Chapter 7

Dynamic Heteroskedasticity and Taiwan Stock Return Nonlinearity

7.1. Introduction

The results for the dynamic normal linear regression models fit in the previous chapter suggest that there are significant autocorrelation effects in the returns for all eighteen series examined and significant day-of-the-week effects, including a negative Monday effect, for four of the indices and two of the individual stocks. However, misspecification tests for these models reveal a number of potential complicating factors that raise questions about these results. A lack of normality, for example, calls into question the validity of the t-statistics used to determine which parameters were significant, as well as indicating the potential for more serious estimation problems.

If this lack of normality were the only complicating factor, then this would pose little problem. Robust regression techniques could simply be called into service to examine and provide measures of the strength and significance of the various statistical relationships of interest. However, the misspecification tests reveal a deeper problem that most robust methods are not equipped to handle. This problem is the existence of nonlinear serial dependencies within these series of returns. While the linear dependencies within the data do not seem to affect the nonlinearity test results, the converse is not necessarily true, and the evident nonlinearity can affect the estimation results, and the inferences obtained from them, in a variety of ways.

If the underlying nonlinear dependencies involve nonlinearities-in-mean, including the types of nonlinearities that the bispectrum test is most powerful in detecting, then ignoring such dependencies would result in an "omitted variables bias" affecting all of the parameters included in the model. If the extant nonlinearity entails nonlinearity-in-variance, on the other hand, then estimation via some variation of iteratively reweighted least squares would be more appropriate, and could lead to different parameter values and inferences, than estimation using ordinary least squares. In such a case, the nonlinear dependencies of the series would be incorporated into the covariance matrix that is used in the estimation.

McLeod and Li's procedure directly tests for the existence of one form of nonlinearity-in-variance within a time series. However, depending on their specific form, nonlinearities-in-mean can also lead to significant results for the McLeod and Li test. In general, just as data generated by a time-varying-parameter MA(q) process are observationally equivalent to data generated by an ARCH(q) process, with both types of processes capable of yielding significant McLeod and Li test results, there are many different types of nonlinear dependencies that can empirically mimic one another. Thus, it can be extremely difficult to determine what modeling and estimation approach to take in the presence of nonlinearity. This problem becomes even more acute with the possibility that multiple forms of nonlinearity may be present within a single time series. The possibility of nonstationarity, as suggested by the results of Chapter Five, would only compound such difficulties.

Keeping these caveats in mind, the emphasis for the remainder of this chapter will be on using a variety of conditionally heteroskedastic model specifications to directly capture the dynamic heteroskedasticity that the McLeod and Li test results suggest is present within the returns of all eighteen of the time series under examination. The results and implications of these models will then be explored. In so doing, this chapter will focus on answering three main questions. First, do these conditionally heteroskedastic nonlinear models appear to be able to account for the nonlinear dependencies within these series of returns? Second, do these models also appear to be more generally well-specified? And third, what are the inferences obtained from these models, and are they consistent with those from the dynamic linear models of Chapter Six?

7.2. The Normal GARCH Model and Taiwan Stock Return Nonlinearity

Among finance and economics applications, the most widely used family of nonlinear models is the AutoRegressive Conditionally Heteroskedastic (ARCH) family of models (see Bollerslev, Chou, and Kroner (1992) for an extensive survey of the development and application of this family of models), which, as its name suggests, is designed specifically to capture nonlinearities that enter a process through its variance. This family of models was originated by Engle (1982), with his development of the ARCH(q) model:

$$\begin{aligned}
&y_t = \varepsilon_t, \\
&\varepsilon_t \sim N(0, h_t) \\
&h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = \omega + \alpha(L)\varepsilon_t^2,
\end{aligned}$$

Such a process has the favorable characteristic that it can generate and account for clusters of volatility, one of the most visible aspects of nonlinearity within financial time series. Furthermore, such processes generate sequences of data whose marginal distributions are leptokurtic, another characteristic aspect of financial time series.

This basic ARCH model was extended by Bollerslev (1986) to obtain the Generalized AutoRegressive Conditional Heteroskedasticity model of orders p and q, the GARCH(p,q) model:

$$\begin{aligned}
&\mathrm{y_t} = \varepsilon_t \\
&\varepsilon_t \sim N(0, h_t) \\
&h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} = \omega + \alpha(L)\varepsilon_t^2 + \beta(L) h_t
\end{aligned}$$

The autocorrelation and partial autocorrelation functions for ε_t^2 can be used as a diagnostic for determining the orders p and q for such a model, but in most cases the orders $p=q=1$ are found to suffice.

To examine the effects of conditional heteroskedasticity on the results for the six index and twelve individual Taiwanese stock returns, the GARCH(p,q) variance specification was combined with the specification for the mean used in Chapter Six to obtain the following joint specification for the mean and the variance:

$$r_t = \phi_0 + \phi_{Mon.} d_{Mon.} + \phi_{Tues.} d_{Tues.} + \phi_{Wed.} d_{Wed.} + \phi_{Fri.} d_{Fri.} (+\phi_{Sat.} d_{Sat.}) + \sum_{i=1}^{6(or7)} \phi_{t-i} r_{t-i} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \beta_i h_{t-i}$$

Thus, in addition to the day-of-the-week effects and autocorrelation effects included in the models used in Chapter Six, this model specification also captures the effects of conditional heteroskedasticity. The results for all of these effects are discussed below. As before, 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 results for this model is presented in Table 7.1, while the full results are shown in Table 7.2. In addition, the results for this model augmented with the price-limit-regime/autocorrelation interaction effects are shown in Table 7.3, while Table 7.4 shows the results for the basic model applied instead to the pre-filtered returns.

Day-of-the-Week Effects

Probably the most interesting results from this model are those for the day-of-the-week effect. Namely, such affects appear to become more significant when the estimation allows for dynamic heteroskedasticity. This change is especially pronounced for the Taiex and the individual Taiwanese stock returns (see Table 7.12 for a comparison of the measured day-of-the-week effects across model specifications).

For the Taiex returns, the Monday effect shifts from having an insignificant, near-zero value under the homoskedastic (constant variance) dynamic linear model of Chapter Six to having a very significant ($p = 0.0117$) negative value under a Normal GARCH variance specification. Similarly, while only two of the individual stocks exhibit significant day-of-the-week effects under the homoskedastic variance specification, under the Normal GARCH specification such effects are significant at a 0.05 level for an additional three stocks, stocks 1441, 1908, and 2010, and marginally significant, with p-values between 0.05 and 0.10, for four more stocks, including stocks 1103, 1209, 1417, and 2101. In most of these cases, the significant effect is a negative Monday effect or a positive Saturday effect, though stock 1103 exhibits a marginally significant positive Friday effect. Interestingly, stock 1706, one of the two stocks that exhibited a significant day-of-the-week effect for the dynamic linear model specification, with a significant negative Wednesday effect, is among the four stocks that do not appear to exhibit any significant day-of-the-week effects under the Normal GARCH specification.

For the index returns, the day-of-the-week effect seems to be somewhat more robust to changes in estimation methods, and the same effects are significant under both methods for the DJIA, FT-30, and Hang Seng returns. Nonetheless, there are some notable differences between the two sets of results for the remaining two indices. The Singapore STI returns exhibit a significant, negative Monday effect under both cases, but a marginally significant, negative Tuesday effect is rendered insignificant and an insignificant, positive Friday effect is rendered significant in moving from the linear to the GARCH model. The changes for the Nikkei returns are even more dramatic. For this index, significant, negative Monday and Tuesday effects under the dynamic linear model are replaced by significant, positive Wednesday and Saturday effects under the GARCH model. Thus, while both models suggest the existence of a significant day-of-the-week effect, the inferences about how this effect manifests itself are highly dependent upon the variance assumptions of the model used to estimate it.

Autocorrelation Effects

As with the day-of-the-week effects, the estimated autocorrelation effects also differ between the linear, homoskedastic models and the nonlinear, GARCH models. However, while this change in models tends to increase the apparent significance of the day-of-the-week effect, its effect on autocorrelation levels appears to be less clear-cut (see Table 7.13 for a comparison of the autocorrelation results across model specifications).

Among the index returns, the number of significant lags decreases for the DJIA, FT-30, and Nikkei returns, and only one lag remains significant for each of these under the GARCH specification. For the FT-30 and Nikkei returns, the remaining significant lag is the first lag, while for the DJIA returns the remaining significant lag is the fourth lag. For each of the three "Asian tigers" included in the sample, on the other hand, additional lags become significant under the GARCH model specification that were not significant under the linear model specification, and three lags are significant under the GARCH specification for each of these three indices. (Note: the four "Asian tigers" include Hong Kong, Singapore, and Taiwan, which are represented in this sample, and South Korea, which is not represented here.)

The autocorrelation results for the individual stocks are also mixed, but in general the GARCH specification engenders fewer significant lags. Among the individual stocks examined, half of the stocks, including stocks 1103, 1417, 1439, 1441, 2010, and 2101, saw a decline in the number of significant lags. In the case of stock 1417, no lags remain significant under the Normal GARCH specification, while for stock 2010, of the four lags that are significant under the homoskedastic specification, only one, at lag one, remains significant under the GARCH model. Of the six remaining stocks, five, including stocks 1706, 1801, 1908, 2312, and 2603, exhibit no differences in significant lags between the two model specification. The remaining stock, stock 1209, is the only stock for which the GARCH specification entails an increase in the number of lags that are estimated to be significant, with two of the longer lags, lags four and six, becoming significant when dynamic heteroskedasticity of this form is taken into account.

Conditional Heteroskedasticity and the Parameterization of Variance

The final major component for the GARCH models of this section are the GARCH or conditional heteroskedasticity effects. Although the examination of the ACF's and PACF's for the squared residuals from Chapter Six suggested a variety of possible GARCH specifications, some with only ARCH effects and others with GARCH effects of higher orders than one, the GARCH(1,1) specification was chosen as the starting point for the GARCH modeling, since this specification has been found to suffice in most applications. For the most part, this specification was also found to suffice in these applications.

For the FT-30 returns, the squared residual ACF and PACF suggested that a simple ARCH(1) model may be adequate, so that the GARCH parameterization would not be needed. However, the extremely large magnitude of the t-statistic for β_1, the GARCH parameter, suggests that this parameter should remain in the model. For this series and most of the others, furthermore, the basic GARCH(1,1) specification was found to remove or be able to account for most of the squared residual autocorrelation, so that the $Q_{xx}(6)$ statistics for the weighted GARCH residuals are insignificant for most of these series. The exceptions, for which the $Q_{xx}(6)$ statistics remain significant, include the Hang Seng Index and stocks 1706, 1801, 2010, and 2101. For the Hang Seng Index, various alternative specifications were tried, such as ARCH(4) and GARCH(3,1), but the significant $Q_{xx}(6)$ results remained for each of these specifications, and a log likelihood test and the AIC suggested that the GARCH(1,1) specification was the best model. For the individual stocks, the lack of kurtosis within their returns came into play, and it was not possible to fit any models of higher orders to these returns (the computer algorithms failed to converge for these higher order models). So, in the end, the GARCH(1,1) specification was used for all eighteen sets of returns.

Examining the parameters from this variance specification reveals a number of pieces of information. First of all, the t-statistics for these variance parameters are extremely large, esp. for the β_1 or GARCH parameter, for which the smallest t-statistic is 16.47, for the Singapore returns. The high values for these statistics provide a measure of the strength of the nonlinearity underlying these returns, even if such underlying nonlinearity does not directly take the form of dynamic heteroskedasticity. Furthermore, the sum of the ARCH and GARCH parameters, $\alpha(L)+\beta(L)$, in this case $\alpha_1+\beta_1$, provides a measure of the "volatility persistence" within a series of returns. So long as this sum is less than one, then the variance of the GARCH process is stationary, and the specification for the process can be re-written in the form of an infinite order ARCH process. The closer this sum is to one, however, the less stable the variance will be in the long run, and the more permanent will be changes in the level of volatility as a result of "volatility shocks." Conversely, the smaller is this sum relative to one, then the more transient will be the effects of the volatility shocks, and the less of an adjustment there will be to expected returns as a consequence of any such shocks.

For the eighteen series examined here, the sum of α_1 and β_1 is very close to one in almost every case, and in only three cases is this sum less than 0.96. For the Nikkei returns, this sum is even greater than one. The fact that this sum is very close to one, or even greater than one, for most of the index and stock return series indicates that volatility is very persistent within these series, and the effects of any volatility shocks on future levels of variance will be more or less permanent.

As noted in Diebold (1986) and later shown in Lamoureux and Lastrapes (1990), on the other hand, such high degrees of persistence in estimated GARCH models can be the result of parameter shifts in the intercept of the variance equation, which can bias the estimation toward an integrated GARCH model. Thus, rather than indicating high levels of volatility persistence, the high values for the sums of α_1 and β_1 for these series may instead by a further reflection of the types of parameter instabilities that were found in Chapter Five. In other words, these high estimated levels of volatility persistence could be an indication of model misspecification due to parameter instability, a possibility that is especially likely given the results of Chapter Five.

Residual Nonlinearity and General Misspecification Testing

The results of the previous subsection give an indication that, for most of these sets of returns, the Normal GARCH model is likely to be misspecified. This subsection will look more closely at the issue of whether such models are in fact misspecified and, more specifically, at the question of whether these models are able to control for the nonlinearity within these series of returns.

As to the latter question of whether these models can account or control for the nonlinearity within these series, for the most part the answer is yes. For the weighted residuals for four of the indices, the Taiex, the DJIA, the FT-30 Index, and the Singapore STI Index, and seven of the stocks, stocks 1103, 1209, 1417, 1439, 1441, 2312, and 2603, neither the bispectrum test of linearity nor the McLeod and Li test detects any significant nonlinearity. Among the rest of the eighteen series, the bispectrum test finds significant nonlinearity among the Nikkei and stock 1908 residuals, indicating that conditional heteroskedasticity is not the whole story behind the nonlinearity within these returns, while the McLeod and Li test finds significant nonlinearity among the residuals of stocks 1706, 1801, 2010, and 2101. The returns for the remaining series, the Hang Seng Index, seem a bit recalcitrant, and the problems encountered in trying to fit a GARCH model to these returns have already been discussed. For the weighted residuals from fitting such a model, both the bispectrum test and the McLeod and Li test indicate significant remaining nonlinear dependencies.

For the stocks and indices with significant residual nonlinearity, the fact that they still exhibit nonlinearity even after the estimated GARCH effects have been filtered out indicates that the Normal GARCH model is not well-specified for these series. However, these results provide only an incomplete picture. Series for which the GARCH model appears to adequately control for the extant nonlinearity may nevertheless be misspecified in other ways. Conversely, for the series displaying significant residual nonlinearity, nonlinearity per se may not be the actual problem; rather, nonstationarity or some other source of misspecification may be driving the nonlinearity results. Because of the possibilities for the confounding of misspecification test results, it is important to get an overview of many different possible sources and directions of statistical model specification and misspecification (see McGuirk, Driscoll, and Alwang (1993) for elaboration of this issue).

