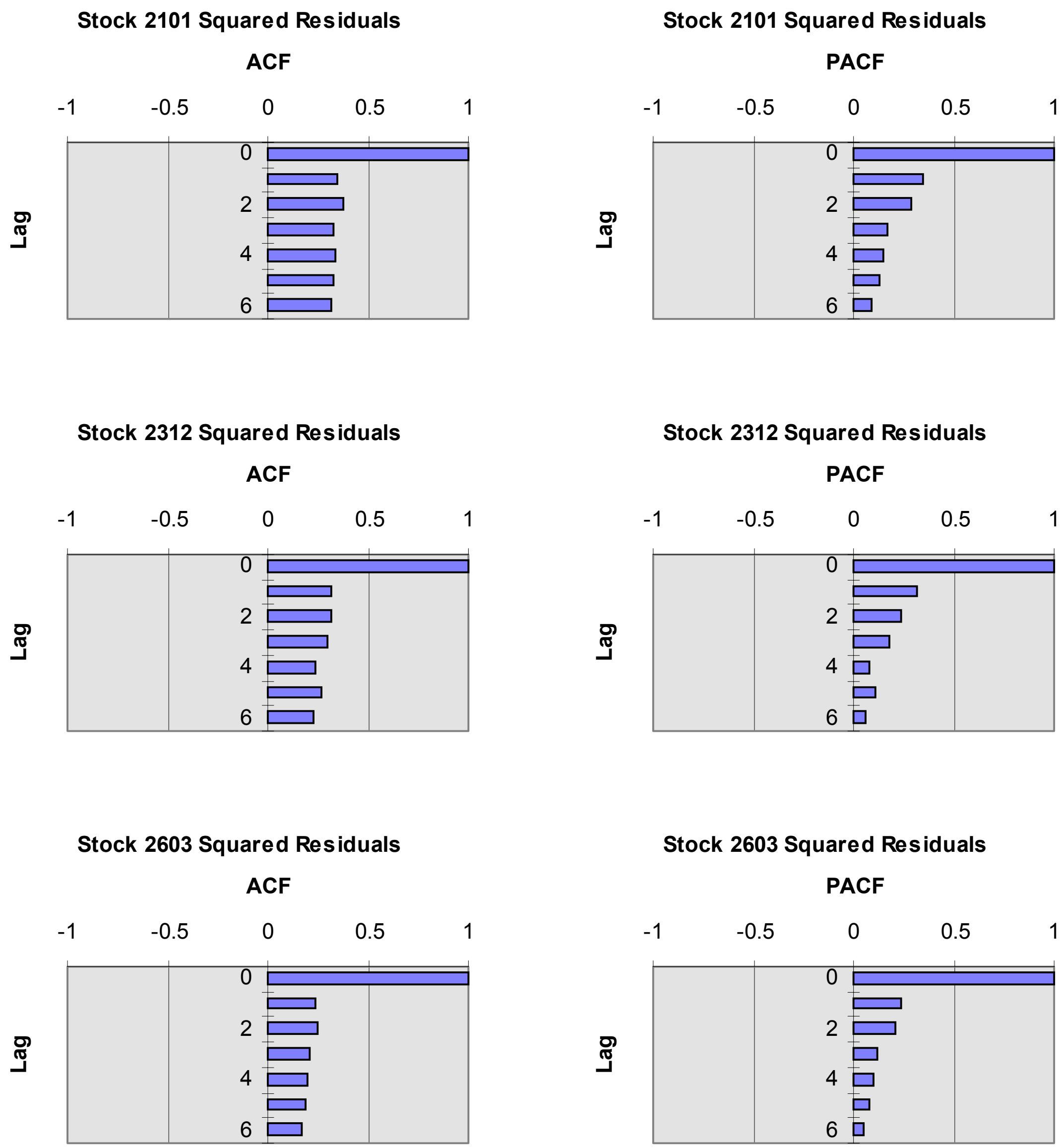
Figures 6.2
Squared Residual ACF's and PACF's (Cont.)



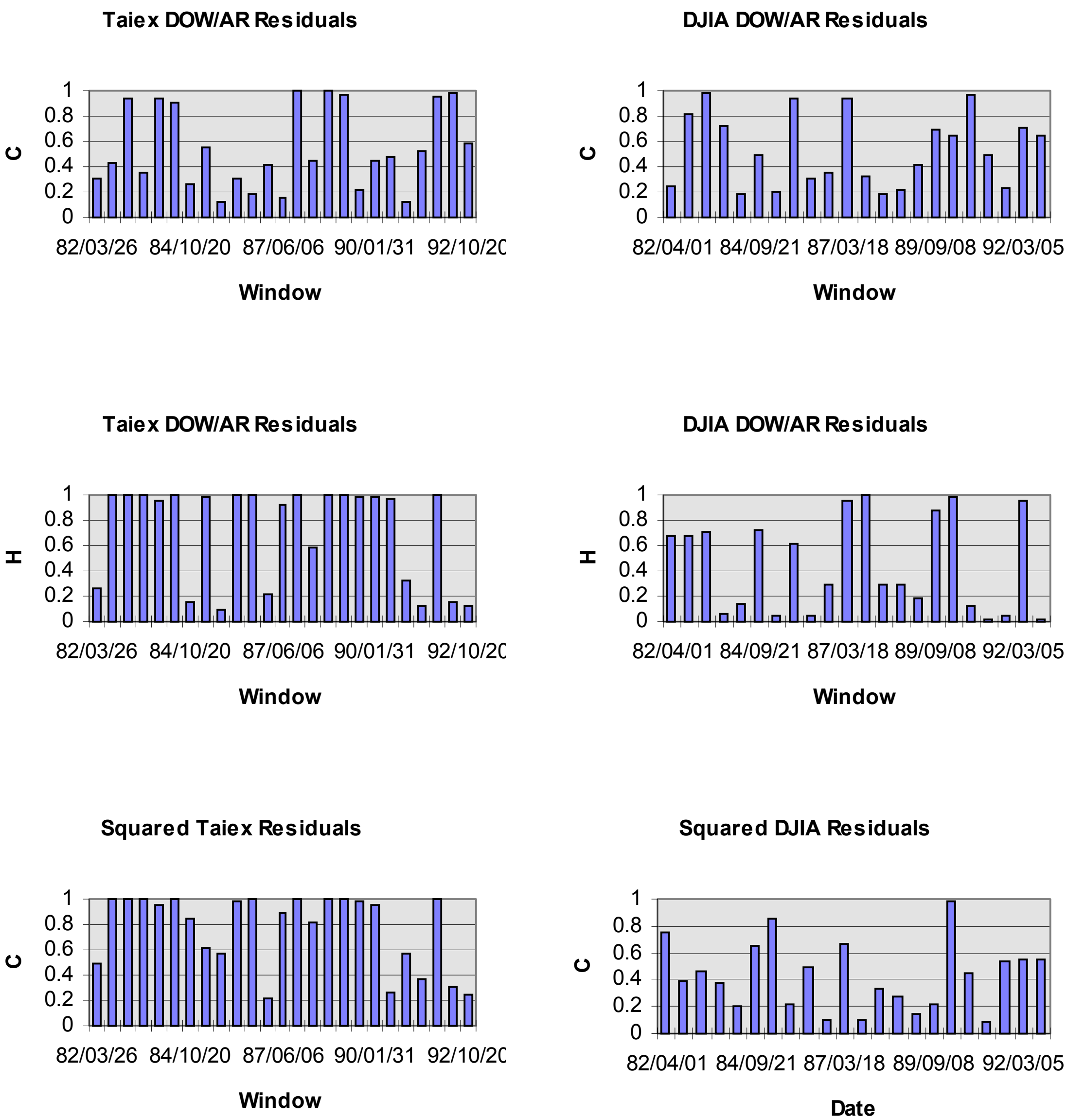
Figures 6.2
Squared Residual ACF's and PACF's (Cont.)