In general, there are three primary aspects of model specification, i.e., three sets of statistical assumptions that underlie any statistical model. These three types of assumptions are distributional, memory, and homogeneity assumptions. On top of these primary assumptions rest additional assumptions regarding the specific functional form of the model to be used. For the basic paradigm of statistical modeling, the Normal linear regression model, the specific functional form is a model that is linear in the parameters for the relevant variables. Under this paradigm, the set of error terms from the linear model follow the primary assumptions summarized by the oft-heard phrase, “Normal IID.” More specifically, the primary assumptions can be summarized as:

$$\underline{\varepsilon} \sim MVN\left(\underline{0}, \sigma^2 I\right).$$

This entails a distributional assumption of normality for the linear model's error terms, along with a homogeneity assumption of an identical marginal distribution for each of the individual error terms. Finally, the memory assumption that is entailed in this specification is independence, or, in other words, a complete lack of memory across observations. In a time series framework, the memory assumptions are crucial, because it is precisely the memory within a set of observations that time series models seek to capture or take into account.

But even if "Normal IID" is not the assumption underlying the original observations, it is often the assumption of what the weighted residuals from a given model should approximate, even if only asymptotically. For example, for the Normal GARCH model, the actual returns from such a model would be assumed to follow a leptokurtic rather than a normal distribution, and, given the volatility clusters such a model would generate, the returns for such a process are obviously not independent. However, because the error terms for such models follow distributions that are conditionally normal, the sequence of variance estimates generated from such a model should be able to standardize the residuals from the model so that the series of weighted residuals are approximately Normal IID. For an alternative process such as a Student's t GARCH, the distribution of the weighted residuals should approximate a Student's t rather than a normal distribution, but the remaining assumptions of IID for the weighted residuals should still hold. Whatever the statistical assumptions underlying a specific model, the goal of misspecification testing is to determine the validity of such assumptions with respect to a given data set.

For the misspecification tests whose results are included in Table 7.2, the tests that are available to examine each of the primary specification assumptions are as follows. Distributional assumptions, specifically normality, are tested via the Bera-Jarque skewness-kurtosis test for normality and by Hinich's bispectrum test for Gaussianity. Memory assumptions, including autocorrelation and nonlinear serial dependency, are tested by the Box-Pierce Q-statistic ($Q_x(6)$), the McLeod and Li test ($Q_{xx}(6)$), and the bispectrum test of linearity. The assumption of homogeneity, the subject of Chapter Five, is examined via the windowed test procedure.

Unfortunately, however, confounding often occurs within misspecification testing, so that misspecification in one area can "mimic" and lead to significant test results for misspecification within another area. In order to control for such confounding and to be able to more accurately assess the true size and power entailed within a battery of misspecification tests, McGuirk, Driscoll, and Alwang (1993) develop a set of joint misspecification tests, one for the mean and one for the variance of a process. These joint tests simultaneously test multiple assumptions, thereby allowing for better identification of the source of misspecification, while simultaneously allowing the statistical size for the battery of tests to be more readily determined. In their basic form as used in this analysis, each of the joint tests contains three components, with each testing for a different aspect of misspecification.

The joint conditional mean test includes a test for trending in the mean, a rejection of which would imply problems with homogeneity or stationarity, a test for linearity, addressing the issue of functional form, and a test for residual autocorrelation, the presence of which would suggest unmodeled memory within the data series. The joint conditional variance test also includes a trend test for homogeneity or stationarity, along with tests for two different types of heteroskedasticity. The static heteroskedasticity test examines whether the variance, proxied by the squared model residuals, is a function of the current regressors in the model, which addresses the issue of functional form, while the dynamic heteroskedasticity test is equivalent to the ARCH test, examining the memory issue of whether current variance levels are a function of previous variance levels. The examination of distributional assumptions is not directly included in these joint tests but is left to separate testing, via such tests as the skewness-kurtosis test for normality or the bispectrum test for Gaussianity.

Examining such tests for the weighted residuals from the Normal GARCH models immediately reveals one source of misspecification that is shared by most of the series. The weighted residuals from a Normal GARCH process should be approximately normally distributed. However, the bispectrum test for Gaussianity leads to a rejection of normality for three of the indices and one of the stocks. More dramatically, under the skewness-kurtosis test, normality is strongly rejected for all six of the indices, and it is also rejected for nine of the twelve stocks. In most cases this rejection is driven by the existence of excess kurtosis within the residuals. This suggests that a model entailing a longer-tailed, leptokurtic conditional distribution, such as a Student's t GARCH model, may have been a more appropriate choice for these sets of returns.

Moving to a Student's t GARCH specification does not seem appropriate for all of these series, however. The GARCH residuals for a number of the individual Taiwanese stocks still bear the effects of the TSE's price limits. Consequently, the sets of residuals for five of the stocks are platykurtic to some degree (i.e., the tails of their marginal distributions taper down more quickly than those for a normal curve so that they exhibit negative levels of "excess" kurtosis), and for three of these stocks this platykurtosis is of a sufficient degree to cause the skewness-kurtosis test to reject normality on its account. For these cases, any justifiable alternative to the Normal GARCH specification would need to entail a platykurtic rather than a leptokurtic conditional distribution.

Fitting Normal GARCH models to these platykurtic series of returns creates an interesting effect. Under a Normal GARCH process, the conditional distribution is assumed to be normal, with zero excess kurtosis. However, as a consequence of the heteroskedasticity that is engendered by a GARCH process, the returns for such a process exhibit excess kurtosis when aggregated across time. Such induced excess kurtosis is removed during the course of filtering out the GARCH effects and generating the heteroskedasticity-weighted residuals. For the platykurtic stock returns, however, the weighted GARCH residuals actually exhibit greater levels of kurtosis than did the original series of returns. This suggests that the estimated GARCH effects are being fitted to, or driven by, the price limits, leading to estimated variance levels during these periods that are low relative to the true underlying levels of volatility, so that the returns that run up against the price limits and are truncated are made to appear farther out within the tails of their distributions than they actually occur. The two methods used to try to control for such price-limit truncation effects appear to make little difference in this regard, as the results in Tables 7.3 and 7.4 demonstrate.

Moving down the list of misspecification tests on Table 7.2, the next set of tests after the tests for normality are the tests for serial dependence. These include the Box-Pierce test for autocorrelation ($Q_x(6)$), which tests for linear serial dependencies among the weighted GARCH residuals, and the McLeod and Li test ($Q_{xx}(6)$) and the Bispectrum test for linearity, both of which test for nonlinear serial dependencies among the GARCH residuals. These tests indicate that, in a majority of cases, the Normal GARCH models do a fairly good job of filtering out or accounting for the serial dependencies within the these sets of returns. There are a few notable exceptions, however. In terms of autocorrelation, the Singapore STI returns appear to be especially recalcitrant, exhibiting significant autocorrelation out to six lags even after all of the significant lags out to the seventh lag have been incorporated into the model.

The tests for nonlinear serial dependencies, on the other hand, reveal problems with a greater number of the series of returns. Among the indices, the set of Hang Seng returns appears to be the recalcitrant series in terms of nonlinear serial dependencies, with both the McLeod and Li test and the bispectrum test for linearity detecting the existence of nonlinearity among this index's GARCH residuals. Moreover, even higher order GARCH models that were fit to this series were unable to filter out all the extant nonlinearity from these returns. Similarly, five of the stock return series exhibit significant residual nonlinearity. The residuals for four of the stocks, including stocks 1706, 1801, 2010, and 2101, display significant McLeod and Li test statistics. For the first two of these stocks, the return truncation effects caused by the price limits precluded the fitting of GARCH models with higher order GARCH terms (such models failed to converge during estimation), while for stocks 2010 and 2101, higher order GARCH models were fit to the data but had little impact on the nonlinearity test results. A fifth stock, stock 1908, exhibits an extremely low McLeod and Li test statistic, but instead exhibits a highly significant bispectrum test statistic for linearity. Especially in the case of this last stock, these results suggest that the extant serial dependencies within these series of returns are more complicated than those of a simple AR-GARCH process.

The next set of misspecification tests listed in Table 7.2 are the joint misspecification tests of McGuirk, et.al. (1993), including joint tests for both the mean and the variance. These tests indicate residual misspecification problems with a majority of the series, including five of the six indices and half of the twelve stocks.

The joint misspecification tests for the mean indicate that the mean equation is misspecified, i.e., that the mean of the return processes is mis-modeled, for three of the indices and one of the stocks. For the Hang Seng index and for stock 2101, this misspecification appears to entail both unmodeled autocorrelation and unmodeled mean nonlinearities. Interestingly, the $Q_x(6)$ test statistic for autocorrelation was not significant in either of these cases. It was significant for the Singapore STI index, however, and the joint mean test also indicates mean misspecification in the form of autocorrelation among the GARCH residuals for this index. The third index for which the joint mean misspecification test indicated problems is the FT-30 index, for which the skewness-kurtosis test was the only other test to indicate any problems, and the rejection in this case appears to be driven by unmodeled mean nonlinearities.

The joint variance misspecification tests indicate problems with the variance specification for three of the indices and five of the stocks. For most of these series, including the Nikkei and Hang Seng residuals and the residuals for stocks 1439, 1706, 1801, 2010, and 2101, the existence of residual dynamic heteroskedasticity is found to be a problem, indicating that the fitted

GARCH models do an inadequate job of accounting for the dynamic heteroskedasticity within the original series of returns. For the Nikkei and Hang Seng indices, furthermore, static heteroskedasticity also appears to be a problem, suggesting the possibility of a day-of-the-week effect for the variances of these series.

The remaining component of the joint variance misspecification test, which tests for variance nonstationarity in the form of trending in variance levels, is significant for the residuals from the Nikkei index and stocks 1439, 1801, and 2101, which also exhibited significant dynamic heteroskedasticity, as well as for the residuals from the Taiex. These significant test results come in spite of the extremely high estimated volatility persistence levels entailed in the GARCH models fitted to these series. One possible explanation for this combination of results is that the variance processes for these series are explosively nonstationary to a degree that cannot be completely captured by an Integrated (or nearly integrated) GARCH specification. An alternative possibility is that the underlying variance processes are subject to parameter instabilities that inflate the estimated levels of volatility persistence, so that filtering out such inflated GARCH effects will induce residual nonstationarity. In either case, these test results provide additional evidence that nonstationarity, of one form or another, is a problem with these data series.

Summarizing the results of this section, the Normal GARCH models fitted are able to account for the extant nonlinearity within a majority of the eighteen series of returns studied. However, in almost every case, such models appear to be misspecified for these sets of returns. For eight of the eighteen series, one or another of the misspecification tests indicates the presence of residual nonlinearity, while another series exhibits significant residual autocorrelation. Thus, half of the Normal GARCH residual series exhibit serial dependencies of one form or another. The joint misspecification tests, furthermore, indicate that these GARCH models are misspecified for all of the index series and five of the seven stock return series. Finally, normality is rejected for all but two of the series, suggesting that, if nothing else, the distributional assumptions of the Normal GARCH model are not appropriate for most of these series. Even apart from these various misspecification tests, however, the very high levels of volatility persistence estimated for most of these sets of returns suggests that parameter instabilities may be inflating these volatility persistence levels. Thus, for the two stocks for which none of the other misspecification tests are significant, their high levels of estimated volatility persistence suggest that the Normal GARCH model may be misspecified even in these two cases.

Given these apparent misspecifications, the inferences drawn from these GARCH models are called into question just as were those drawn from the dynamic linear model of Chapter Six. Because a lack of normality was a common source of misspecification for most of the series of returns studied, and because leptokurtosis was the cause of this rejection in a number of cases, it is possible that changing to a leptokurtic model specification will allow for more valid inferences to be obtained. Thus, the focus of the modeling efforts in the next section will be on such a model, the Student's t GARCH model.

7.3. Student's t GARCH and Taiwan Stock Return Nonlinearity

After finding that the GARCH(p,q) model accounted for only some, but not all, of the leptokurtosis within most of the financial time series to which it had been applied, Bollerslev

(1987) changed the conditional distribution for the GARCH model from Normal to Student's t to develop the Student's t GARCH model of orders *p* and *q*, or GARCH(*p,q*)-t model:

$$
\begin{aligned}
& y_t = \varepsilon_t \\
& \varepsilon_t \sim t_v(0, h_t) \\
& h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i-1}^{p} \beta_i h_{t-i},
\end{aligned}
$$

where v is the number of degrees of freedom for the conditional Student's t distribution. For finite v, this process will exhibit leptokurtosis not only in the original data series, but also in the series of standardized residuals. Hsieh (1989) finds that this model can adequately describe series of foreign exchange rates for the Canadian Dollar and the Swiss Franc, and the increased ability of this model to account for excess kurtosis, combined with the fact that normality is rejected due to excess kurtosis among the standardized GARCH residuals for all six of the indices and seven of the twelve Taiwanese stocks in our sample, suggests that the Student's t GARCH model is also an appropriate alternative specification to try for those series for which the Normal GARCH model does not appear to be adequately specified.

This model specification differs from the Normal GARCH specification used in the previous section only by the distributional assumptions, so that the full model that is fit appears to be almost identical:

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

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

A summary of the results for this model is presented in Table 7.5, while the full results for this model are shown in Table 7.6. Tables 7.7 and 7.8 present, respectively, the results for the Student's t GARCH model including price-limit interaction terms and the results for this GARCH model applied instead to the pre-filtered series of returns.

Note that because the Student's t distribution converges to the Normal distribution as the degrees of freedom v tend to infinity, with the degrees of freedom parameter defining how leptokurtic the distribution is, then the more leptokurtic a series is, the smaller the estimated degrees of freedom parameter will be. Conversely, if a series exhibits negative excess kurtosis, or if the Normal GARCH specification seems adequate distributionally, then the estimated degrees of freedom coefficient will increase toward infinity, its value for the normal distribution, and the estimation algorithm will not converge. Thus, it is impossible to fit a Student's t GARCH model to those series for which the Normal GARCH model appears to be distributionally well specified, namely stocks 2312 and 2603, or to those series whose standardized residuals from that model exhibit negative or approximately zero excess kurtosis, which includes stocks 1439, 1706, 1801, and 2101. Therefore, there are only results for the Student's t GARCH model for the six indices and for the six stocks whose GARCH residuals exhibited excess kurtosis, including stocks 1103, 1209, 1417, 1441, 1908, and 2010.

Day-of-the-Week Effects

As was found in the previous section, many of the inferences from the Normal GARCH model differ from those of the dynamic linear (homoskedastic) model. Similarly, in many cases, a Student's t GARCH specification yields yet a third set of inferences. As with the other specifications, though, the day-of-the-week effect that is most commonly found to be significant under the Student's t GARCH models is a negative Monday effect, which is significant (at least at a 0.10 level) in half of the twelve cases for which a GARCH-t model could be fit. Three of the twelve series, on the other hand, including the DJIA returns and the returns for stocks 1908 and 2010, exhibited no significant day-of-the-week effects under the GARCH-t model specification.

Comparing the Student's t GARCH results to those for the Normal GARCH model and the dynamic linear model, in only three cases do all three model specifications yield the same inferences for the day-of-the-week effect. The DJIA returns exhibit no significant day-of-the-week effects under any of the three model specifications. The Hang Seng returns, on the other hand, exhibit a significant, negative Monday effect under all three models, while the FT-30 returns exhibit both the negative Monday effect and a positive Friday effect in all three cases. For a fourth series, the Singapore STI returns, a negative Monday effect is significant under all three model specifications, but the significance of other days' effects varies across models and are different under each specification.

Of the remaining eight cases for which all three models were not in agreement, the results for the GARCH-t model agree with those of the Normal GARCH model in four cases. This includes the Taiex returns and the returns for stocks 1209, 1417, and 1441. For all four of these cases, the Normal GARCH and GARCH-t model specifications elicited at least marginally significant day-of-the-week effects, while no such effects appeared to be significant under the dynamic linear model specification.

For the remaining four cases, including the Nikkei returns and the returns for stocks 1103, 1908, and 2010, the Normal GARCH and the GARCH-t specifications each yield different inferences. For stocks 1908 and 2010, the Normal GARCH specification yields significant day-of-the-week effects, but no such effects are found to be significant under either the dynamic linear model or the Student's t GARCH model. For stock 1103, the dynamic linear model results suggest the absence of any day-of-the-week effect, but the Normal GARCH results indicate the presence of a marginally significant, positive Friday effect, while the GARCH-t results suggest that the extant day-of-the-week effect instead entails a marginally significant, negative Tuesday effect. Finally, for the Nikkei returns, negative Monday and Tuesday effects are significant under the dynamic linear model, positive Wednesday and Friday effects are significant under the Normal GARCH model, and the GARCH-t model combines the significant Wednesday and Friday effects from the Normal GARCH model with a marginally significant negative Tuesday effect from the linear model specification.

Autocorrelation Effects

Probably the major difference between the Normal GARCH and the GARCH-t specifications is the reduction in the number significant autocorrelation effects brought about by the latter specification. For half of the series examined, including the Taiex, FT-30, Nikkei, and Hang Seng indices and stocks 1417 (for which there are no significant lags) and 1908, the same set of lags are significant under both specifications. However, the remaining series all exhibit fewer significant lags under Student's t GARCH than under Normal GARCH. For three of the series, including the DJIA returns and the returns for stocks 1417 and 2010, no lags are found to be significant for the Student's t GARCH specification. And although a number of series exhibited significant autocorrelations at as many as four different lags under the Normal GARCH specification, only two of the series, including the Taiex returns, with significant autocorrelations at lags one, three, and four, and the Hang Seng returns, for which lags one, three, and five are significant, exhibit significant autocorrelations at more than two different lags under Student's t GARCH.

Conditional Heteroskedasticity and the Parameterization of Variance

Overall, the variance parameterization results for the GARCH-t models are similar to those for the Normal GARCH models. The only major difference is, of course, that the GARCH-t parameterization includes the degrees of freedom parameter, ν, that characterizes how leptokurtic the conditional distribution is. Given the kurtosis measures from the Normal GARCH results, it is not surprising that the Taiex index and the Taiwanese stocks tend to have higher estimated values for ν, ranging from a low of 9.28 for stock 1908, to 20.29 for the Taiex index, to 46.85 for stock 1417. Of course this is a downward-biased sample, since it does not include the six remaining Taiwanese stocks for which the estimated degrees of freedom were effectively infinite. At the other end of the degrees of freedom spectrum are the DJIA, the Hang Seng Index, and the Singapore STI Index, for each of which ν is less than five, indicating very high levels of conditional leptokurtosis for these series. For the Nikkei returns, ν is slightly higher at 6.69, while for the FT-30 returns it is closer to the level of the Taiwanese stocks at 11.26.

Apart from the differences in level of ν between the Taiwan-related and the non-Taiwanese series of returns, there seems to be little difference between the Normal GARCH variance results and the GARCH-t variance results. The α's and β's all tend to remain highly significant, and the GARCH (β) effects tend to remain much larger than the ARCH (α) effects. Furthermore, although the sum of α and β drops below one for the Nikkei returns and rises above one for stock 1209, these estimated levels of volatility persistence remain close to one for all twelve of the series of returns for which the Student's t GARCH model was estimated. As was noted with the Normal GARCH results, this finding suggests the possibility that the variances for these series are nonstationary, and the that the effects of volatility shocks will have a long-lasting, possibly permanent, effect on variance levels. Alternatively, these high estimated volatility persistence levels could reflect parameter instabilities within the variance process, suggesting the possibility that these Student's t GARCH models are poorly specified.

Residual Nonlinearity and General Misspecification Testing

The Student's t GARCH models appear to do a fairly good job of controlling for the nonlinearity within the sets of returns studied, especially for the stock return series. The GARCH-t residuals yield significant nonlinearity test statistics for only three of the indices, the FT-30, the Nikkei, and the Hang Seng, and only one of the stocks, stock 2010. Interestingly, for most of these cases the rejection comes from the McLeod and Li test is significant, suggesting that the Student's t distributional specification affects the GARCH model's ability to capture simple autocorrelations within the squared returns. One potential solution to this problem, which was not tried, would simply be to use higher values for p or q in the variance specification. For the Hang Seng and Nikkei residuals, however, significant bispectrum nonlinearity test results suggest more of a challenge in developing possible alternative specifications.

Moving on to the more general misspecification tests, the first set of assumptions to test are the distributional assumptions. In this case, normality is rejected by the skewness-kurtosis test for all twelve of the residual series, with leptokurtosis exhibited by each. However, such results are what is expected under the model assumption of Student's t distributed data, so these results are more a validation of correct specification than an indication of misspecification. Furthermore, for six of the twelve series to which the GARCH-t model was fit, including the Taiex and DJIA index returns and the stock returns for stocks 1103, 1209, 1417, and 1908, the skewness-kurtosis test is the only significant misspecification test. Thus, the Student's t GARCH model may be an adequately specified model for these sets of returns.

On the other hand, for three of the other index series, including the Nikkei, the Hang Seng, and the Singapore STI series, the bispectrum test for Gaussianity also leads to a rejection of normality. Because this test is sensitive to departures from normality in directions other than those exhibited by Student's t distributed data, these test results suggest additional problems. In all three of these cases, though, there are additional significant misspecification test results to help guide respecification efforts.

The next set of tests are the joint misspecification tests. Due to idiosyncrasies in the software used to perform these tests, such tests could not be run on any series for which there were no autocorrelation terms. Thus, there are no results for these tests for the GARCH residuals for the DJIA or for stocks 1417 and 2010. For the latter stock, the McLeod and Li test is significant, suggesting problems with the variance specification in this case. However, for the other two series, there are no other significant test results to suggest any problems with the GARCH-t specification.

Among the five index return series and four stock return series for which the joint tests could be performed, four of the indices but only one of the stocks yielded significant misspecification tests. For the four indices, the FT-30, Nikkei, Hang Seng, and Singapore STI indices, the joint tests suggest that all of these are misspecified in terms of both their means and their variances. For stock 1441, the lone stock with significant joint test results, the mean is found to be misspecified, with unmodeled residual autocorrelation.

Taking all of these test results into consideration, the GARCH-t model appears to be misspecified for four of the six indices and two of the six stocks. Conversely, the GARCH-t model appears to be fairly well specified for the Taiex returns as well as the returns for most of the individual Taiwanese stocks. Thus, the Student's t GARCH model appears to be a more appropriate model for these returns than does the Normal GARCH model. However, as was the case with the Normal GARCH models, the fitted Student's t GARCH models yield extremely high levels of volatility persistence, continuing to suggest the possible existence of nonstationarities within these sets of returns. Interestingly, for the series for which the GARCH-t models otherwise appear to be well-specified, these estimated volatility persistence levels are especially high, with the lowest having a value of 0.98.

7.4. The Student's t AutoRegressive Model with Dynamic Heteroskedasticity and Taiwan Stock Return Nonlinearity

An alternative to the Student's t GARCH model that has been found to describe the dynamics of several foreign exchange rate series more adequately than the GARCH-t model (see McGuirk, Robertson, and Spanos (1993)) is the Student' t AutoRegressive Model with Dynamic Heteroskedasticity of orders l and p and degrees of freedom n, or STAR(l,p;n) model of Spanos (1993) (see also Andreou, Pittis, and Spanos (1997)). This model assumes that the data are marginally as well as conditionally Student's t distributed, and it is derived from the multivariate Student's t distribution. The STAR model takes the form:

$$\begin{aligned} y_t &= \beta_0 + \sum_{i=1}^{l} \beta_i y_{t-i} + \varepsilon_t, \\ \varepsilon_t &\sim t_n(0,\omega_t^2) \\ \omega_t^2 &= \left[\frac{n}{n+t-3}\right]\sigma^2\left[1+\sum_{i=1}^{t-1}\sum_{j=-p}^{p} q_{|j|}(y_{t-i}-\mu)(y_{t-i-j}-\mu)\right] \end{aligned},$$

where $\varepsilon_t \equiv y_t - E(y_t|\Im_{t-1})$, $\mu \equiv E(y_t)$, and $n > 2$ is the number of degrees of freedom. In this model, the conditional mean is linear in the conditioning variables, and the conditional variance is a quadratic function of all past conditioning information but is parameterized with only p+1 unknown q_j's, so that it is equivalent to a sequentially smoothed version of the unconditional variance. Due to this alternative variance specification, covariance stationarity is not a concern with this model, despite the fact that the effect of "volatility shocks" will perpetually remain within the memory of this model.

Due to the more complicated structure of this model, however, it is difficult to include such systematic effects as a day-of-the-week effect within the parameterization of this model. Thus, the model that will be used in this section will be the basic model, with orders $l = p$, but without any day-of-the-week effects. Even at this, another problem remains. While the GARCH-t specification allows for the degrees of freedom parameter to be estimated along with the other parameters of the model, under the STAR variance specification, the marginal variance, σ^2, and the degrees of freedom, n, cannot be estimated simultaneously, so the degrees of freedom must be fixed ahead of time. Given that the STAR model assumes that the underlying data are marginally Student's t distributed, one way to obtain estimates for n is to use the formula relating the level of kurtosis for a Student's t distribution to its degrees of freedom, namely:

$$\alpha_4 = 3 + \frac{6}{n-4},$$

and enter the sample kurtosis from the data to be modeled into the equation to solve for n:

$$n \approx \frac{6}{\hat{\alpha}_4 - 3} + 4 .$$

For the sets of returns under consideration (i.e., those whose original returns exhibited leptokurtosis), this approach yields the following degrees of freedom estimates, rounded to the nearest integer:

Series	n_{STAR}	$v_{GARCH\text{-}t}$
Taiex	7	20.29
DJIA	5	4.90
FT-30	5	11.26
Nikkei	5	6.69
HSI	5	4.80
STI	5	4.94
1103	10	10.62
1209	6	12.12
1417	n.a.	46.85
1441	19	13.07
1908	5	9.28
2010	13	23.10

Note that reasonable estimates for the degrees of freedom require that the estimated levels of excess kurtosis be strictly positive. Consequently, the STAR model could not be fitted to those series whose returns were platykurtic. For the series examined, a summary of the results obtained for the STAR model, using the degrees of freedom given above, is presented in Table 7.9, and the full results are shown in Table 7.10. The results for the pre-filtered returns are presented in Table 7.11.

Day-of-the-Week Effects

As mentioned before, due to the more complicated structure of this model, it is more difficult to incorporate structural day-of-the-week effects into its parameterization. Consequently, only the basic model without such effects was used, so there are no results for the day-of-the-week effects for this model to compare with those of the previous models.

Autocorrelation Effects

The STAR model formulation requires fitting all of the lags up to lag $l = p$, and, in general, more of these lags tend to be significant than for the Normal GARCH and GARCH-t models. Comparing the STAR results to the GARCH-t results, all of the autocorrelations that are significant under the GARCH-t specification are also significant under STAR, but for six of the series, including the DJIA and Singapore indices and stocks 1103, 1441, 1908, and 2010, additional lags are significant under STAR that are not significant under GARCH-t.

Comparisons between the STAR specification and the Normal GARCH and dynamic linear model specifications, on the other hand, are not as clear-cut, and in a number of cases these latter specifications entail greater numbers of significant lags. For the Nikkei returns, for example, the first, second, and third lags all appear to be significant under the dynamic linear model, while only the first lag is significant for the STAR model, as well as for both sets of GARCH specifications. In some cases, the different specifications even entail different sets of significant lags. An example of this is found with the DJIA returns, for which the dynamic linear model finds the second, fourth, and fifth lags to be significant, the Normal GARCH model finds significant autocorrelation only at the fourth lag, no lags are significant under the Student's t GARCH model, and, finally, lags one and six are significant under the STAR specification. Given such disparities of results, the importance of finding the "correct" model is clearly underscored.

Residual Nonlinearity and General Misspecification Testing

Unfortunately, while the STAR specification has been found to be adequate for many foreign exchange rate series, the same does not seem to be true for most of the series of stock and index returns considered here. The bispectrum and McLeod an Li tests indicate the existence of residual nonlinearities within all of the index series and all but two of the stock series examined. Of the nine sets of residuals that exhibit significant nonlinear serial dependencies, furthermore, two also exhibit significant autocorrelation, as measured by the Box-Pierce Q-statistics. Thus, the STAR model does not seem to do a good job of accounting for the memory within these sets of returns.

The Normal GARCH and GARCH-t models performed somewhat better at controlling for the memory within these series, but, in so doing, they generated extremely high levels of volatility persistence, which in turn suggested the existence of nonstationarities within the variance processes for these models. Under the STAR specification, there is no "volatility persistence" parameter to suggest the existence of such nonstationarities. Nevertheless, the joint variance tests indicate that the STAR model variance is misspecified, whether for trending, static heteroskedasticity, or dynamic heteroskedasticity, for all but one of the indices and all but one of the stocks. The lone stock for which the joint variance test is not significant, stock 2010, exhibited significant static heteroskedasticity ($p = 0.006$), but, by itself, this was not enough to drive the joint test statistic to be significant. In addition, the joint mean test indicates mean misspecification, including the unmodeled nonlinearities-in-mean, for three of the indices, the DJIA, the Nikkei, and the Singapore STI index.

In summary, the STAR model appears to be somewhat well specified only for stock 2010, and, to a lesser degree, for the Hang Seng Index, but not for any of the other stock or index return series. Thus, in general, the STAR model seems to work best for those series whose variance specifications seemed the most recalcitrant with the other model specifications. More specifically, the STAR formulation seems to work best for those series whose GARCH residuals exhibited significant McLeod and Li test statistics, i.e., for those series whose GARCH residuals displayed significant GARCH effects, in which case the GARCH-type variance formulation is clearly insufficient.