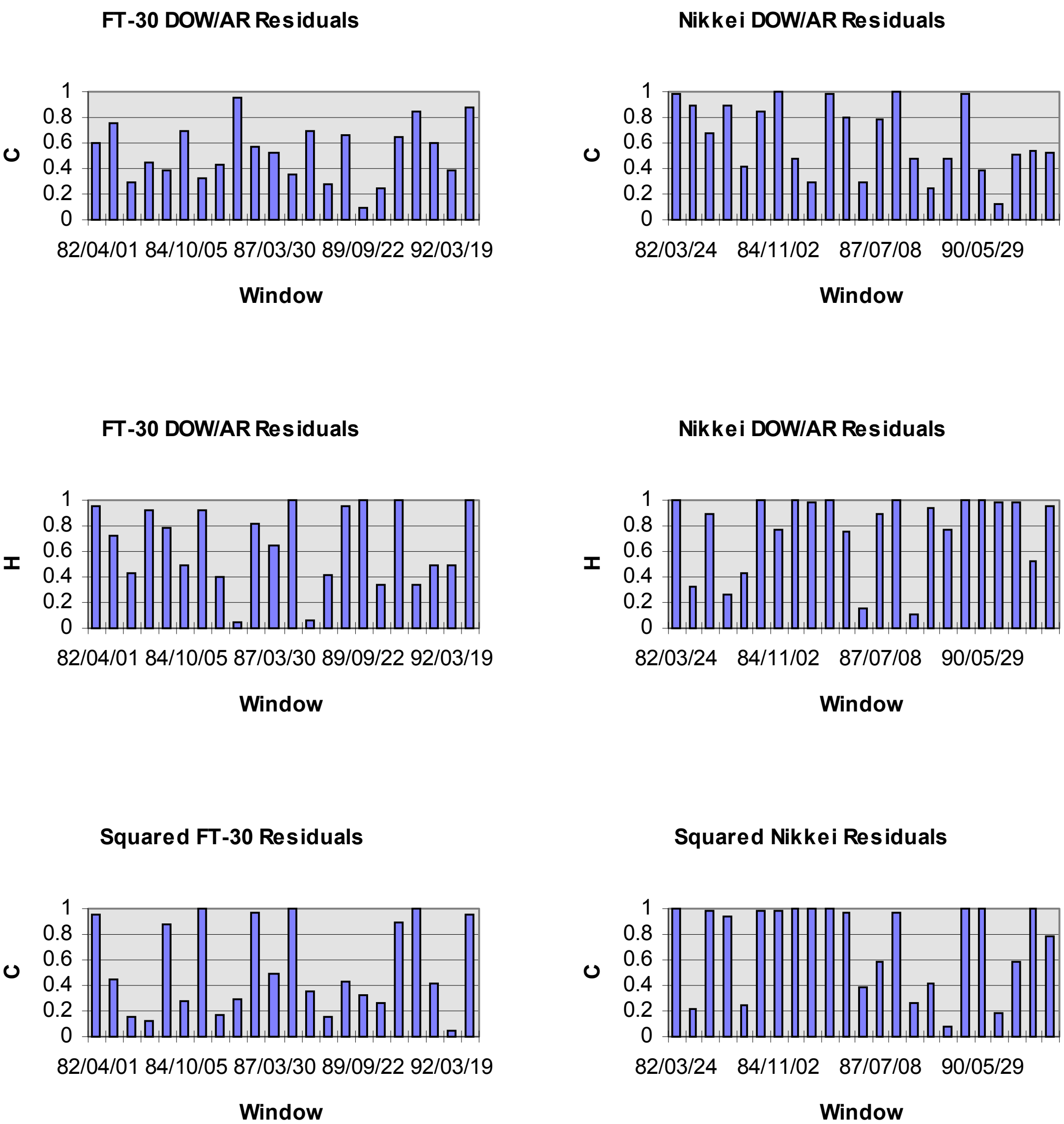
Figures 6.2
Squared Residual ACF's and PACF's (Cont.)



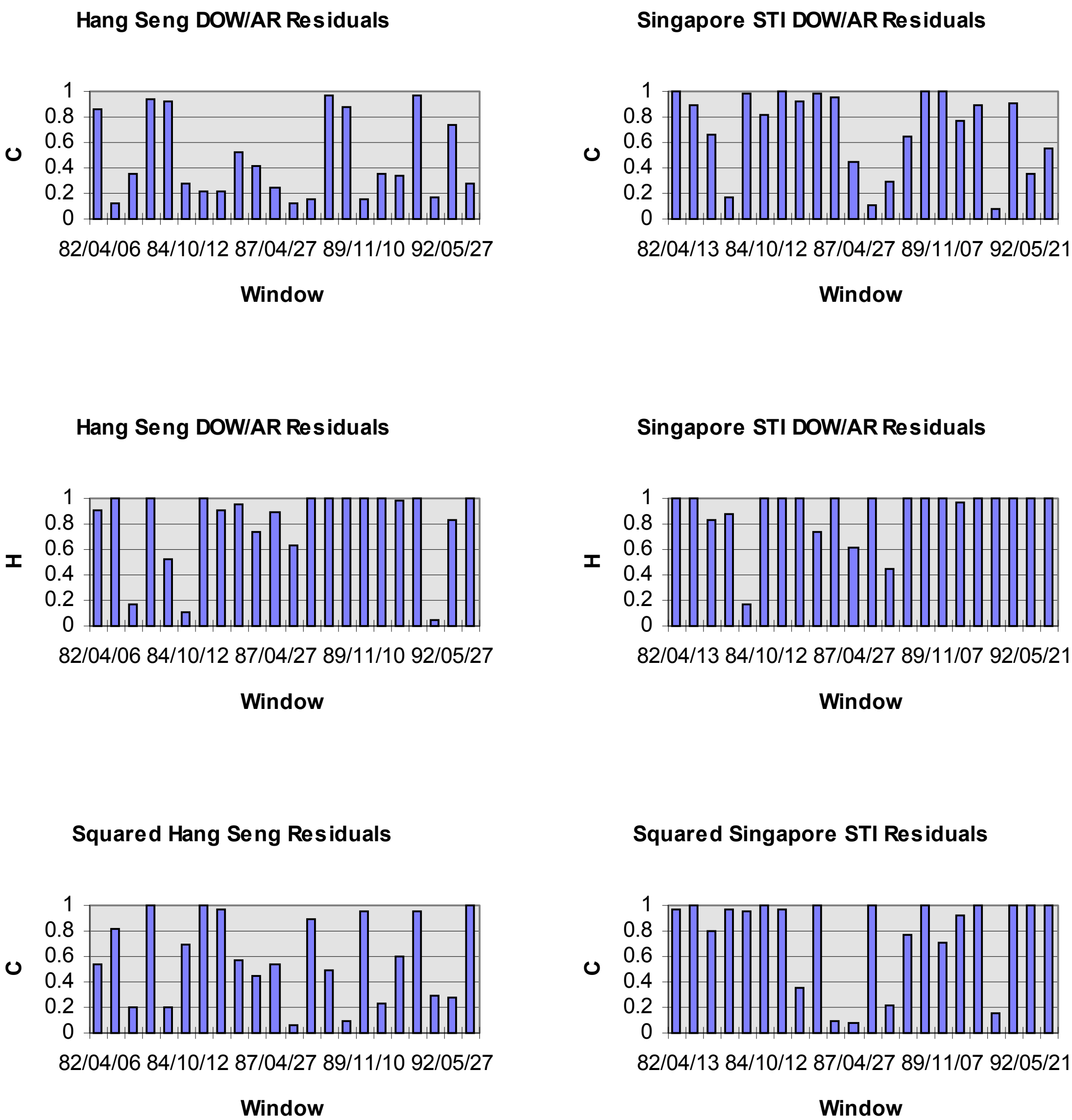
Figures 6.2
Squared Residual ACF's and PACF's (Cont.)



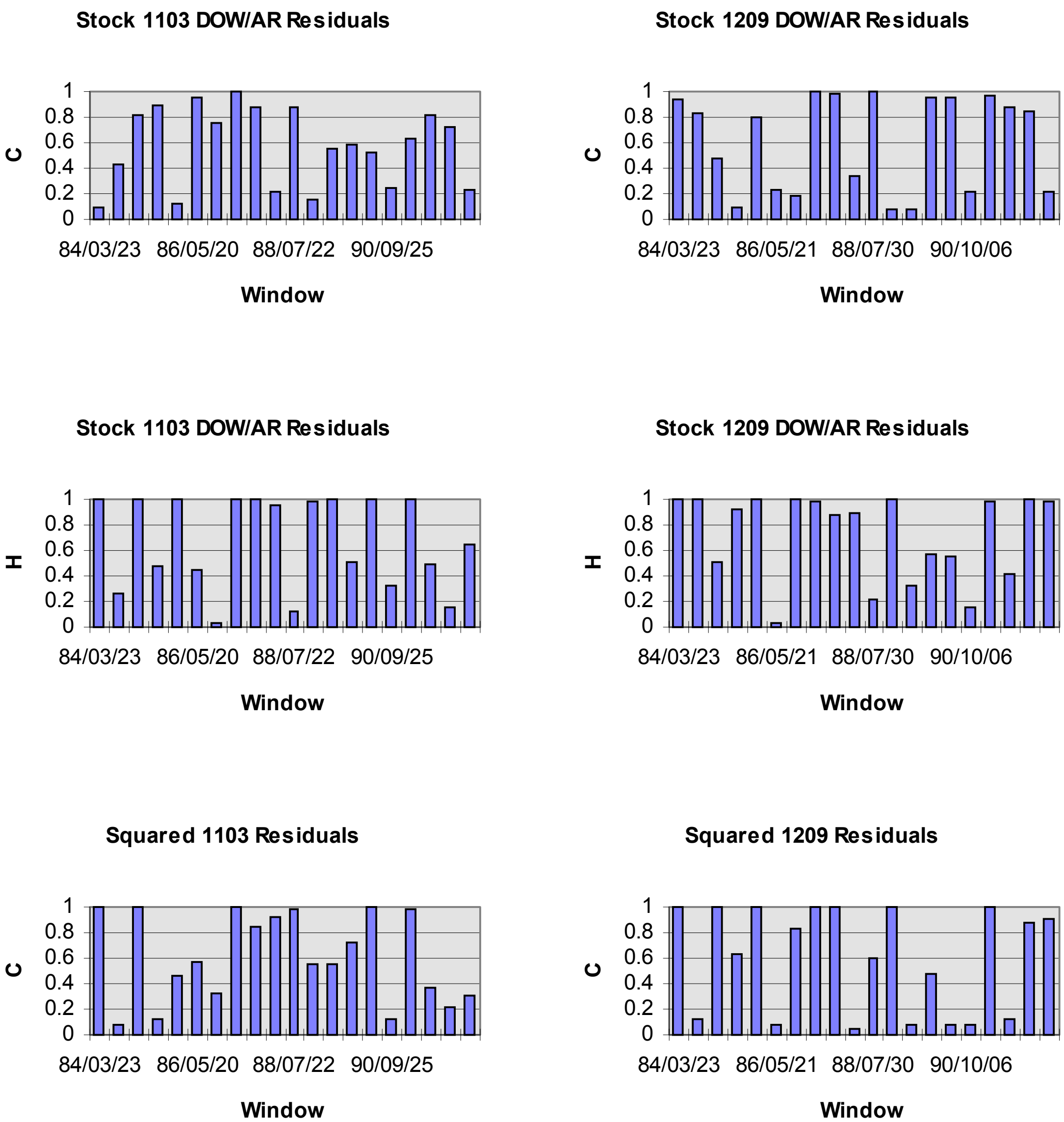
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals



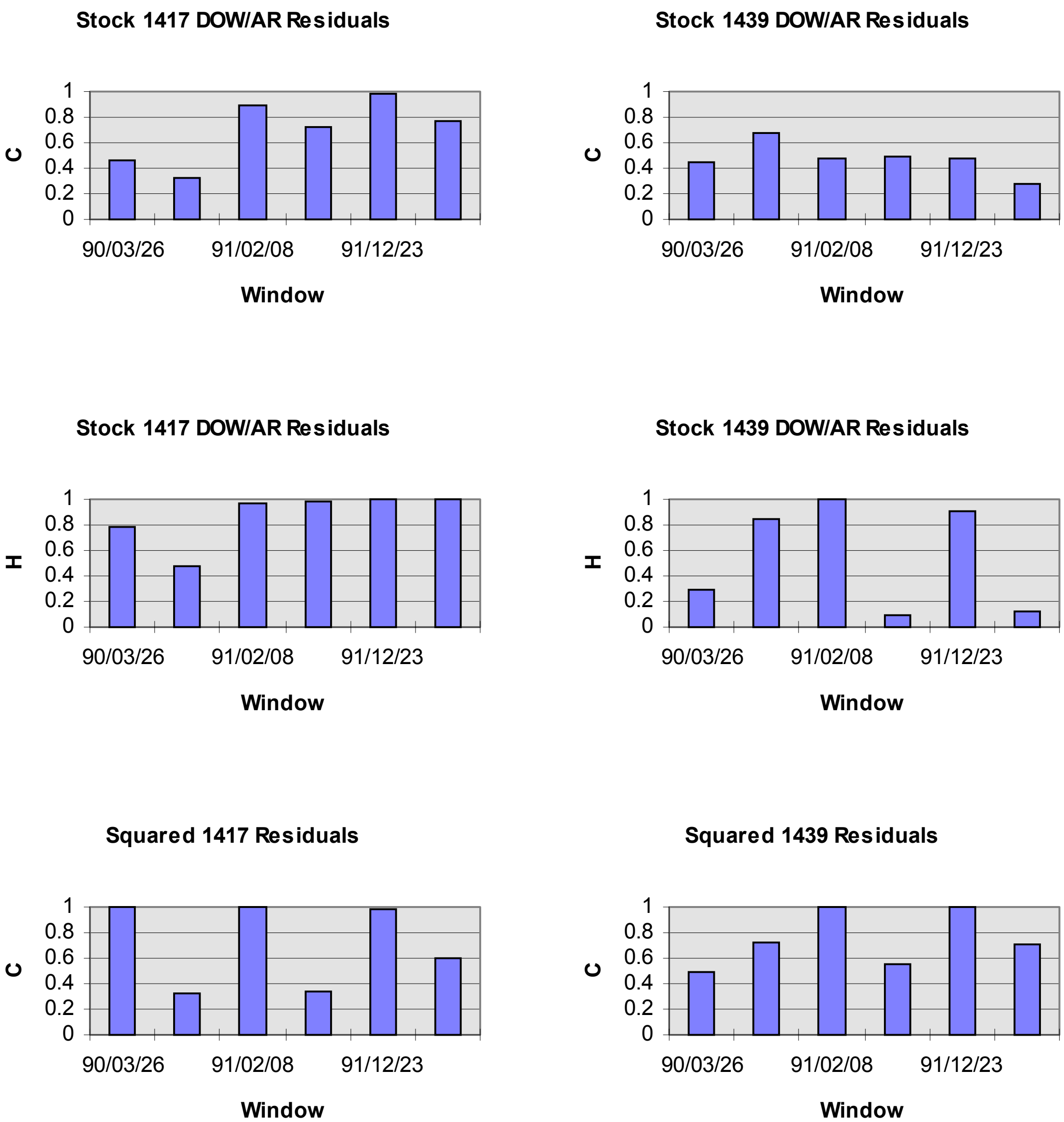
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)