7.5. Nonlinearity, Changes in Inferences, and the Quest for a Well-Specified Model

The results of the preceding sections clearly demonstrate the effects that nonlinearity can have on a data series, along with the importance of taking nonlinearity and other statistical features of the data into account when engaging in statistical modeling and hypothesis testing. Failure to take such features into account can have a drastic impact on the statistical inferences that are drawn from a given data set. This is illustrated by the changes in the estimated day-of-the-week effects, and the changes in the lags at which autocorrelation effects appear to be significant, that occur in moving from a linear model to different types of conditionally heteroskedastic models for data that are subject to nonlinear serial dependencies. The changes in inferences for the day-of-the-week effects are summarized in Table 7.12, while the changes for the autocorrelation effects are summarized in Table 7.13. In both cases, while there are a number of sets of returns for which the inferences remain unchanged across model specifications, there are many more for which the effects that are estimated to be significant are different depending on which specification is used to obtain the results.

This brings the subject back to nonlinearity and proper model specification (a summary of the misspecification test results under each conditionally heteroskedastic model is presented in Table 7.13). When different models yield different conclusions, which conclusions should be followed? The answer is, those derived from the model that is statistically well-specified for the data being modeled. But this means that such a model would need to be able to account for all of the statistical features of the data, including nonlinear serial dependencies within the data. Unfortunately, there are a number of possible sources of such dependencies, and it is still difficult in many situations to distinguish between them, let alone incorporate their effects within a statistical model. This difficulty is illustrated by the fact that, for most of the time series studied, none of the models that were examined appeared to be completely statistically adequate; the residuals for each of these models exhibited significant misspecification of one form or another, but typically some form of nonlinearity. In such cases, the quest for a well-specified model must continue. But, beyond the complicating factors already mentioned, this quest faces the additional potential complication that, as with many linear time series models, more than one model specification may appear to be well-specified for the data, and each of such models may lead to somewhat different inferences. Thus, headaches may remain for the financial researcher even after the quest for statistically adequate models has been concluded.

A remaining question that has not yet been answered is why the choice of model should make such a difference. One possible answer is directly related to the types of models examined in this chapter. All of these models, the Normal GARCH, the Student's t GARCH, and the STAR model, are conditionally heteroskedastic models. That is, the nonlinear dependencies embodied in these models enters the process through the variance of the process, and this variance is changing over time. Consequently, estimating such models generally entails variations on the use of weighted least squares (WLS), with each possible model specification entailing a different WLS formulation.

In least squares (OLS) estimation, the estimation results are generally pulled toward, or driven by, extreme points within the data, such as, for example, the return on the Nikkei for October 20,

1987. Since this return occurred on a Tuesday, it would pull the Tuesday effect down toward its level. Furthermore, since this was such an extreme return, it would exert much greater leverage on the Tuesday effect than would most other returns that occurred on Tuesdays. However, when the variance of a process is allowed to change over time, there is some confounding of mean and variance effects, and whether a observation is considered "extreme" or not is a function of the variance for the process.

Thus, an observation that is considered extreme under the assumption of homoskedasticity may be very small, statistically speaking, once changes in variance are taken into account. So, returning to the above example, the high-magnitude negative return for the Nikkei for October 20, 1987, occurred during a period of very high volatility, so that, once this volatility is taken into account and the observations are rescaled to reflect the volatility at the time, this return will no longer be as extreme and will no longer exert the same leverage on the estimation results. So, in effect, each of the conditionally heteroskedastic models fitted above entails a different specification for the variance, hence different scalings for each of the observations, so that each model in turn embodies its own set of extreme, high-leverage observations. Hence, each model obtains its own unique results.

A second possible answer for why the choice of statistical model would make such a difference in estimation results has more serious implications. This possibility, following the results of Chapter Five, and also consistent with the high levels of volatility persistence found in this chapter, is that the underlying data are simply nonstationary, with no single stable underlying statistical structure for any model to emulate. Fitting a model to such data entails imposing a structure on the data that is not really there, and in forcing such data into the structure of a given model, different types of models will pick up different aspects or features of the data. In the extreme case, such a possibility would have the unfortunate effect of rendering empirical work largely meaningless, with any results obtained depending upon the specific model specification chosen.

Table 7.1
Normal GARCH(1,1) Model
Key Statistics and Test Results

Series	Day-of-the-Week Effects	Autocorrelations (Lags)	Volatility Persistence ($\alpha+\beta$)	Significant Misspecification Tests
Taiex	-M	1,3,4	0.998	SK,JV(T)
DJIA	-	4	0.962	SK
FT-30	-M,+F	1	0.921	SK,JM(L)
Nikkei	+W,+S	1	**1.014**	SK,JV(T,S,D)
HSI	-M	1,3,5	0.978	SK,Q_{xx},B(G,L), JM(L,A),JV(S,D)
STI	-M,+F	1,6,7	0.894	SK,Q_x,B(G),JM(A)
1103	(+F)	1,3	0.969	SK
1209	(-M)	1,3,4,6	0.9995	SK
1417	(+S)	-	0.990	SK
1439	-	1	0.975	SK,JV(T,D)
1441	-M,(+S)	1,3	0.988	SK
1706	-	1,3	0.994	SK,Q_{xx},JV(D)
1801	+S	1,3	0.997	Q_{xx},JV(T,D)
1908	+S	1,3	0.937	SK,B(G,L)
2010	-M	1	0.985	SK,Q_{xx},JV(D)
2101	(-M)	1,3,4,6	0.980	SK,Q_{xx},JM(L,A), JV(T,D)
2312	-	1,3,5	0.983	-
2603	-	1,3	0.991	-

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.

Key: SK is the Bera-Jarque Skewness-Kurtosis Test; B(G,L) represents the Gaussianity and Linearity components, respectively, of the Bispectrum Test; JM(T,L,A) represents the Trend, Linearity, and Autocorrelation components, respectively, of the Joint Conditional Mean Test; while JV(T,S,D) stands for the Trend, Static Heteroskedasticity, and Dynamic Heteroskedasticity components of the Joint Conditional Variance Test.

Table 7.2
Results for the Normal GARCH Model

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Mean Parameters:						
ϕ_0	0.118903	0.081727	0.054761	0.035286	0.169164	0.076186
t-stat.	2.40	2.12	1.37	1.25	3.25	1.94
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	**-0.173436**	-0.018408	**-0.166902**	0.036688	**-0.282095**	**-0.194061**
t-stat.	**-2.52**	-0.34	**-2.94**	0.93	**-3.93**	**-3.67**
$\phi_{Tuesday}$	-0.093873	-0.003477	0.041586	-0.059737	0.022073	-0.083151
t-stat.	-1.35	-0.06	0.73	-1.53	0.30	-1.53
$\phi_{Wednesday}$	-0.002362	-0.000728	0.062209	**0.16156**	0.047809	0.080897
t-stat.	-0.03	-0.01	1.11	**4.11**	0.66	1.49
ϕ_{Friday}	-8.04E-02	-0.036627	**0.117517**	0.029835	0.030747	**0.130795**
t-stat.	-1.16	-0.68	**2.09**	0.75	0.41	**2.35**
$\phi_{Saturday}$	-0.088595			**0.143516**		
t-stat.	-1.26			**3.11**		
Autocorrelation Effects						
ϕ_1	0.120143		0.07583	0.140909	0.135871	0.242281
t-stat.	6.52		3.74	7.01	6.06	10.53
ϕ_2						
t-stat.						
ϕ_3	0.103018				0.044671	
t-stat.	5.72				2.11	
ϕ_4	0.042687	-0.05068				
t-stat.	2.34	-2.46				
ϕ_5					-0.069308	
t-stat.					-3.35	
ϕ_6						-0.062204
t-stat.						-3.18
ϕ_7						0.060724
t-stat.						3.30
Variance Parameters:						
ω	0.015011	0.045389	0.084627	0.02281	0.148928	0.193366
t-stat.	3.34	4.45	4.25	5.55	7.19	8.07
α_1	0.094784	0.090085	0.095589	0.248917	0.238503	0.321412
t-stat.	9.02	8.55	6.03	12.02	11.31	9.72
β_1	0.903099	0.871783	0.825464	0.764676	0.739592	0.572904
t-stat.	88.01	50.63	27.90	44.79	39.53	16.47
$\alpha+\beta$	0.997883	0.961868	0.921053	**1.013593**	0.978095	0.894316

Table 7.2
Results for the Normal GARCH Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Misspecification Tests: (significant results are highlighted)						
No. of Obs.	3142	2809	2799	2991	2750	2755
Skewness	-0.190	-0.822	-0.550	-0.709	-1.144	-1.483
Kurtosis	0.443	10.590	5.911	6.951	7.869	17.062
S-K Test	**44.54**	**13,422.19**	**4,214.12**	**6,269.52**	**7,680.48**	**34,340.83**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency						
Qx(6)	4.22	9.09	3.34	4.95	8.73	**15.23**
p-value	0.646	0.168	0.765	0.550	0.190	**0.019**
Qxx(6)	7.96	2.25	11.75	7.52	**45.74**	1.33
p-value	0.241	0.896	0.068	0.275	**0.000**	0.970
Bispectrum Test:						
Gaussianity	1.42	0.68	1.50	**3.10**	**3.78**	**3.24**
p-value	0.078	0.247	0.067	**0.001**	**0.000**	**0.001**
Linearity	1.07	-0.17	-0.05	**2.33**	**3.91**	1.04
p-value	0.143	0.566	0.521	**0.010**	**0.000**	0.148
Joint Conditional Mean Test						
Joint Test	1.03	1.11	**2.12**	1.78	**3.03**	**2.84**
p-value	0.413	0.351	**0.031**	0.076	**0.002**	**0.004**
Trend	0.09	0.43	1.10	0.77	0.84	0.29
p-value	0.759	0.510	0.294	0.379	0.361	0.591
Linearity	2.79	0.13	**6.08**	**4.81**	**4.55**	0.29
p-value	0.095	0.723	**0.014**	**0.028**	**0.033**	0.590
A/C	0.96	1.36	2.07	1.67	**3.88**	**3.32**
p-value	0.453	0.226	0.053	0.123	**0.001**	**0.003**
Joint Conditional Variance Test						
Joint Test	**2.17**	0.30	1.66	**2.39**	**6.57**	0.18
p-value	**0.027**	0.965	0.104	**0.014**	**0.000**	0.993
Trend	**9.38**	0.04	0.08	**5.93**	1.75	0.04
p-value	**0.002**	0.833	0.782	**0.015**	0.186	0.840
Static HS.	0.90	0.01	1.31	**7.13**	**4.14**	0.15
p-value	0.343	0.911	0.252	**0.008**	**0.042**	0.699
Dyn. HS.	1.27	0.36	1.19	**2.40**	**8.38**	0.20
p-value	0.266	0.905	0.311	**0.026**	**0.000**	0.978
Windowed Tests for Stability (wl=125, th=0.01)						
No. of Windows	25	22	22	23	22	22
% Sig.Win.	12.00%	0.00%	4.55%	0.00%	0.00%	0.00%
% Sig. C	8.00%	0.00%	0.00%	0.00%	0.00%	0.00%
% Sig. H	4.00%	0.00%	4.55%	0.00%	0.00%	0.00%

Table 7.2
Results for the Normal GARCH Model (Cont.)

Stock:	1103	1209	1417	1439	1441	1706
Mean Parameters:						
ϕ_0	0.050764	0.053155	-0.00465	0.224635	-0.095213	0.020489
t-stat.	0.55	0.57	-0.02	0.76	-0.43	0.17
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	-0.077736	-0.222877	-0.203852	-0.47257	**-0.643041**	-0.044991
t-stat.	-0.60	-1.71	-0.71	-1.13	**-2.10**	-0.26
$\phi_{Tuesday}$	-0.134028	-0.131671	-0.459616	-0.613416	-0.246688	0.017834
t-stat.	-1.03	-1.01	-1.56	-1.46	-0.80	0.10
$\phi_{Wednesday}$	0.047305	-0.063397	-0.396052	-0.468166	-0.167167	-0.203348
t-stat.	0.36	-0.47	-1.33	-1.11	-0.53	-1.16
ϕ_{Friday}	0.217756	0.151722	0.116046	-0.442505	0.363076	-0.19548
t-stat.	1.66	1.14	0.38	-1.03	1.13	-1.12
$\phi_{Saturday}$	-0.161035	0.041798	0.574823	0.099632	0.587663	0.051527
t-stat.	-1.21	0.31	1.88	0.22	1.83	0.29
Autocorrelation Effects						
ϕ_1	0.052591	0.093741		0.15764	0.075839	0.224937
t-stat.	2.53	4.43		4.60	2.13	11.42
ϕ_2						
t-stat.						
ϕ_3	0.073048	0.054089			0.086352	0.047119
t-stat.	3.58	2.59			2.40	2.43
ϕ_4		0.048853				
t-stat.		2.37				
ϕ_5						
t-stat.						
ϕ_6		0.039807				
t-stat.		2.01				
ϕ_7						
t-stat.						
Variance Parameters:						
ω	0.192093	0.099297	0.169839	0.412036	0.171045	0.087982
t-stat.	4.40	3.52	2.25	1.86	1.92	2.22
α_1	0.136501	0.151455	0.136972	0.094284	0.102333	0.097596
t-stat.	5.28	7.92	4.37	3.72	3.47	6.22
β_1	0.832499	0.848085	0.853285	0.880928	0.885842	0.896619
t-stat.	28.10	45.57	27.29	25.94	26.61	52.13
$\alpha+\beta$	0.969	0.99954	0.990257	0.975212	0.988175	0.994215

Table 7.2
Results for the Normal GARCH Model (Cont.)