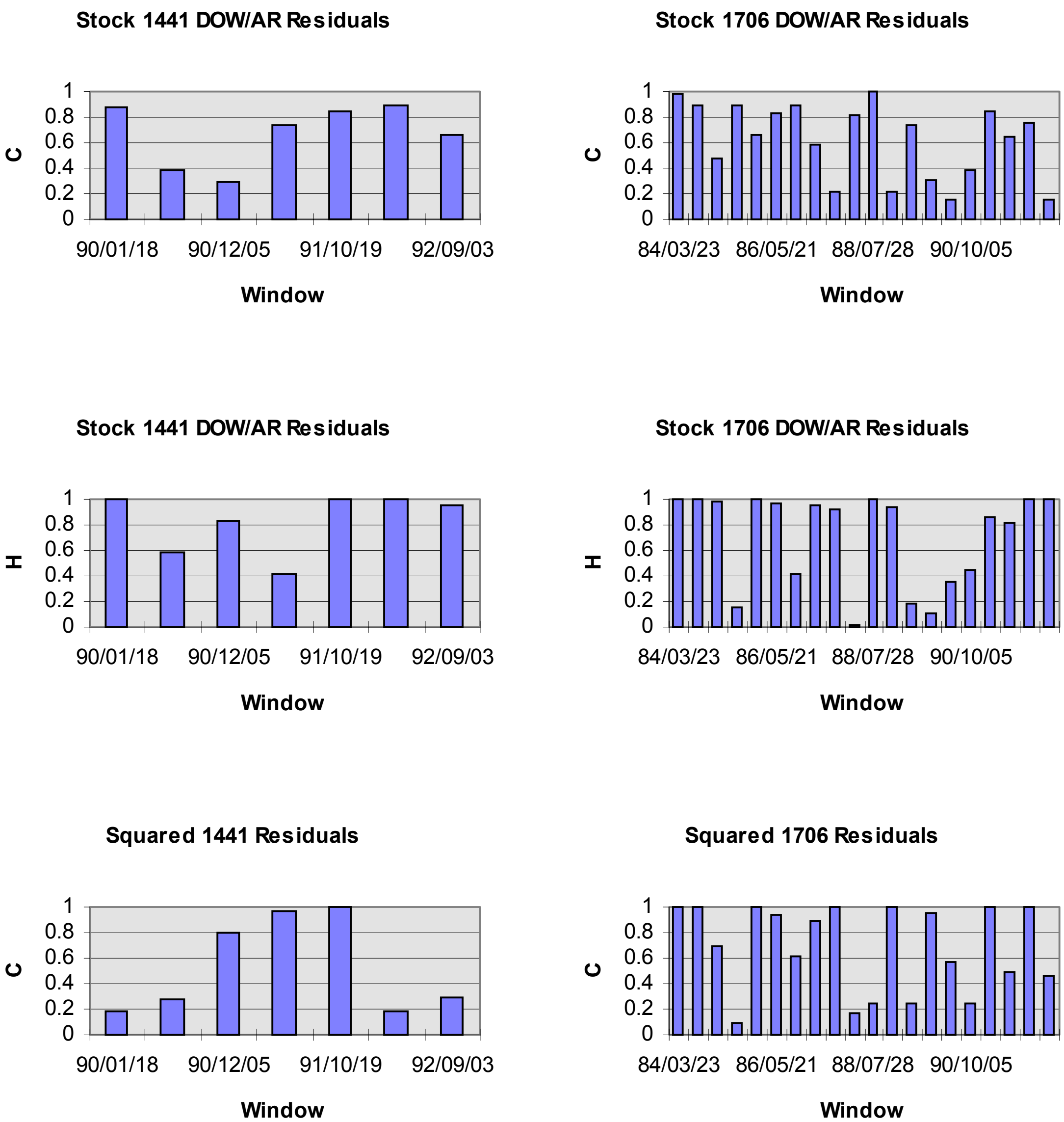
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)



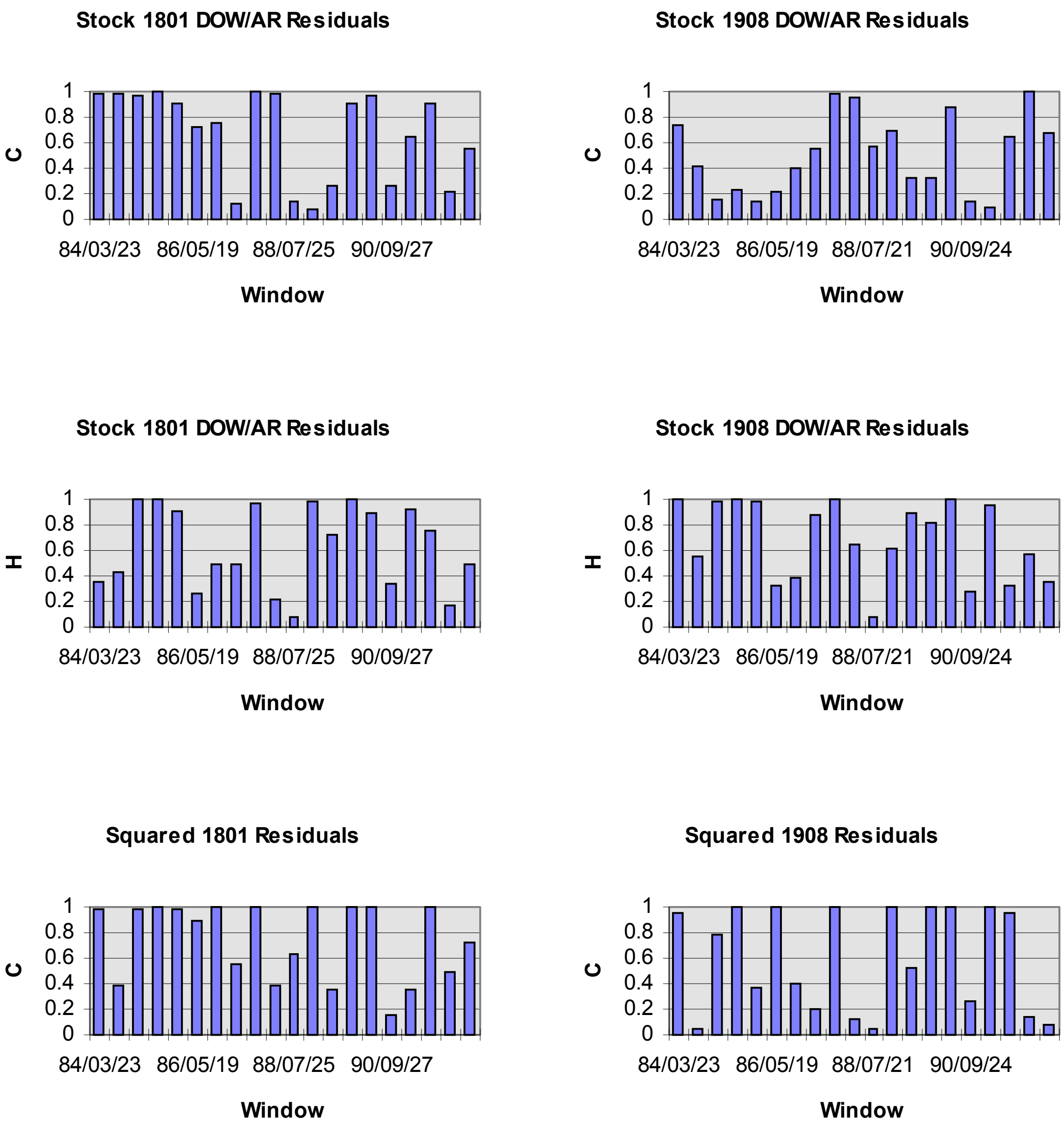
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)



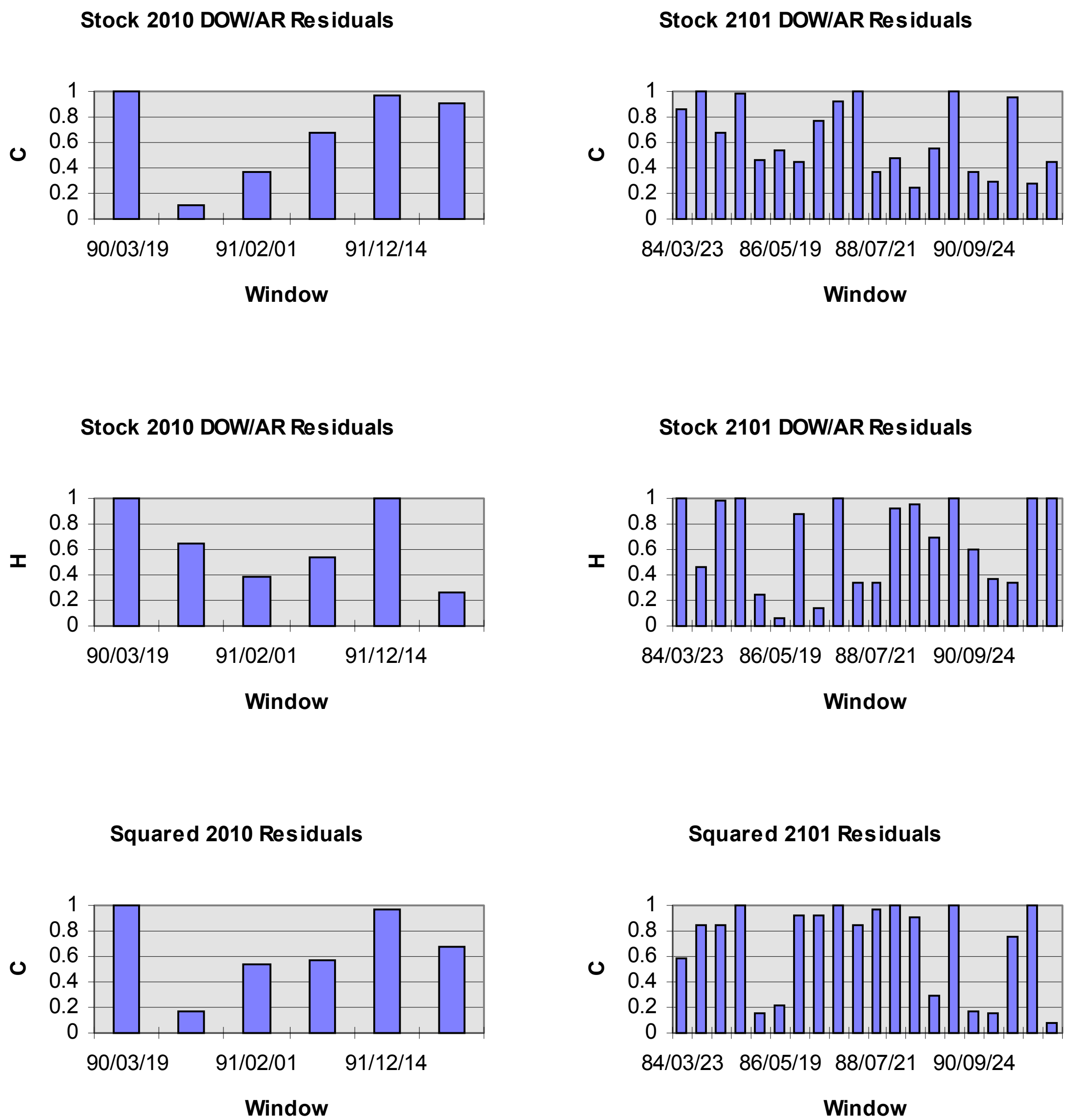
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)



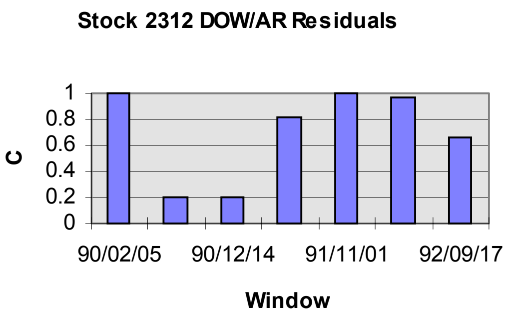
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)

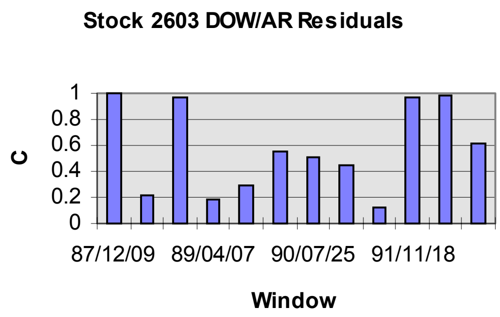


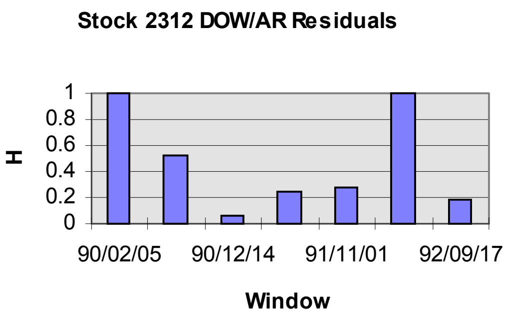
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)

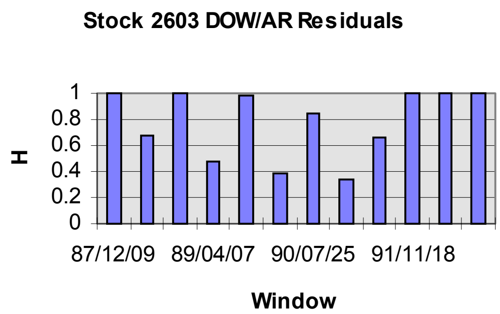


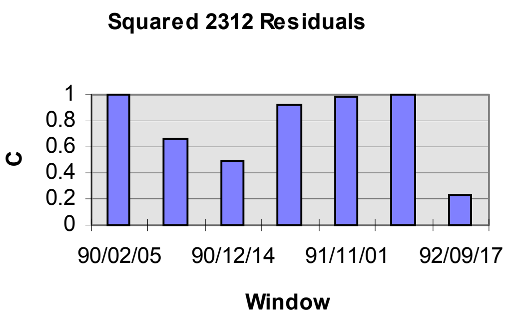
Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)

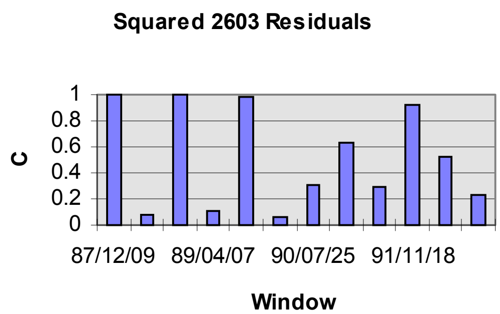












Figures 6.3
Windowed Test Result Significance Levels for DOW/AR Model Residuals (Cont.)

Table 6.1
Summary Statistics for Sample Index and Stock Returns

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Descriptive Statistics						
# Obs.	3142	2810	2800	2991	2750	2755
Mean	0.00066	0.00048	0.00052	0.00026	0.00056	0.00027
Std. Dev.	0.0192	0.0113	0.0107	0.0115	0.0186	0.0130
Skewness	-0.331	-4.202	-1.018	-0.576	-5.212	-3.289
Kurtosis	2.179	99.538	11.988	22.051	97.149	54.444
S-K Test	679.00	1,168,308.3	17,250.41	60,763.87	1,093,881.8	345,227.27
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Tests for Serial Dependencies						
Qx(6)	115.28	20.44	23.07	49.26	31.09	99.49
p-value	0.000	0.002	0.001	0.000	0.000	0.000
Qxx(6)	2,938.25	124.03	1,100.86	337.00	32.22	870.34
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	62.28	22.43	11.63	57.04	42.16	44.78
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	22.67	20.03	9.21	18.47	16.00	14.92
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	25	22	22	23	22	22
% Sig. C	12.00%	0.00%	0.00%	17.39%	4.55%	45.45%
% Sig. H	36.00%	4.55%	22.73%	47.83%	63.64%	54.55%

Table 6.1
Summary Statistics for Sample Indices and Stocks (Cont.)

Stock:	1103	1209	1417	1439	1441	1706
Descriptive Statistics						
# Obs.	2579	2572	850	850	900	2563
Mean	0.000283	0.000077	-0.00187	-0.00103	-0.00076	-0.00089
Std. Dev.	0.0256	0.0295	0.0373	0.0433	0.0365	0.0335
Skewness	-0.273	-0.703	-0.103	-0.025	-0.171	-0.047
Kurtosis	1.142	4.619	-0.355	-1.001	0.411	-0.579
S-K Test	172.02	2,498.15	5.95	35.55	10.72	36.68
p-value	0.000	0.000	0.051	0.000	0.005	0.000
Tests for Serial Dependencies						
Qx(6)	36.26	109.64	36.25	58.63	54.40	176.42
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Qxx(6)	1,382.26	285.57	1,032.17	504.93	269.38	1,704.58
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	33.24	31.35	14.78	3.75	8.03	10.57
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	13.90	9.65	3.82	1.13	4.51	10.72
p-value	0.000	0.000	0.000	0.129	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	20	20	6	6	7	20
% Sig. C	15.00%	30.00%	16.67%	33.33%	14.29%	45.00%
% Sig. H	45.00%	40.00%	50.00%	16.67%	42.86%	35.00%

Table 6.1
Summary Statistics for Sample Indices and Stocks (Cont.)