Stock:	1103	1209	1417	1439	1441	1706
Misspecification Tests: (significant results are highlighted)						
No. of Obs.	2579	2572	850	850	900	2563
Skewness	-0.364	-0.602	-0.206	-0.031	-0.132	-0.056
Kurtosis	2.518	5.280	0.155	-0.755	1.143	-0.371
S-K Test	**737.69**	**3,135.77**	**6.86**	**20.28**	**51.46**	**16.02**
p-value	**0.000**	**0.000**	**0.032**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency						
Qx(6)	1.74	5.34	10.30	7.42	5.01	6.59
p-value	0.942	0.501	0.113	0.283	0.542	0.361
Qxx(6)	2.14	1.18	1.24	11.98	0.67	**17.76**
p-value	0.906	0.978	0.975	0.062	0.995	**0.007**
Bispectrum Test:						
Gaussianity	-0.53	-0.19	-0.85	-0.43	0.61	-1.76
p-value	0.700	0.577	0.801	0.667	0.270	0.961
Linearity	-0.63	0.64	-0.73	-0.60	-0.83	0.00
p-value	0.737	0.262	0.768	0.726	0.796	0.501
Joint Conditional Mean Test						
Joint Test	0.48	1.03		0.98	1.89	0.80
p-value	0.872	0.411		0.448	0.058	0.603
Trend	0.37	0.01		0.00	0.05	0.04
p-value	0.544	0.906		0.968	0.819	0.848
Linearity	1.51	0.84		0.03	0.59	0.22
p-value	0.219	0.359		0.874	0.441	0.638
A/C	0.27	1.18		1.29	**2.42**	1.03
p-value	0.952	0.311		0.257	**0.025**	0.401
Joint Conditional Variance Test						
Joint Test	0.82	0.47		**2.09**	0.78	**2.90**
p-value	0.583	0.878		**0.034**	0.620	**0.003**
Trend	**3.96**	2.13		3.13	0.64	2.49
p-value	**0.047**	0.144		0.077	0.422	0.115
Static HS.	0.12	0.20		0.37	**4.00**	2.08
p-value	0.729	0.654		0.540	**0.046**	0.150
Dyn. HS.	0.44	0.26		**2.28**	0.36	2.04
p-value	0.850	0.956		**0.035**	0.906	0.057
Windowed Tests for Stability (wl=125, th=0.01)						
No. of Windows	20	20	6	6	7	20
% Sig.Win.	5.00%	20.00%	33.33%	0.00%	14.29%	15.00%
% Sig. C	0.00%	10.00%	16.67%	0.00%	0.00%	5.00%
% Sig. H	5.00%	10.00%	16.67%	0.00%	14.29%	10.00%

Table 7.2
Results for the Normal GARCH Model (Cont.)

Stock:	**1801**	**1908**	**2010**	**2101**	**2312**	**2603**
Mean Parameters:						
ϕ_0	-0.188542	-0.110477	-0.021012	0.077164	-0.120578	-0.092776
t-stat.	-1.78	-0.93	-0.11	0.69	-0.51	-0.61
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	0.134713	0.140991	**-0.56912**	-0.264707	-0.154931	0.004866
t-stat.	0.89	0.82	**-2.10**	-1.68	-0.47	0.02
$\phi_{Tuesday}$	0.240854	0.162589	-0.152194	0.017102	-0.298165	0.078314
t-stat.	1.63	0.95	-0.55	0.11	-0.90	0.37
$\phi_{Wednesday}$	0.192752	-0.030532	-0.198185	0.055038	0.134848	-0.027016
t-stat.	1.28	-0.18	-0.70	0.35	0.41	-0.13
ϕ_{Friday}	0.142477	0.120437	0.370077	-0.094713	0.397108	0.193759
t-stat.	0.94	0.71	1.32	-0.60	1.17	0.89
$\phi_{Saturday}$	**0.297548**	**0.334842**	-0.036869	0.037562	0.11287	0.315516
t-stat.	**1.99**	**1.96**	-0.13	0.24	0.34	1.46
Autocorrelation Effects						
ϕ_1	0.17994	0.07375	0.070753	0.11487	0.067365	0.087029
t-stat.	8.96	3.34	1.94	5.63	1.97	3.29
ϕ_2						
t-stat.						
ϕ_3	0.06572	0.093187		0.055718	0.078397	0.064385
t-stat.	3.35	4.31		2.77	2.26	2.45
ϕ_4				0.061069		
t-stat.				3.03		
ϕ_5					-0.071531	
t-stat.					-2.10	
ϕ_6				0.040242		
t-stat.				2.01		
ϕ_7						
t-stat.						
Variance Parameters:						
ω	0.046118	0.561396	0.150591	0.152915	0.203477	0.078491
t-stat.	2.48	6.07	2.22	3.42	2.10	2.06
α_1	0.090414	0.112936	0.111316	0.096933	0.098581	0.078521
t-stat.	7.08	7.30	4.10	6.41	3.78	4.27
β_1	0.907052	0.824451	0.873215	0.883152	0.884733	0.912645
t-stat.	70.33	38.00	28.56	46.30	29.30	44.32
$\alpha+\beta$	0.997466	0.937387	0.984531	0.980085	0.983314	0.991166

Table 7.2
Results for the Normal GARCH Model (Cont.)

Stock:	1801	1908	2010	2101	2312	2603
Misspecification Tests: (significant results are highlighted)						
No. of Obs.	2555	2580	856	2580	892	1504
Skewness	0.008	-2.290	-0.273	-0.120	-0.073	-0.070
Kurtosis	-0.181	35.399	0.263	0.008	-0.182	-0.088
S-K Test	3.51	**136,804.50**	**13.06**	**6.14**	2.00	1.71
p-value	0.173	**0.000**	**0.001**	**0.046**	0.367	0.426
Tests for Serial Dependency						
Qx(6)	3.64	5.94	7.09	9.33	3.02	4.76
p-value	0.725	0.430	0.312	0.156	0.806	0.575
Qxx(6)	**27.04**	0.18	**12.94**	**13.39**	9.29	3.87
p-value	**0.000**	1.000	**0.044**	**0.037**	0.158	0.695
Bispectrum Test:						
Gaussianity	-2.75	**3.03**	-0.16	0.58	-1.79	-0.33
p-value	0.997	**0.001**	0.565	0.281	0.963	0.629
Linearity	-1.96	**2.46**	-0.38	-0.13	-0.74	-0.50
p-value	0.975	**0.007**	0.649	0.553	0.772	0.692
Joint Conditional Mean Test						
Joint Test	0.72	0.92	1.64	**4.05**	0.90	0.71
p-value	0.674	0.499	0.109	**0.000**	0.517	0.682
Trend	0.87	1.42	0.07	0.17	0.14	0.66
p-value	0.352	0.233	0.792	0.682	0.706	0.417
Linearity	0.04	0.39	0.52	**15.40**	0.90	0.19
p-value	0.851	0.534	0.472	**0.000**	0.344	0.662
A/C	0.80	0.94	**2.12**	**2.24**	1.01	0.80
p-value	0.567	0.463	**0.049**	**0.037**	0.418	0.572
Joint Conditional Variance Test						
Joint Test	**3.92**	0.04	**1.97**	**3.68**	1.30	0.54
p-value	**0.000**	1.000	**0.047**	**0.000**	0.241	0.825
Trend	3.39	0.04	1.91	**10.81**	1.51	0.67
p-value	0.066	0.850	0.167	**0.001**	0.220	0.413
Static HS.	1.01	0.10	1.12	2.14	0.75	0.01
p-value	0.315	0.756	0.290	0.144	0.387	0.938
Dyn. HS.	**2.89**	0.05	2.07	**2.45**	1.40	0.58
p-value	**0.008**	1.000	0.054	**0.023**	0.213	0.745
Windowed Tests for Stability (wl=125, th=0.01)						
No. of Windows	20	20	6	20	7	12
% Sig.Win.	15.00%	5.00%	16.67%	25.00%	14.29%	16.67%
% Sig. C	15.00%	5.00%	16.67%	10.00%	0.00%	16.67%
% Sig. H	0.00%	0.00%	16.67%	15.00%	14.29%	8.33%

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model

Series:	**Taiex**	**1103**	**1209**	**1706**
Mean Parameters:				
ϕ_0	0.1136	0.0412	0.0530	-0.0203
t-stat.	2.28	0.44	0.56	-0.17
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	**-0.1694**	-0.0645	-0.2219	-0.0034
t-stat.	**-2.44**	-0.50	-1.70	-0.02
$\phi_{Tuesday}$	-0.0914	-0.1293	-0.1359	0.0460
t-stat.	-1.31	-0.99	-1.04	0.27
$\phi_{Wednesday}$	0.0003	0.0529	-0.0658	-0.1583
t-stat.	0.00	0.40	-0.49	-0.91
ϕ_{Friday}	-0.0763	0.2214	0.1527	-0.1499
t-stat.	-1.09	1.68	1.14	-0.87
$\phi_{Saturday}$	-0.0825	-0.1509	0.0449	0.0968
t-stat.	-1.16	-1.14	0.33	0.56
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.2185	0.0525	-0.0275	0.3172
t-stat.	3.65	0.82	-0.39	5.23
$\phi_{PLR(3)}$	-0.0402	-0.0851	-0.0016	0.0613
t-stat.	-0.62	-1.25	-0.02	0.97
$\phi_{PLR(4)}$	-0.0479	-0.0908	-0.0844	-0.0655
t-stat.	-1.12	-1.89	-1.75	-1.47
Autocorrelation Effects				
ϕ_1	0.1143	0.0888	0.1290	0.2017
t-stat.	4.52	2.61	3.80	6.68
ϕ_2				
t-stat.				
ϕ_3	0.0991	0.0720	0.0549	0.0386
t-stat.	5.51	3.54	2.63	2.00
ϕ_4	0.0397		0.0480	
t-stat.	2.18		2.34	
ϕ_5				
t-stat.				
ϕ_6			0.0388	
t-stat.			1.96	
Variance Parameters:				
ω	0.0148	0.1818	0.1000	0.1037
t-stat.	3.33	4.07	3.53	2.43
α_1	0.0934	0.1306	0.1511	0.1005
t-stat.	9.07	4.86	7.95	6.27
β_1	0.9046	0.8398	0.8482	0.8919
t-stat.	90.06	27.08	45.91	49.66
$\alpha+\beta$	0.998	0.970	0.999	0.992

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	Taiex	1103	1209	1706
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3142	2579	2572	2563
Skewness	-0.185	-0.361	-0.607	-0.055
Kurtosis	0.473	2.527	5.340	-0.293
S-K Test	**47.17**	**741.13**	**3,206.18**	**10.41**
p-value	**0.000**	**0.000**	**0.000**	**0.005**
Tests for Serial Dependency				
Qx(6)	4.43	2.25	5.30	6.89
p-value	0.618	0.895	0.506	0.331
Qxx(6)	7.33	2.23	1.14	**16.89**
p-value	0.292	0.897	0.980	**0.010**
Bispectrum Test:				
Gaussianity	1.550	-0.613	-0.179	-1.793
p-value	0.061	0.730	0.571	0.963
Linearity	**1.872**	-1.210	0.608	0.271
p-value	**0.031**	0.887	0.272	0.393
Joint Conditional Mean Test				
Joint Test	1.03	0.47	1.90	**2.15**
p-value	0.412	0.875	0.055	**0.029**
Trend	0.00	0.82	0.11	0.16
p-value	0.987	0.366	0.735	0.694
Linearity	0.96	0.57	0.00	**7.98**
p-value	0.327	0.451	0.980	**0.005**
A/C	1.21	0.41	**2.52**	1.48
p-value	0.298	0.874	**0.020**	0.180
Joint Conditional Variance Test				
Joint Test	**2.96**	0.80	0.45	**2.66**
p-value	**0.003**	0.601	0.892	**0.007**
Trend	**11.15**	**4.15**	2.35	**4.57**
p-value	**0.001**	**0.042**	0.125	**0.033**
Static HS.	**7.74**	0.01	0.06	0.14
p-value	**0.005**	0.942	0.808	0.705
Dyn. HS.	1.24	0.41	0.24	**2.68**
p-value	0.282	0.875	0.965	**0.013**
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	4.00%	5.00%	25.00%	10.00%
% Sig. C	0.00%	0.00%	15.00%	0.00%
% Sig. H	4.00%	5.00%	10.00%	10.00%

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	**1801**	**1908**	**2101**	**2603**
Mean Parameters:				
ϕ_0	-0.1978	-0.1216	0.0506	-0.1594
t-stat.	-1.89	-1.01	0.46	-1.05
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.1493	0.1463	-0.2439	0.0586
t-stat.	0.99	0.84	-1.56	0.27
$\phi_{Tuesday}$	0.2378	0.1684	0.0478	0.1133
t-stat.	1.60	0.97	0.31	0.53
$\phi_{Wednesday}$	0.1938	-0.0188	0.0682	0.0390
t-stat.	1.29	-0.11	0.44	0.18
ϕ_{Friday}	0.1580	0.1364	-0.0705	0.2105
t-stat.	1.05	0.79	-0.45	0.97
$\phi_{Saturday}$	**0.3005**	**0.3484**	0.0581	0.4113
t-stat.	**2.04**	**2.00**	0.37	1.89
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.1473	0.1344	0.3371	-0.2827
t-stat.	2.37	1.86	5.43	-2.31
$\phi_{PLR(3)}$	0.0081	0.1294	0.1490	-0.5390
t-stat.	0.12	1.86	2.23	-4.29
$\phi_{PLR(4)}$	-0.0529	-0.0088	0.1113	-0.5878
t-stat.	-1.13	-0.17	2.39	-5.11
Autocorrelation Effects				
ϕ_1	0.1778	0.0429	0.0156	0.5885
t-stat.	5.59	1.13	0.50	5.34
ϕ_2				
t-stat.				
ϕ_3	0.0619	0.0925	0.0485	0.0440
t-stat.	3.16	4.28	2.42	1.69
ϕ_4			0.0590	
t-stat.			2.96	
ϕ_5				
t-stat.				
ϕ_6			0.0392	
t-stat.			1.97	
Variance Parameters:				
ω	0.0456	0.5601	0.1496	0.0634
t-stat.	2.49	6.12	3.44	1.93
α_1	0.0888	0.1139	0.0949	0.0687
t-stat.	7.06	7.32	6.45	4.13
β_1	0.9086	0.8237	0.8854	0.9240
t-stat.	71.46	38.20	47.57	49.89
$\alpha+\beta$	0.997	0.938	0.980	0.993

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	1801	1908	2101	2603
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	2555	2580	2580	1504
Skewness	0.011	-2.299	-0.124	-0.070
Kurtosis	-0.163	35.507	0.078	0.018
S-K Test	2.89	**137,638.07**	**7.21**	1.25
p-value	0.236	**0.000**	**0.027**	0.535
Tests for Serial Dependency				
Qx(6)	3.61	5.75	7.06	3.79
p-value	0.729	0.452	0.315	0.705
Qxx(6)	**28.32**	0.19	**13.19**	5.60
p-value	**0.000**	1.000	**0.040**	0.470
Bispectrum Test:				
Gaussianity	-2.710	**3.022**	0.842	-0.364
p-value	0.997	**0.001**	0.200	0.642
Linearity	-1.985	**2.791**	-0.243	0.093
p-value	0.976	**0.003**	0.596	0.463
Joint Conditional Mean Test				
Joint Test	**2.51**	1.09	**3.16**	0.81
p-value	**0.010**	0.370	**0.001**	0.597
Trend	0.87	1.89	0.11	0.53
p-value	0.351	0.170	0.741	0.466
Linearity	0.88	0.00	**10.88**	0.02
p-value	0.347	0.990	**0.001**	0.891
A/C	**3.13**	1.13	2.06	1.01
p-value	**0.005**	0.340	0.055	0.416
Joint Conditional Variance Test				
Joint Test	**3.92**	0.03	**3.37**	0.87
p-value	**0.000**	1.000	**0.001**	0.545
Trend	**4.11**	0.02	**12.35**	0.59
p-value	**0.043**	0.875	**0.000**	0.442
Static HS.	0.00	0.00	0.01	0.61
p-value	0.974	0.965	0.908	0.436
Dyn. HS.	**3.82**	0.03	**2.37**	0.80
p-value	**0.001**	1.000	**0.028**	0.573
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	20	20	20	12
% Sig.Win.	15.00%	5.00%	20.00%	0.00%
% Sig. C	15.00%	5.00%	10.00%	0.00%
% Sig. H	0.00%	0.00%	10.00%	0.00%