Stock:	1801	1908	2010	2101	2312	2603
Descriptive Statistics						
# Obs.	2555	2580	856	2580	892	1504
Mean	-0.00009	-0.00011	-0.0008	0.000435	-0.00051	0.000018
Std. Dev.	0.0307	0.0295	0.0354	0.0299	0.0376	0.0303
Skewness	-0.110	-0.983	-0.226	-0.206	-0.052	-0.082
Kurtosis	-0.216	9.660	0.714	0.007	-0.498	-0.106
S-K Test	10.11	10,447.01	25.47	18.21	9.60	2.38
p-value	0.006	0.000	0.000	0.000	0.008	0.304
Tests for Serial Dependencies						
Qx(6)	167.66	72.46	46.97	227.64	42.17	33.87
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Qxx(6)	1,655.73	46.57	568.10	3,600.53	663.42	483.38
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	10.98	25.94	10.88	32.47	8.60	11.84
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	8.82	24.08	11.45	14.30	7.70	9.93
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	20	20	6	20	7	12
% Sig. C	40.00%	20.00%	16.67%	25.00%	28.57%	16.67%
% Sig. H	25.00%	30.00%	33.33%	35.00%	28.57%	50.00%

Table 6.2
Significant Day-of-the-Week Effects and Autocorrelation Lags for the Normal Linear Model

Series	Day-of-the-Week Effects	Autocorrelations (Lags)
Taiex	-	1,3
DJIA	-	2,4,5
FT-30	-M,+F	1,4
Nikkei	-M,-T	1,2,6
HSI	-M	3
STI	-M,(-T)	1,2
1103	-	1,2,3
1209	-	1,3
1417	-	1,3
1439	-	1,3
1441	-	1,2,3
1706	-W	1,3
1801	+S	1,3
1908	-	1,3
2010	-	1,2,3,5
2101	-	1,2,3,4,5
2312	-	1,3,5
2603	-	1,3

Note: The day-of-the-week effects shown have p-values of less than 0.10. Those appearing in parentheses have p-values between 0.05 and 0.10, while those not in parentheses have p-values of 0.05 or less.

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model

Index:	**Taiex**	**DJIA**	**FT-30**	**Nikkei**	**HSI**	**STI**
Model Coefficients:						
ϕ_0	-0.0186	-0.0130	-0.0140	0.0499	0.0146	0.0278
t-stat.	-0.43	-0.30	-0.33	1.20	0.35	0.66
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	0.0136	-0.0221	**-0.1544**	**-0.1680**	**-0.2015**	**-0.1240**
t-stat.	0.25	-0.34	**-2.56**	**-2.74**	**-3.49**	**-2.22**
$\phi_{Tuesday}$	0.0169	0.0490	0.0257	**-0.1314**	0.0128	-0.0910
t-stat.	0.29	0.78	0.43	**-2.14**	0.22	-1.64
$\phi_{Wednesday}$	-0.0196	0.0424	0.0723	0.0361	0.0632	0.0303
t-stat.	-0.35	0.68	1.29	0.63	1.07	0.55
ϕ_{Friday}	0.0341	-0.0072	**0.1155**	-0.0472	0.0413	0.0443
t-stat.	0.61	-0.12	**2.06**	-0.83	0.70	0.80
$\phi_{Saturday}$	0.0747			0.0803		
t-stat.	1.22			1.05		
Autocorrelation Effects						
ϕ_1	0.1432		0.0699	0.0735		0.1255
t-stat.	8.15		3.71	4.04		6.61
ϕ_2		-0.0559		-0.0933		0.0993
t-stat.		-2.96		-5.12		5.23
ϕ_3	0.1092				0.1001	
t-stat.	6.21				5.27	
ϕ_4		-0.0409	0.0561			
t-stat.		-2.17	2.97			
ϕ_5		0.0503				
t-stat.		2.67				
ϕ_6				-0.0503		
t-stat.				-2.76		
ϕ_7						
t-stat.						

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Misspecification Tests:						
No. of Obs.	3142	2809	2799	2991	2750	2755
Skewness	-0.25362	-4.29574	-0.84289	-0.54045	-4.9971	-2.18438
Kurtosis	2.482466	100.226	10.54869	22.5287	96.01653	50.31514
S-K Test	840.48	1,184,352.19	13,308.86	63,398.07	1,067,808.74	292,799.03
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Tests for Serial Dependency						
Qx(6)	3.94	1.91	1.63	4.28	6.11	2.53
p-value	0.414	0.591	0.804	0.233	0.296	0.639
Qxx(6)	2392.06	77.35	1235.87	371.91	28.85	1347.03
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	60.825	23.123	10.512	58.601	37.226	40.446
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	22.426	14.977	7.626	16.426	13.594	14.202
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	25	22	22	23	22	22
Raw Residuals:						
% Sig.Win.	48.00%	9.09%	18.18%	47.83%	45.45%	72.73%
% Sig. C	12.00%	4.55%	0.00%	8.70%	0.00%	22.73%
% Sig. H	44.00%	4.55%	18.18%	43.48%	45.45%	68.18%
Squared Residuals:						
% Sig. C	40.00%	0.00%	13.64%	30.43%	13.64%	40.91%

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model (Cont.)

Stock:	**1103**	**1209**	**1417**	**1439**	**1441**	**1706**
Model Coefficients:						
ϕ_0	-0.0355	-0.0383	-0.0133	0.0762	-0.0011	0.0458
t-stat.	-0.74	-0.79	-0.16	0.90	-0.01	0.94
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	0.0646	0.0383	0.0086	-0.0711	-0.0943	-0.0099
t-stat.	1.02	0.61	0.08	-0.65	-0.94	-0.15
$\phi_{Tuesday}$	-0.0099	-0.0077	0.0230	-0.1196	-0.0075	-0.0399
t-stat.	-0.15	-0.12	0.20	-1.06	-0.07	-0.62
$\phi_{Wednesday}$	0.0152	0.0366	-0.1056	-0.1092	-0.0581	**-0.1530**
t-stat.	0.23	0.59	-0.97	-1.03	-0.55	**-2.58**
ϕ_{Friday}	0.1023	0.0870	0.0216	-0.1172	0.0622	-0.0799
t-stat.	1.55	1.40	0.20	-1.09	0.58	-1.35
$\phi_{Saturday}$	0.0431	0.0791	0.1484	-0.0299	0.1331	0.0126
t-stat.	0.62	1.19	1.26	-0.26	1.21	0.19
Autocorrelation Effects						
ϕ_1	0.0649	0.1656	0.1470	0.1913	0.1112	0.2384
t-stat.	3.31	8.53	4.31	5.64	3.34	12.41
ϕ_2	-0.0414				0.0704	
t-stat.	-2.11				2.10	
ϕ_3	0.0968	0.0899	0.0872	0.0760	0.1395	0.0553
t-stat.	4.92	4.63	2.56	2.24	4.18	2.87
ϕ_4						
t-stat.						
ϕ_5						
t-stat.						
ϕ_6						
t-stat.						
ϕ_7						
t-stat.						

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model (Cont.)

Stock:	1103	1209	1417	1439	1441	1706
Misspecification Tests:						
No. of Obs.	2579	2572	850	850	900	2563
Skewness	-0.26486	-0.68557	-0.06597	0.000484	-0.16254	-0.03698
Kurtosis	1.141939	4.961364	-0.31771	-0.85356	0.469112	-0.34188
S-K Test	170.28	2,839.40	4.19	25.80	12.22	13.07
p-value	0.000	0.000	0.123	0.000	0.002	0.001
Tests for Serial Dependency						
Qx(6)	2.21	0.91	5.43	5.81	4.36	2.2
p-value	0.531	0.922	0.246	0.214	0.225	0.7
Qxx(6)	1241.59	224.64	729.21	284.27	166.27	929.91
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	33.184	29.108	12.833	3.544	7.06	10.344
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	15.057	10.22	7.722	1.037	4.379	9.818
p-value	0.000	0.000	0.000	0.150	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	20	20	6	6	7	20
Raw Residuals:						
% Sig.Win.	45.00%	50.00%	33.33%	16.67%	42.86%	35.00%
% Sig. C	5.00%	15.00%	0.00%	0.00%	0.00%	10.00%
% Sig. H	45.00%	35.00%	33.33%	16.67%	42.86%	35.00%
Squared Residuals:						
% Sig. C	20.00%	35.00%	33.33%	33.33%	14.29%	35.00%

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model (Cont.)