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model

Series:	Taiex	1103	1209	1706
Mean Parameters:				
ϕ_0	0.1136	0.0412	0.0530	-0.0203
t-stat.	2.28	0.44	0.56	-0.17
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	**-0.1694**	-0.0645	-0.2219	-0.0034
t-stat.	**-2.44**	-0.50	-1.70	-0.02
$\phi_{Tuesday}$	-0.0914	-0.1293	-0.1359	0.0460
t-stat.	-1.31	-0.99	-1.04	0.27
$\phi_{Wednesday}$	0.0003	0.0529	-0.0658	-0.1583
t-stat.	0.00	0.40	-0.49	-0.91
ϕ_{Friday}	-0.0763	0.2214	0.1527	-0.1499
t-stat.	-1.09	1.68	1.14	-0.87
$\phi_{Saturday}$	-0.0825	-0.1509	0.0449	0.0968
t-stat.	-1.16	-1.14	0.33	0.56
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.2185	0.0525	-0.0275	0.3172
t-stat.	3.65	0.82	-0.39	5.23
$\phi_{PLR(3)}$	-0.0402	-0.0851	-0.0016	0.0613
t-stat.	-0.62	-1.25	-0.02	0.97
$\phi_{PLR(4)}$	-0.0479	-0.0908	-0.0844	-0.0655
t-stat.	-1.12	-1.89	-1.75	-1.47
Autocorrelation Effects				
ϕ_1	0.1143	0.0888	0.1290	0.2017
t-stat.	4.52	2.61	3.80	6.68
ϕ_2				
t-stat.				
ϕ_3	0.0991	0.0720	0.0549	0.0386
t-stat.	5.51	3.54	2.63	2.00
ϕ_4	0.0397		0.0480	
t-stat.	2.18		2.34	
ϕ_5				
t-stat.				
ϕ_6			0.0388	
t-stat.			1.96	
Variance Parameters:				
ω	0.0148	0.1818	0.1000	0.1037
t-stat.	3.33	4.07	3.53	2.43
α_1	0.0934	0.1306	0.1511	0.1005
t-stat.	9.07	4.86	7.95	6.27
β_1	0.9046	0.8398	0.8482	0.8919
t-stat.	90.06	27.08	45.91	49.66
$\alpha+\beta$	0.998	0.970	0.999	0.992

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	Taiex	1103	1209	1706
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3142	2579	2572	2563
Skewness	-0.185	-0.361	-0.607	-0.055
Kurtosis	0.473	2.527	5.340	-0.293
S-K Test	**47.17**	**741.13**	**3,206.18**	**10.41**
p-value	**0.000**	**0.000**	**0.000**	**0.005**
Tests for Serial Dependency				
Qx(6)	4.43	2.25	5.30	6.89
p-value	0.618	0.895	0.506	0.331
Qxx(6)	7.33	2.23	1.14	**16.89**
p-value	0.292	0.897	0.980	**0.010**
Bispectrum Test:				
Gaussianity	1.550	-0.613	-0.179	-1.793
p-value	0.061	0.730	0.571	0.963
Linearity	**1.872**	-1.210	0.608	0.271
p-value	**0.031**	0.887	0.272	0.393
Joint Conditional Mean Test				
Joint Test	1.03	0.47	1.90	**2.15**
p-value	0.412	0.875	0.055	**0.029**
Trend	0.00	0.82	0.11	0.16
p-value	0.987	0.366	0.735	0.694
Linearity	0.96	0.57	0.00	**7.98**
p-value	0.327	0.451	0.980	**0.005**
A/C	1.21	0.41	**2.52**	1.48
p-value	0.298	0.874	**0.020**	0.180
Joint Conditional Variance Test				
Joint Test	**2.96**	0.80	0.45	**2.66**
p-value	**0.003**	0.601	0.892	**0.007**
Trend	**11.15**	**4.15**	2.35	**4.57**
p-value	**0.001**	**0.042**	0.125	**0.033**
Static HS.	**7.74**	0.01	0.06	0.14
p-value	**0.005**	0.942	0.808	0.705
Dyn. HS.	1.24	0.41	0.24	**2.68**
p-value	0.282	0.875	0.965	**0.013**
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	4.00%	5.00%	25.00%	10.00%
% Sig. C	0.00%	0.00%	15.00%	0.00%
% Sig. H	4.00%	5.00%	10.00%	10.00%

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	**1801**	**1908**	**2101**	**2603**
Mean Parameters:				
ϕ_0	-0.1978	-0.1216	0.0506	-0.1594
t-stat.	-1.89	-1.01	0.46	-1.05
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	0.1493	0.1463	-0.2439	0.0586
t-stat.	0.99	0.84	-1.56	0.27
$\phi_{Tuesday}$	0.2378	0.1684	0.0478	0.1133
t-stat.	1.60	0.97	0.31	0.53
$\phi_{Wednesday}$	0.1938	-0.0188	0.0682	0.0390
t-stat.	1.29	-0.11	0.44	0.18
ϕ_{Friday}	0.1580	0.1364	-0.0705	0.2105
t-stat.	1.05	0.79	-0.45	0.97
$\phi_{Saturday}$	**0.3005**	**0.3484**	0.0581	0.4113
t-stat.	**2.04**	**2.00**	0.37	1.89
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.1473	0.1344	0.3371	-0.2827
t-stat.	2.37	1.86	5.43	-2.31
$\phi_{PLR(3)}$	0.0081	0.1294	0.1490	-0.5390
t-stat.	0.12	1.86	2.23	-4.29
$\phi_{PLR(4)}$	-0.0529	-0.0088	0.1113	-0.5878
t-stat.	-1.13	-0.17	2.39	-5.11
Autocorrelation Effects				
ϕ_1	0.1778	0.0429	0.0156	0.5885
t-stat.	5.59	1.13	0.50	5.34
ϕ_2				
t-stat.				
ϕ_3	0.0619	0.0925	0.0485	0.0440
t-stat.	3.16	4.28	2.42	1.69
ϕ_4			0.0590	
t-stat.			2.96	
ϕ_5				
t-stat.				
ϕ_6			0.0392	
t-stat.			1.97	
Variance Parameters:				
ω	0.0456	0.5601	0.1496	0.0634
t-stat.	2.49	6.12	3.44	1.93
α_1	0.0888	0.1139	0.0949	0.0687
t-stat.	7.06	7.32	6.45	4.13
β_1	0.9086	0.8237	0.8854	0.9240
t-stat.	71.46	38.20	47.57	49.89
$\alpha+\beta$	0.997	0.938	0.980	0.993

Table 7.3
Results for the Day-of-the-Week/Price-Limit/AR-GARCH Model (Cont.)

Series:	1801	1908	2101	2603
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	2555	2580	2580	1504
Skewness	0.011	-2.299	-0.124	-0.070
Kurtosis	-0.163	35.507	0.078	0.018
S-K Test	2.89	**137,638.07**	**7.21**	1.25
p-value	0.236	**0.000**	**0.027**	0.535
Tests for Serial Dependency				
Qx(6)	3.61	5.75	7.06	3.79
p-value	0.729	0.452	0.315	0.705
Qxx(6)	**28.32**	0.19	**13.19**	5.60
p-value	**0.000**	1.000	**0.040**	0.470
Bispectrum Test:				
Gaussianity	-2.710	**3.022**	0.842	-0.364
p-value	0.997	**0.001**	0.200	0.642
Linearity	-1.985	**2.791**	-0.243	0.093
p-value	0.976	**0.003**	0.596	0.463
Joint Conditional Mean Test				
Joint Test	**2.51**	1.09	**3.16**	0.81
p-value	**0.010**	0.370	**0.001**	0.597
Trend	0.87	1.89	0.11	0.53
p-value	0.351	0.170	0.741	0.466
Linearity	0.88	0.00	**10.88**	0.02
p-value	0.347	0.990	**0.001**	0.891
A/C	**3.13**	1.13	2.06	1.01
p-value	**0.005**	0.340	0.055	0.416
Joint Conditional Variance Test				
Joint Test	**3.92**	0.03	**3.37**	0.87
p-value	**0.000**	1.000	**0.001**	0.545
Trend	**4.11**	0.02	**12.35**	0.59
p-value	**0.043**	0.875	**0.000**	0.442
Static HS.	0.00	0.00	0.01	0.61
p-value	0.974	0.965	0.908	0.436
Dyn. HS.	**3.82**	0.03	**2.37**	0.80
p-value	**0.001**	1.000	**0.028**	0.573
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	20	20	20	12
% Sig.Win.	15.00%	5.00%	20.00%	0.00%
% Sig. C	15.00%	5.00%	10.00%	0.00%
% Sig. H	0.00%	0.00%	10.00%	0.00%

Table 7.4
GARCH Model Results for the Pre-Filtered Returns

Series	Taiex	1103	1209	1706
Mean Parameters:				
ϕ_0	0.1444	-0.0088	0.0568	-0.0029
t-stat.	2.84	-0.09	0.58	-0.02
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	**-0.1410**	-0.0295	-0.2197	-0.0121
t-stat.	**-1.99**	-0.22	-1.63	-0.07
$\phi_{Tuesday}$	-0.1291	-0.1737	-0.0824	0.0095
t-stat.	-1.83	-1.28	-0.61	0.05
$\phi_{Wednesday}$	-0.0172	0.0726	-0.0512	-0.1840
t-stat.	-0.24	0.53	-0.37	-1.03
ϕ_{Friday}	-0.1338	0.2255	0.2281	-0.1575
t-stat.	-1.86	1.62	1.65	-0.87
$\phi_{Saturday}$	-0.0997	-0.2135	0.0505	0.0726
t-stat.	-1.38	-1.56	0.36	0.40
Autocorrelation Effects				
ϕ_1			-0.0818	
t-stat.			-3.87	
ϕ_2				
t-stat.				
ϕ_3	0.0859	0.0618	0.0663	0.0464
t-stat.	4.74	3.01	3.18	2.32
ϕ_4	0.0616		0.0416	0.0428
t-stat.	3.38		2.03	2.14
ϕ_5				
t-stat.				
ϕ_6			0.0512	
t-stat.			2.57	
ϕ_7				
t-stat.				
Variance Parameters:				
ω	0.0169	0.1006	0.1209	0.1034
t-stat.	3.40	2.26	3.72	2.42
α_1	0.0980	0.0803	0.1525	0.0937
t-stat.	8.75	3.35	7.80	6.25
β_1	0.8995	0.9026	0.8430	0.8984
t-stat.	82.15	29.82	43.01	53.58
$\alpha+\beta$	0.997	0.983	0.996	0.992

Table 7.4
GARCH Model Results for the Pre-Filtered Returns (Cont.)

Series	Taiex	1103	1209	1706
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3136	2573	2566	2557
Skewness	-0.222	-0.314	-0.579	-0.025
Kurtosis	0.453	1.939	4.868	-0.474
S-K Test	**52.52**	**444.83**	**2,670.24**	**24.13**
p-value	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency				
Qx(6)	2.44	3.18	4.21	3.68
p-value	0.875	0.785	0.649	0.720
Qxx(6)	7.44	2.70	1.29	**18.23**
p-value	0.282	0.846	0.972	**0.006**
Bispectrum Test:				
Gaussianity	**1.84**	-0.90	0.31	-1.63
p-value	**0.033**	0.815	0.380	0.949
Linearity	**2.17**	-1.28	1.14	0.00
p-value	**0.015**	0.899	0.128	0.498
Joint Conditional Mean Test				
Joint Test	1.43	1.11	0.93	1.80
p-value	0.177	0.356	0.493	0.072
Trend	3.25	2.75	0.46	3.78
p-value	0.072	0.097	0.498	0.052
Linearity	1.47	1.00	0.00	**6.88**
p-value	0.225	0.318	0.967	**0.009**
A/C	0.90	0.71	1.15	0.79
p-value	0.490	0.641	0.329	0.576
Joint Conditional Variance Test				
Joint Test	**2.04**	0.61	0.68	**2.82**
p-value	**0.039**	0.766	0.709	**0.004**
Trend	**8.48**	1.78	3.31	**4.53**
p-value	**0.004**	0.182	0.069	**0.033**
Static HS.	0.18	0.17	1.38	0.02
p-value	0.668	0.679	0.241	0.880
Dyn. HS.	1.20	0.47	0.19	**2.87**
p-value	0.304	0.830	0.979	**0.009**
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	16.00%	10.00%	20.00%	15.00%
% Sig. C	8.00%	5.00%	15.00%	5.00%
% Sig. H	8.00%	10.00%	10.00%	10.00%

Table 7.4
GARCH Model Results for the Pre-Filtered Returns (Cont.)

Series	1801	1908	2101	2603
Mean Parameters:				
ϕ_0	-0.3473	-0.0691	-0.0675	-0.1277
t-stat.	-2.91	-0.58	-0.58	-0.80
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	**0.3333**	0.1711	-0.2613	0.0879
t-stat.	**1.99**	0.99	-1.60	0.38
$\phi_{Tuesday}$	0.2460	0.1592	-0.0029	0.1134
t-stat.	1.48	0.93	-0.02	0.51
$\phi_{Wednesday}$	0.2725	-0.1008	0.0931	-0.0642
t-stat.	1.63	-0.60	0.58	-0.28
ϕ_{Friday}	0.2383	0.0141	-0.0909	0.2892
t-stat.	1.43	0.08	-0.56	1.27
$\phi_{Saturday}$	0.2935	0.2122	-0.0013	0.2334
t-stat.	1.78	1.23	-0.01	1.02
Autocorrelation Effects				
ϕ_1	-0.0515	-0.0577	-0.0883	
t-stat.	-2.51	-2.59	-4.32	
ϕ_2				
t-stat.				
ϕ_3	0.0698	0.1017	0.0564	0.0746
t-stat.	3.50	4.77	2.83	2.80
ϕ_4			0.0846	
t-stat.			4.21	
ϕ_5			0.0555	
t-stat.			2.73	
ϕ_6			0.0597	
t-stat.			2.97	
ϕ_7				0.0754
t-stat.				2.85
Variance Parameters:				
ω	0.0601	0.5471	0.1468	0.0681
t-stat.	2.39	5.49	3.35	1.99
α_1	0.0826	0.1303	0.0861	0.0681
t-stat.	6.42	7.12	6.45	4.71
β_1	0.9124	0.8137	0.8947	0.9245
t-stat.	66.33	34.63	51.98	57.60
$\alpha+\beta$	0.995	0.944	0.981	0.993

Table 7.4
GARCH Model Results for the Pre-Filtered Returns (Cont.)