Stock:	**1801**	**1908**	**2010**	**2101**	**2312**	**2603**
Model Coefficients:						
ϕ_0	-0.0505	-0.0290	0.0238	-0.0129	-0.0686	-0.0551
t-stat.	-1.04	-0.60	0.29	-0.25	-0.86	-0.87
Day-of-the-Week Effects						
ϕ_{Monday}	0.0988	0.0296	-0.0833	-0.0339	0.1035	0.0843
t-stat.	1.56	0.47	-0.79	-0.55	1.03	1.03
$\phi_{Tuesday}$	0.0473	-0.0043	-0.0553	0.0296	0.0192	0.0605
t-stat.	0.74	-0.07	-0.52	0.47	0.18	0.70
$\phi_{Wednesday}$	-0.0033	0.0024	-0.1076	0.0182	0.0317	-0.0169
t-stat.	-0.06	0.04	-1.00	0.30	0.29	-0.20
ϕ_{Friday}	0.0252	0.0579	0.0901	-0.0082	0.1780	0.0979
t-stat.	0.42	0.91	0.83	-0.14	1.62	1.15
$\phi_{Saturday}$	**0.1413**	0.0914	0.0239	0.0722	0.0891	0.1142
t-stat.	**2.17**	1.36	0.22	1.13	0.79	1.29
Autocorrelation Effects						
ϕ_1	0.2360	0.1161	0.1627	0.1774	0.1207	0.0957
t-stat.	12.28	5.95	4.75	9.00	3.64	3.74
ϕ_2			0.0687	0.0443		
t-stat.			1.97	2.21		
ϕ_3	0.0649	0.0933	0.0699	0.0855	0.1337	0.1015
t-stat.	3.37	4.78	2.02	4.27	4.02	3.96
ϕ_4				0.0376		
t-stat.				1.88		
ϕ_5			-0.0690	0.0425	-0.0821	
t-stat.			-2.03	2.15	-2.47	
ϕ_6						
t-stat.						
ϕ_7						
t-stat.						

Table 6.3
Results for the Linear Day-of-the-Week/Autoregressive Model (Cont.)

Stock:	1801	1908	2010	2101	2312	2603
Misspecification Tests:						
No. of Obs.	2555	2580	856	2580	892	1504
Skewness	-0.11257	-0.97136	-0.27887	-0.11391	-0.09586	-0.10954
Kurtosis	-0.03971	10.03284	0.822166	0.220707	-0.4356	-0.07897
S-K Test	5.56	11,226.44	35.20	10.82	8.42	3.40
p-value	0.062	0.000	0.000	0.004	0.015	0.183
Tests for Serial Dependency						
Qx(6)	3.29	4.05	0.15	2.27	4.2	2.99
p-value	0.511	0.399	0.926	0.132	0.241	0.559
Qxx(6)	993.95	50.58	358.37	1769.59	417.62	397.78
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Bispectrum Test:						
Gaussianity	10.551	24.68	11.404	27.184	8.974	11.586
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Linearity	7.287	23.161	11.172	16.739	8.342	11.105
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)						
# Windows	20	20	6	20	7	12
Raw Residuals:						
% Sig.Win.	30.00%	25.00%	33.33%	45.00%	42.86%	41.67%
% Sig. C	20.00%	10.00%	16.67%	15.00%	28.57%	8.33%
% Sig. H	15.00%	20.00%	33.33%	35.00%	28.57%	41.67%
Squared Residuals:						
% Sig. C	45.00%	35.00%	16.67%	25.00%	28.57%	16.67%

Table 6.4
Results for the Linear Day-of-the-Week/Autoregressive Model with Price Limit/Excess Autocorrelation Coefficients

Series:	Taiex	1103	1209	1706
Model Coefficients:				
ϕ_0	-0.0294	-0.0406	-0.0360	0.0306
t-stat.	-0.67	-0.84	-0.73	0.63
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.0263	0.0706	0.0390	-0.0023
t-stat.	0.47	1.11	0.62	-0.04
$\phi_{Tuesday}$	0.0245	-0.0060	-0.0098	-0.0313
t-stat.	0.42	-0.09	-0.15	-0.49
$\phi_{Wednesday}$	-0.0124	0.0149	0.0293	**-0.1421**
t-stat.	-0.22	0.23	0.49	**-2.40**
ϕ_{Friday}	0.0405	0.1019	0.0794	-0.0671
t-stat.	0.74	1.58	1.32	-1.13
$\phi_{Saturday}$	0.0874	0.0538	0.0789	0.0280
t-stat.	1.44	0.78	1.19	0.43
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.1898	0.1027	-0.0981	0.2812
t-stat.	2.67	1.36	-1.41	2.83
$\phi_{PLR(3)}$	-0.1072	-0.0982	-0.0844	0.0612
t-stat.	-1.80	-1.51	-1.36	0.98
$\phi_{PLR(4)}$	-0.0785	-0.0843	-0.1057	-0.0595
t-stat.	-1.92	-1.68	-2.44	-1.41
Autocorrelation Effects				
ϕ_1	0.1811	0.1143	0.2406	0.2442
t-stat.	5.29	2.68	6.72	7.41
ϕ_2		-0.0516		
t-stat.		-2.47		
ϕ_3	0.1018	0.0957	0.0820	0.0511
t-stat.	5.80	4.83	4.24	2.64
ϕ_4				
t-stat.				
ϕ_5				
t-stat.				
ϕ_6				
t-stat.				
ϕ_7				
t-stat.				

Table 6.4
Results for the Linear Day-of-the-Week/Autoregressive Model with Price Limit/Excess Autocorrelation Coefficients (Cont.)

Series:	Taiex	1103	1209	1706
Misspecification Tests:				
No. of Obs.	3142	2579	2572	2563
Skewness	-0.24456	-0.25874	-0.68506	-0.03291
Kurtosis	2.485875	1.176394	4.954291	-0.33762
S-K Test	840.33	177.49	2,831.58	12.64
p-value	0.000	0.000	0.000	0.002
Tests for Serial Dependency				
Qx(6)	6.37	2.94	1.73	2.85
p-value	0.173	0.401	0.785	0.583
Qxx(6)	2452.69	1237.91	227.54	984.97
p-value	0.000	0.000	0.000	0.000
Bispectrum Test:				
Gaussianity	60.97	33.42	29.19	11.15
p-value	0.000	0.000	0.000	0.000
Linearity	23.40	13.80	9.88	10.42
p-value	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)				
# Windows	25	20	20	20
Raw Residuals:				
% Sig.Win.	40.00%	45.00%	45.00%	30.00%
% Sig. C	4.00%	5.00%	15.00%	5.00%
% Sig. H	40.00%	45.00%	35.00%	30.00%
Squared Residuals:				
% Sig. C	40.00%	25.00%	35.00%	30.00%

Table 6.4
Results for the Linear Day-of-the-Week/Autoregressive Model with Price Limit/Excess Autocorrelation Coefficients (Cont.)

Series:	**1801**	**1908**	**2101**	**2603**
Model Coefficients:				
ϕ_0	-0.0545	-0.0299	-0.0155	-0.0753
t-stat.	-1.12	-0.62	-0.32	-1.17
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.1054	0.0269	-0.0382	0.1116
t-stat.	1.65	0.43	-0.62	1.35
$\phi_{Tuesday}$	0.0497	-0.0072	0.0400	0.0760
t-stat.	0.78	-0.11	0.63	0.88
$\phi_{Wednesday}$	-0.0014	0.0045	0.0205	0.0039
t-stat.	-0.02	0.07	0.32	0.05
ϕ_{Friday}	0.0293	0.0621	-0.0038	0.1078
t-stat.	0.49	0.95	-0.06	1.33
$\phi_{Saturday}$	**0.1425**	0.0927	0.0765	0.1423
t-stat.	**2.19**	1.37	1.19	1.61
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.0842	0.0963	0.2986	0.1146
t-stat.	0.98	1.25	3.66	1.10
$\phi_{PLR(3)}$	-0.0118	0.1200	0.1817	-0.1149
t-stat.	-0.19	1.84	2.84	-1.24
$\phi_{PLR(4)}$	-0.0549	0.0321	0.1794	-0.1426
t-stat.	-1.29	0.70	3.82	-1.89
Autocorrelation Effects				
ϕ_1	0.2570	0.0765	0.0313	0.1850
t-stat.	7.75	2.10	0.81	2.57
ϕ_2			0.0413	
t-stat.			2.02	
ϕ_3	0.0602	0.0938	0.0899	0.0898
t-stat.	3.11	4.78	4.57	3.50
ϕ_4			0.0494	
t-stat.			2.48	
ϕ_5			0.0460	
t-stat.			2.30	
ϕ_6				
t-stat.				
ϕ_7				
t-stat.				

Table 6.4
Results for the Linear Day-of-the-Week/Autoregressive Model with Price Limit/Excess Autocorrelation Coefficients (Cont.)

Series:	1801	1908	2101	2603
Misspecification Tests:				
No. of Obs.	2555	2580	2580	1504
Skewness	-0.10852	-0.98432	-0.12098	-0.10134
Kurtosis	-0.04874	10.10257	0.282858	-0.01886
S-K Test	5.27	11,388.28	14.89	2.60
p-value	0.072	0.000	0.001	0.273
Tests for Serial Dependency				
Qx(6)	4.79	4.45	3.61	4.77
p-value	0.310	0.349	0.058	0.312
Qxx(6)	1029.31	44.91	1702.49	404.22
p-value	0.000	0.000	0.000	0.000
Bispectrum Test:				
Gaussianity	10.90	24.92	27.61	11.52
p-value	0.000	0.000	0.000	0.000
Linearity	7.20	22.66	15.02	10.09
p-value	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)				
# Windows	20	20	20	12
Raw Residuals:				
% Sig.Win.	35.00%	30.00%	30.00%	41.67%
% Sig. C	25.00%	10.00%	10.00%	8.33%
% Sig. H	15.00%	25.00%	25.00%	41.67%
Squared Residuals:				
% Sig. C	45.00%	35.00%	25.00%	25.00%

Table 6.5
Results for the Linear Day-of-the-Week/Autoregressive Model for the Linearly Pre-Filtered Returns

Series:	Taiex	1103	1209	1706
Model Coefficients:				
ϕ_0	-0.0110	-0.0526	-0.0476	0.0692
t-stat.	-0.25	-1.09	-0.98	1.43
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.0159	0.1008	0.0401	-0.0323
t-stat.	0.28	1.59	0.64	-0.49
$\phi_{Tuesday}$	0.0037	-0.0050	-0.0001	-0.0784
t-stat.	0.06	-0.07	0.00	-1.17
$\phi_{Wednesday}$	-0.0305	0.0445	0.0581	**-0.1733**
t-stat.	-0.50	0.65	0.85	**-2.55**
ϕ_{Friday}	0.0226	**0.1350**	0.1042	-0.1183
t-stat.	0.37	**1.98**	1.53	-1.74
$\phi_{Saturday}$	0.0625	0.0417	0.0863	-0.0091
t-stat.	1.01	0.60	1.25	-0.13
Autocorrelation Effects				
ϕ_1				
t-stat.				
ϕ_2		-0.0368		
t-stat.		-1.87		
ϕ_3	0.1041	0.0903	0.0934	0.0526
t-stat.	5.86	4.59	4.74	2.65
ϕ_4	0.0396			0.0366
t-stat.	2.23			1.85
ϕ_5				
t-stat.				
ϕ_6				
t-stat.				
ϕ_7				
t-stat.				

Table 6.5
Results for the Linear Day-of-the-Week/Autoregressive Model for the Linearly Pre-Filtered Returns (Cont.)

Series:	Taiex	1103	1209	1706
Misspecification Tests:				
No. of Obs.	3142	2579	2572	2563
Skewness	-0.29046	-0.1949	-0.70719	-0.00159
Kurtosis	2.480217	1.043334	4.912099	-0.35057
S-K Test	849.51	133.30	2,800.18	13.13
p-value	0.000	0.000	0.000	0.001
Tests for Serial Dependency				
Qx(6)	2.09	2.19	1.61	0.81
p-value	0.719	0.701	0.900	0.936
Qxx(6)	2354.77	1213.41	212.92	889.63
p-value	0.000	0.000	0.000	0.000
Bispectrum Test:				
Gaussianity	61.8125	31.717	29.3967	10.4903
p-value	0.000	0.000	0.000	0.000
Linearity	23.64031	14.89723	10.43098	10.98794
p-value	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)				
# Windows	25	20	20	20
Raw Residuals:				
% Sig.Win.	48.00%	45.00%	50.00%	30.00%
% Sig. C	12.00%	5.00%	25.00%	5.00%
% Sig. H	44.00%	45.00%	30.00%	30.00%
Squared Residuals:				
% Sig. C	44.00%	20.00%	30.00%	30.00%

Table 6.5
Results for the Linear Day-of-the-Week/Autoregressive Model for the Linearly Pre-Filtered Returns (Cont.)

Series:	**1801**	**1908**	**2101**	**2603**
Model Coefficients:				
ϕ_0	-0.0457	-0.0226	-0.0241	-0.0648
t-stat.	-0.95	-0.47	-0.47	-1.01
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.0857	0.0249	-0.0177	0.1235
t-stat.	1.32	0.39	-0.27	1.54
$\phi_{Tuesday}$	0.0222	-0.0103	0.0381	0.0544
t-stat.	0.33	-0.15	0.57	0.64
$\phi_{Wednesday}$	0.0074	0.0009	0.0377	-0.0132
t-stat.	0.11	0.01	0.55	-0.15
ϕ_{Friday}	0.0301	0.0468	0.0003	0.1280
t-stat.	0.44	0.69	0.00	1.50
$\phi_{Saturday}$	0.1344	0.0761	0.0845	0.1006
t-stat.	1.95	1.11	1.25	1.17
Autocorrelation Effects				
ϕ_1				
t-stat.				
ϕ_2			0.0436	
t-stat.			2.21	
ϕ_3	0.0679	0.0868	0.0928	0.1211
t-stat.	3.43	4.41	4.71	4.72
ϕ_4			0.0590	0.0622
t-stat.			3.00	2.41
ϕ_5			0.0472	
t-stat.			2.39	
ϕ_6			0.0383	
t-stat.			1.94	
ϕ_7				0.0780
t-stat.				3.01

Table 6.5
Results for the Linear Day-of-the-Week/Autoregressive Model for the Linearly Pre-Filtered Returns (Cont.)

Series:	**1801**	**1908**	**2101**	**2603**
Misspecification Tests:				
No. of Obs.	2555	2580	2580	1504
Skewness	-0.04002	-0.88656	-0.04427	-0.08156
Kurtosis	-0.06844	9.526627	0.256208	0.071865
S-K Test	1.18	10,094.31	7.90	1.99
p-value	0.554	0.000	0.019	0.370
Tests for Serial Dependency				
Qx(6)	1.28	5.29	2.58	4.23
p-value	0.937	0.381	0.108	0.238
Qxx(6)	901.37	49.78	1543.85	347.92
p-value	0.000	0.000	0.000	0.000
Bispectrum Test:				
Gaussianity	10.3792	23.9235	25.8854	13.0196
p-value	0.000	0.000	0.000	0.000
Linearity	7.17526	18.2646	17.58411	10.68774
p-value	0.000	0.000	0.000	0.000
Windowed Tests for Stability (wl=125, th=0.01)				
# Windows	20	20	20	12
Raw Residuals:				
% Sig.Win.	35.00%	30.00%	45.00%	50.00%
% Sig. C	25.00%	10.00%	20.00%	16.67%
% Sig. H	20.00%	25.00%	30.00%	50.00%
Squared Residuals:				
% Sig. C	35.00%	35.00%	25.00%	16.67%