Series	1801	1908	2101	2603
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	2549	2574	2574	1498
Skewness	0.010	-1.935	-0.105	-0.061
Kurtosis	-0.262	27.754	-0.064	0.038
S-K Test	**7.30**	**84,120.96**	5.12	1.01
p-value	**0.026**	**0.000**	0.077	0.605
Tests for Serial Dependency				
Qx(6)	3.80	8.48	2.27	9.82
p-value	0.704	0.205	0.893	0.132
Qxx(6)	**27.09**	0.27	8.68	5.26
p-value	**0.000**	1.000	0.193	0.511
Bispectrum Test:				
Gaussianity	-2.46	**2.10**	0.94	0.41
p-value	0.993	**0.018**	0.173	0.343
Linearity	-1.77	**1.66**	-0.18	-0.22
p-value	0.962	**0.048**	0.570	0.588
Joint Conditional Mean Test				
Joint Test	1.89	1.02	**2.37**	**2.86**
p-value	0.057	0.422	**0.015**	**0.004**
Trend	**7.17**	1.23	**4.92**	**8.83**
p-value	**0.007**	0.267	**0.027**	**0.003**
Linearity	0.61	0.90	0.52	0.30
p-value	0.434	0.342	0.473	0.586
A/C	1.29	1.10	2.09	**2.16**
p-value	0.259	0.361	0.051	**0.045**
Joint Conditional Variance Test				
Joint Test	**4.23**	0.06	**2.65**	0.92
p-value	**0.000**	1.000	**0.007**	0.498
Trend	**5.27**	0.12	**10.12**	1.02
p-value	**0.022**	0.724	**0.001**	0.312
Static HS.	2.23	0.13	0.89	0.32
p-value	0.136	0.718	0.345	0.572
Dyn. HS.	**4.75**	0.07	1.54	1.03
p-value	**0.000**	0.999	0.162	0.403
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	20	20	20	12
% Sig.Win.	10.00%	10.00%	20.00%	25.00%
% Sig. C	10.00%	10.00%	5.00%	25.00%
% Sig. H	0.00%	5.00%	15.00%	8.33%

Table 7.5
Student's t GARCH(1,1) Model
Key Statistics and Test Results

Series	Day-of-the-Week Effects	Autocorrelations (Lags)	Volatility Persistence ($\alpha+\beta$)	Significant Misspecification Tests
Taiex	-M	1,3,4	0.999	SK
DJIA	-	-	0.980	SK
FT-30	-M,+F	1	0.945	SK,Q_{xx},JM(L,A), JV(D)
Nikkei	(-T),+W,+S	1	0.992	SK,B(G,L),JM(L), JV(T,S,D)
HSI	-M	1,3,5	0.952	SK,Q_{xx},B(G,L),JM(A), JV(S,D)
STI	-M,(+W)	1,6	0.886	SK,B(G),JM(A)
1103	(-T)	3	0.994	SK
1209	(-M)	1,3	**1.003**	SK
1417	(+S)	-	0.993	SK
1439	n.a.	n.a.	n.a.	n.a.
1441	(-M),+S	3	0.999	SK,JM(A)
1706	n.a.	n.a.	n.a.	n.a.
1801	n.a.	n.a.	n.a.	n.a.
1908	-	1,3	0.990	SK
2010	-	-	0.990	SK,Q_{xx}
2101	n.a.	n.a.	n.a.	n.a.
2312	n.a.	n.a.	n.a.	n.a.
2603	n.a.	n.a.	n.a.	n.a.

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.

Key: SK is the Bera-Jarque Skewness-Kurtosis Test; B(G,L) represents the Gaussianity and Linearity components, respectively, of the Bispectrum Test; JM(T,L,A) represents the Trend, Linearity, and Autocorrelation components, respectively, of the Joint Conditional Mean Test; while JV(T,S,D) stands for the Trend, Static Heteroskedasticity, and Dynamic Heteroskedasticity components of the Joint Conditional Variance Test.

Table 7.6
Results for the Student's t GARCH Model

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Mean Parameters:						
ϕ_0	0.1242	0.0514	0.0416	0.0370	0.1262	0.0527
t-stat.	2.55	1.53	1.08	1.31	2.67	1.58
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	**-0.1711**	0.0183	**-0.1338**	-0.0053	**-0.1480**	**-0.1321**
t-stat.	**-2.47**	0.38	**-2.41**	-0.13	**-2.13**	**-2.74**
$\phi_{Tuesday}$	-0.0951	-0.0138	0.0695	-0.0654	-0.0064	-0.0740
t-stat.	-1.38	-0.29	1.27	-1.65	-0.10	-1.55
$\phi_{Wednesday}$	-0.0124	-0.0091	0.0628	**0.1694**	0.0880	0.0860
t-stat.	-0.18	-0.19	1.17	**4.28**	1.34	1.83
ϕ_{Friday}	-0.0858	-0.0184	**0.1226**	0.0249	0.0391	0.0183
t-stat.	-1.25	-0.38	**2.25**	0.63	0.59	0.39
$\phi_{Saturday}$	-0.0906			**0.1341**		
t-stat.	-1.30			**3.01**		
Autocorrelation Effects						
ϕ_1	0.1181		0.0609	0.1209	0.0977	0.2463
t-stat.	6.38		3.11	6.31	4.90	12.40
ϕ_2						
t-stat.						
ϕ_3	0.1026				0.0572	
t-stat.	5.66				2.97	
ϕ_4	0.0436					
t-stat.	2.38					
ϕ_5					-0.0421	
t-stat.					-2.29	
ϕ_6						-0.0390
t-stat.						-2.25
ϕ_7						
t-stat.						
Variance Parameters:						
ω	0.0153	0.0189	0.0553	0.0182	0.1295	0.1402
t-stat.	3.04	3.54	3.74	4.36	4.65	5.68
α_1	0.1023	0.0358	0.0751	0.1648	0.1532	0.2215
t-stat.	8.32	5.00	5.54	7.70	6.16	6.83
β_1	0.8965	0.9437	0.8697	0.8267	0.7993	0.6641
t-stat.	76.10	93.33	36.92	41.73	28.61	16.56
ν	20.2901	4.9039	11.2594	6.6938	4.7958	4.9418
t-stat.	5.97	0.45	1.74	0.74	0.42	0.43
$\alpha+\beta$	0.999	0.980	0.945	0.992	0.952	0.886

Table 7.6
Results for the Student's t GARCH Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Misspecification Tests: (significant results are highlighted)						
No. of Obs.	3142	2809	2799	2991	2750	2755
Skewness	-0.198	-1.478	-0.586	-0.958	-1.341	-1.784
Kurtosis	0.470	22.324	6.542	11.210	9.466	20.968
S-K Test	**49.31**	**59,352.49**	**5,150.12**	**16,113.01**	**11,071.43**	**51,816.99**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency						
Qx(6)	4.55	11.41	5.22	6.49	10.67	12.44
p-value	0.603	0.077	0.516	0.370	0.099	0.053
Qxx(6)	6.28	6.73	**19.02**	7.52	**96.06**	2.27
p-value	0.393	0.347	**0.004**	0.276	**0.000**	0.894
Bispectrum Test:						
Gaussianity	1.21	0.92	1.29	**3.99**	**5.49**	**3.24**
p-value	0.113	0.178	0.098	**0.000**	**0.000**	**0.001**
Linearity	1.07	1.54	-0.27	**3.64**	**6.11**	0.99
p-value	0.143	0.061	0.608	**0.000**	**0.000**	0.160
Joint Conditional Mean Test						
Joint Test	1.02		**2.36**	**2.06**	**3.52**	**2.72**
p-value	0.416		**0.016**	**0.036**	**0.000**	**0.006**
Trend	0.12		1.13	1.27	0.97	0.36
p-value	0.733		0.288	0.260	0.325	0.550
Linearity	2.70		**5.96**	**5.69**	2.98	0.44
p-value	0.101		**0.015**	**0.017**	0.085	0.508
A/C	0.97		**2.40**	1.96	**4.44**	**3.23**
p-value	0.443		**0.026**	0.067	**0.000**	**0.004**
Joint Conditional Variance Test						
Joint Test	1.99		**2.46**	**1.97**	**15.58**	0.31
p-value	0.044		**0.012**	**0.047**	**0.000**	0.963
Trend	9.40		0.04	**4.09**	1.66	0.06
p-value	0.002		0.848	**0.043**	0.198	0.810
Static HS.	1.12		0.54	**5.08**	**19.33**	0.21
p-value	0.291		0.463	**0.024**	**0.000**	0.643
Dyn. HS.	1.07		**2.35**	**2.10**	**20.30**	0.29
p-value	0.381		**0.029**	**0.050**	**0.000**	0.941
Windowed Tests for Stability (wl=125, th=0.01)						
No. of Windows	25	22	22	23	22	22
% Sig.Win.	8.00%	0.00%	4.55%	0.00%	0.00%	4.55%
% Sig. C	8.00%	0.00%	0.00%	0.00%	0.00%	4.55%
% Sig. H	0.00%	0.00%	4.55%	0.00%	0.00%	0.00%

Table 7.6
Results for the Student's t GARCH Model (Cont.)

Index:	1103	1209	1417	1441	1908	2010
Mean Parameters:						
ϕ_0	0.1153	0.0874	-0.0084	-0.1437	0.0893	-0.0673
t-stat.	1.35	0.98	-0.04	-0.69	0.90	-0.34
Day-of-the-Week Effects (significant effects are highlighted)						
ϕ_{Monday}	-0.1179	-0.2169	-0.1850	-0.5487	-0.0825	-0.4410
t-stat.	-0.98	-1.71	-0.64	-1.86	-0.58	-1.60
$\phi_{Tuesday}$	-0.2201	-0.1591	-0.4299	-0.2026	-0.0985	-0.1118
t-stat.	-1.81	-1.27	-1.47	-0.69	-0.70	-0.41
$\phi_{Wednesday}$	-0.0061	-0.0991	-0.3679	-0.1561	0.0446	-0.1554
t-stat.	-0.05	-0.77	-1.24	-0.52	0.32	-0.56
ϕ_{Friday}	0.0597	0.0390	0.1117	0.3295	0.0078	0.3785
t-stat.	0.50	0.31	0.37	1.11	0.05	1.38
$\phi_{Saturday}$	-0.1452	-0.0195	0.5670	**0.6103**	-0.0066	0.0912
t-stat.	-1.20	-0.15	1.87	**2.06**	-0.05	0.32
Autocorrelation Effects						
ϕ_1		0.1033			0.0698	
t-stat.		4.87			3.30	
ϕ_2						
t-stat.						
ϕ_3	0.0816	0.0577		0.0795	0.0764	
t-stat.	4.03	2.81		2.25	3.75	
ϕ_4						
t-stat.						
ϕ_5						
t-stat.						
ϕ_6						
t-stat.						
ϕ_7						
t-stat.						
Variance Parameters:						
ω	0.0910	0.0511	0.1489	0.1000	0.1841	0.1310
t-stat.	3.03	2.56	2.01	1.64	3.88	1.96
α_1	0.1435	0.1306	0.1388	0.1185	0.1688	0.1247
t-stat.	5.79	6.89	4.26	4.21	8.06	4.07
β_1	0.8505	0.8724	0.8546	0.8805	0.8217	0.8651
t-stat.	34.38	50.44	27.22	33.33	41.32	27.47
ν	10.6243	12.1170	46.8547	13.0733	9.2817	23.1047
t-stat.	1.71	1.99	54.61	4.24	1.20	15.18
$\alpha+\beta$	0.994	**1.003**	0.993	0.999	0.990	0.990

Table 7.6
Results for the Student's t GARCH Model (Cont.)

Index:	1103	1209	1417	1441	1908	2010
Misspecification Tests:						
(significant results are highlighted)						
No. of Obs.	2579	2572	850	900	2580	856
Skewness	-0.525	-0.693	-0.210	-0.108	-3.857	-0.295
Kurtosis	4.992	6.443	0.200	1.720	75.351	0.467
S-K Test	**2,792.98**	**4,649.79**	**7.64**	**112.26**	**616,039.36**	**20.15**
p-value	**0.000**	**0.000**	**0.022**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency						
Qx(6)	10.58	9.49	10.22	10.59	5.81	12.26
p-value	0.102	0.148	0.116	0.102	0.445	0.056
Qxx(6)	2.36	1.10	1.26	1.32	0.20	**14.28**
p-value	0.884	0.981	0.974	0.971	1.000	**0.027**
Bispectrum Test:						
Gaussianity	-1.45	0.14	-0.84	0.16	-0.57	-0.17
p-value	0.926	0.443	0.801	0.435	0.716	0.567
Linearity	-1.43	0.63	-0.74	-1.25	-0.36	-0.55
p-value	0.923	0.266	0.769	0.894	0.641	0.710
Joint Conditional Mean Test						
Joint Test	1.45	1.17		**2.09**	0.71	
p-value	0.170	0.311		**0.034**	0.683	
Trend	0.68	0.00		0.01	1.71	
p-value	0.410	1.000		0.930	0.191	
Linearity	0.31	1.11		0.23	0.17	
p-value	0.576	0.293		0.630	0.683	
A/C	1.78	1.35		**2.74**	0.62	
p-value	0.099	0.231		**0.012**	0.714	
Joint Conditional Variance Test						
Joint Test	0.43	0.26		1.10	0.19	
p-value	0.905	0.978		0.361	0.993	
Trend	0.14	0.64		0.05	0.88	
p-value	0.710	0.425		0.831	0.349	
Static HS.	0.98	0.21		**7.33**	0.22	
p-value	0.323	0.648		**0.007**	0.642	
Dyn. HS.	0.24	0.20		0.66	0.03	
p-value	0.963	0.976		0.686	1.000	
Windowed Tests for Stability						
(wl=125, th=0.01)						
No. of Windows	20	20	6	7	20	6
% Sig.Win.	5.00%	25.00%	33.33%	14.29%	5.00%	16.67%
% Sig. C	0.00%	15.00%	16.67%	0.00%	5.00%	16.67%
% Sig. H	5.00%	10.00%	16.67%	14.29%	0.00%	16.67%

Table 7.7
Results for the Day-of-the-Week/Price-Limit/AR-GARCH-t Model

Series:	**Taiex**	**1103**	**1209**	**1908**
Mean Parameters:				
ϕ_0	0.1183	0.0989	0.0717	0.0801
t-stat.	2.44	1.15	0.81	0.80
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	**-0.1664**	-0.0963	-0.2007	-0.0785
t-stat.	**-2.40**	-0.80	-1.59	-0.55
$\phi_{Tuesday}$	-0.0921	-0.2162	-0.1474	-0.0910
t-stat.	-1.34	-1.78	-1.18	-0.65
$\phi_{Wednesday}$	-0.0105	0.0097	-0.0893	0.0471
t-stat.	-0.15	0.08	-0.70	0.33
ϕ_{Friday}	-0.0815	0.0662	0.0630	0.0290
t-stat.	-1.19	0.55	0.50	0.20
$\phi_{Saturday}$	-0.0841	-0.1282	0.0036	0.0059
t-stat.	-1.21	-1.06	0.03	0.04
Price Limit / Autocorrelation Effects				
$\phi_{PLR(2)}$	0.2414	0.1710	0.1797	0.1756
t-stat.	3.95	2.45	2.56	2.53
$\phi_{PLR(3)}$	-0.0365	-0.0358	0.0280	0.1440
t-stat.	-0.55	-0.51	0.39	2.03
$\phi_{PLR(4)}$	-0.0497	-0.0619	-0.0721	-0.0224
t-stat.	-1.17	-1.31	-1.50	-0.47
Autocorrelation Effects				
ϕ_1	0.1111	0.0388	0.1053	0.0412
t-stat.	4.38	1.19	3.12	1.27
ϕ_2				
t-stat.				
ϕ_3	0.0985	0.0815	0.0550	0.0756
t-stat.	5.44	4.05	2.69	3.72
ϕ_4	0.0406			
t-stat.	2.22			
Variance Parameters:				
ω	0.0152	0.0836	0.0527	0.1842
t-stat.	3.02	2.83	2.59	3.90
α_1	0.1011	0.1359	0.1330	0.1687
t-stat.	8.34	5.45	7.07	8.12
β_1	0.8978	0.8586	0.8703	0.8219
t-stat.	77.54	34.21	51.04	41.86
ν	18.1934	10.2682	11.3272	8.9861
t-stat.	4.91	1.65	1.81	1.16
$\alpha+\beta$	0.999	0.995	**1.003**	0.991

Table 7.7
Results for the Day-of-the-Week/Price-Limit/AR-GARCH-t Model (Cont.)

Series:	Taiex	1103	1209	1908
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3142	2579	2572	2580
Skewness	-0.191	-0.531	-0.786	-3.816
Kurtosis	0.504	5.020	7.923	74.024
S-K Test	**52.40**	**2,826.14**	**6,984.66**	**594,626.23**
p-value	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency				
Qx(6)	4.62	4.68	6.75	5.15
p-value	0.593	0.585	0.344	0.525
Qxx(6)	5.85	2.39	0.95	0.21
p-value	0.441	0.881	0.988	1.000
Bispectrum Test:				
Gaussianity	1.33	-1.36	0.11	-0.59
p-value	0.091	0.913	0.455	0.721
Linearity	**1.98**	-1.19	0.65	0.13
p-value	**0.024**	0.883	0.258	0.448
Joint Conditional Mean Test				
Joint Test	0.95	0.48	1.82	0.75
p-value	0.477	0.874	0.069	0.646
Trend	0.00	0.73	0.05	2.17
p-value	0.977	0.392	0.820	0.141
Linearity	0.75	0.89	0.17	0.04
p-value	0.386	0.346	0.682	0.840
A/C	1.14	0.39	**2.34**	0.62
p-value	0.338	0.883	**0.029**	0.716
Joint Conditional Variance Test				
Joint Test	**2.90**	0.35	0.25	0.17
p-value	**0.003**	0.946	0.981	0.994
Trend	**11.13**	0.05	0.70	1.01
p-value	**0.001**	0.829	0.403	0.316
Static HS.	**8.66**	0.33	0.39	0.12
p-value	**0.003**	0.568	0.530	0.733
Dyn. HS.	1.01	0.35	0.19	0.03
p-value	0.417	0.908	0.980	1.000
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	0.00%	5.00%	25.00%	5.00%
% Sig. C	0.00%	0.00%	15.00%	5.00%
% Sig. H	0.00%	5.00%	10.00%	0.00%

Table 7.8
GARCH-t Model Results for the Pre-Filtered Returns

Series:	Taiex	1103	1209	1908
Mean Parameters:				
ϕ_0	0.1557	-0.0088	0.1052	0.0554
t-stat.	3.13	-0.10	1.12	0.53
Day-of-the-Week Effects (significant effects are highlighted)				
ϕ_{Monday}	-0.1373	0.0116	-0.2089	-0.1108
t-stat.	-1.93	0.09	-1.57	-0.73
$\phi_{Tuesday}$	-0.1320	-0.2095	-0.1250	-0.1500
t-stat.	-1.90	-1.63	-0.95	-1.01
$\phi_{Wednesday}$	-0.0352	0.0820	-0.0935	0.0150
t-stat.	-0.50	0.64	-0.68	0.10
ϕ_{Friday}	-0.1346	0.1692	0.1139	-0.0029
t-stat.	-1.91	1.31	0.85	-0.02
$\phi_{Saturday}$	-0.1048	-0.1585	-0.0145	-0.0311
t-stat.	-1.48	-1.22	-0.11	-0.21
Autocorrelation Effects				
ϕ_1	-0.0408		-0.0722	-0.0528
t-stat.	-2.18		-3.43	-2.51
ϕ_2				
t-stat.				
ϕ_3	0.0850	0.0661	0.0690	0.0654
t-stat.	4.65	3.27	3.35	3.20
ϕ_4	0.0646			
t-stat.	3.54			
ϕ_5				
t-stat.				
ϕ_6				
t-stat.				
ϕ_7				
t-stat.				
Variance Parameters:				
ω	0.0172	0.0630	0.0661	0.2056
t-stat.	3.10	2.29	2.74	3.80
α_1	0.1059	0.0941	0.1243	0.1517
t-stat.	8.05	4.83	6.61	7.56
β_1	0.8926	0.8986	0.8744	0.8324
t-stat.	70.86	41.94	48.23	40.55
ν	19.0000	13.7552	13.6406	10.4067
t-stat.	5.20	2.67	2.41	1.41
$\alpha+\beta$	0.998	0.993	0.999	0.984

Table 7.8
GARCH-t Model Results for the Pre-Filtered Returns (Cont.)

Series:	Taiex	1103	1209	1908
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3136	2573	2566	2574
Skewness	-0.245	-0.374	-0.680	-2.824
Kurtosis	0.505	2.821	6.101	47.752
S-K Test	**64.50**	**912.05**	**4,172.57**	**247,687.35**
p-value	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency				
Qx(6)	2.86	3.70	9.32	6.21
p-value	0.827	0.718	0.157	0.400
Qxx(6)	4.54	2.02	1.11	0.28
p-value	0.604	0.918	0.981	1.000
Bispectrum Test:				
Gaussianity	**1.67**	-1.39	0.74	0.13
p-value	**0.048**	0.918	0.229	0.449
Linearity	**2.20**	-1.32	0.52	0.12
p-value	**0.014**	0.906	0.300	0.453
Joint Conditional Mean Test				
Joint Test	1.13	1.15	1.38	0.73
p-value	0.341	0.329	0.199	0.662
Trend	**4.31**	2.97	0.45	0.90
p-value	**0.038**	0.085	0.504	0.344
Linearity	0.00	0.66	0.12	0.06
p-value	0.946	0.415	0.732	0.811
A/C	0.72	0.77	1.73	0.76
p-value	0.636	0.592	0.109	0.603
Joint Conditional Variance Test				
Joint Test	1.70	0.29	0.51	0.17
p-value	0.093	0.971	0.847	0.995
Trend	**8.65**	0.19	1.60	0.78
p-value	**0.003**	0.667	0.206	0.376
Static HS.	0.32	0.06	1.92	0.16
p-value	0.572	0.804	0.166	0.689
Dyn. HS.	0.82	0.30	0.30	0.03
p-value	0.556	0.939	0.937	1.000
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	12.00%	10.00%	30.00%	10.00%
% Sig. C	8.00%	5.00%	25.00%	10.00%
% Sig. H	4.00%	10.00%	10.00%	5.00%

Table 7.9
STAR Model
Key Statistics and Test Results

Series	Autocorrelations (Lags)	Significant Misspecification Tests
Taiex	1,3,4	SK,Q_{xx},B(G,L),JV(T,S,D)
DJIA	1,6	SK,Q_{xx},B(G),JM(L,A),JV(S,D)
FT-30	1	SK,Q_{xx},B(G,L),JV(S,D)
Nikkei	1	SK,Q_x,Q_{xx},B(G,L),JM(T,L),JV(T,S,D)
HSI	1,3,5	SK,B(G,L)
STI	1,2,5,6,7	SK,Q_x,Q_{xx},B(G,L),JM(L),JV(S,D)
1103	1,3	SK,Q_{xx},B(G,L),JV(T,S)
1209	1,3	SK,Q_{xx},B(G,L),JV(T,S)
1417	n.a.	n.a.
1439	n.a.	n.a.
1441	1,2,3	SK,JV(T,D)
1706	n.a.	n.a.
1801	n.a.	n.a.
1908	1,3,5	SK,B(G,L),JV(T)
2010	1,2,3,5	SK
2101	n.a.	n.a.
2312	n.a.	n.a.
2603	n.a.	n.a.

Key: SK is the Bera-Jarque Skewness-Kurtosis Test; B(G,L) represents the Gaussianity and Linearity components, respectively, of the Bispectrum Test; JM(T,L,A) represents the Trend, Linearity, and Autocorrelation components, respectively, of the Joint Conditional Mean Test; while JV(T,S,D) stands for the Trend, Static Heteroskedasticity, and Dynamic Heteroskedasticity components of the Joint Conditional Variance Test.

Table 7.10
Results for the Student's t Autoregressive Model with Dynamic Heteroscedasticity

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Mean (Autoregressive) Parameters:						
β_0	0.0759	0.0572	0.0735	0.0605	0.1162	0.0388
t-stat.	7.57	8.34	7.10	7.22	12.21	9.03
β_1	0.1514	0.0412	0.0547	0.1226	0.1295	0.2747
t-stat.	8.97	3.16	2.66	5.79	8.13	15.26
β_2	0.0057	-0.0146			-0.0042	0.0231
t-stat.	0.34	-0.95			-0.27	2.09
β_3	0.1126	-0.0182			0.0641	0.0038
t-stat.	7.15	-1.40			4.09	0.29
β_4	0.0443	-0.0207			0.0304	-0.0159
t-stat.	2.73	-1.50			1.95	-1.59
β_5		-0.0030			-0.0365	0.0272
t-stat.		-0.18			-2.34	2.71
β_6		-0.0285				-0.0380
t-stat.		-2.24				-3.74
β_7						0.0217
t-stat.						2.29
Variance Parameters:						
n (fixed)	7	5	5	5	5	5
σ^2	1.362	0.487	0.540	0.355	0.947	0.483
t-stat.	33.73	31.75	30.57	28.41	28.38	36.71
Q_11	0.1434	0.1999	0.1986	0.1995	0.2040	0.2068
t-stat.	33.12	42.13	33.94	27.56	30.32	52.65
Q_21	-0.0220	-0.0087	-0.0101	-0.0248	-0.0252	-0.0548
t-stat.	-9.00	-4.29	-2.62	-5.17	-7.55	-26.49
Q_22	0.1470	0.1973	0.1988	0.2026	0.2082	0.2239
t-stat.	30.03	42.19	34.13	26.99	30.24	50.45
Q_31	-0.0015	0.0036			0.0022	-0.0048
t-stat.	-0.61	1.50			0.67	-2.05
Q_32	-0.0219	-0.0078			-0.0235	-0.0542
t-stat.	-8.81	-3.88			-7.00	-25.46
Q_33	0.1453	0.1968			0.2090	0.2229
t-stat.	29.41	42.37			30.31	49.98
Q_41	-0.0172	0.0037			-0.0119	0.0003
t-stat.	-7.06	1.62			-3.69	0.09
Q_42	0.0017	0.0032			0.0054	-0.0033
t-stat.	0.69	1.41			1.67	-1.16
Q_43	-0.0203	-0.0063			-0.0221	-0.0532
t-stat.	-8.09	-3.32			-6.64	-25.47
Q_44	0.1460	0.1956			0.2050	0.2226
t-stat.	29.75	42.51			30.14	50.21

Table 7.10
Results for the STAR Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Variance Parameters (cont.):						
Q_51	-0.0064	0.0043			-0.0061	0.0030
t-stat.	-2.55	2.16			-1.85	1.02
Q_52	-0.0165	0.0044			-0.0112	0.0003
t-stat.	-6.70	1.99			-3.38	0.11
Q_53	-0.0003	0.0041			0.0062	-0.0021
t-stat.	-0.14	1.96			1.85	-0.78
Q_54	-0.0183	-0.0055			-0.0200	-0.0523
t-stat.	-7.42	-2.96			-6.27	-25.66
Q_55	0.1439	0.1954			0.2024	0.2206
t-stat.	31.07	42.33			30.13	50.21
Q_61		0.0002			0.0078	-0.0053
t-stat.		0.09			2.31	-1.71
Q_62		0.0044			-0.0055	0.0045
t-stat.		2.26			-1.69	1.46
Q_63		0.0041			-0.0120	-0.0009
t-stat.		1.91			-3.74	-0.30
Q_64		0.0038			0.0053	-0.0009
t-stat.		1.87			1.69	-0.36
Q_65		-0.0053			-0.0172	-0.0517
t-stat.		-2.89			-5.52	-25.28
Q_66		0.1971			0.1975	0.2189
t-stat.		42.33			29.97	50.07
Q_71		0.0055				0.0081
t-stat.		2.28				2.07
Q_72		0.0008				-0.0072
t-stat.		0.41				-2.39
Q_73		0.0038				0.0054
t-stat.		2.01				1.96
Q_74		0.0042				-0.0002
t-stat.		1.97				-0.06
Q_75		0.0032				-0.0007
t-stat.		1.59				-0.30
Q_76		-0.0043				-0.0504
t-stat.		-2.40				-25.02
Q_77		0.1967				0.2151
t-stat.		42.15				50.43

Table 7.10
Results for the STAR Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Variance Parameters (cont.):						
Q_81						-0.0043
t-stat.						-1.33
Q_82						0.0084
t-stat.						2.45
Q_83						-0.0045
t-stat.						-1.75
Q_84						0.0029
t-stat.						1.26
Q_85						0.0001
t-stat.						0.06
Q_86						-0.0002
t-stat.						-0.10
Q_87						-0.0469
t-stat.						-24.58
Q_88						0.1971
t-stat.						51.58

Table 7.10
Results for the STAR Model (Cont.)

Index:	Taiex	DJIA	FT-30	Nikkei	HSI	STI
Misspecification Tests: (significant results are highlighted)						
No. of Obs.	3142	2809	2799	2991	2750	2755
Skewness	-0.215	-1.864	-0.398	-0.689	-0.470	-0.560
Kurtosis	1.702	32.489	3.638	19.773	7.577	11.444
S-K Test	**402.83**	**124,857.41**	**1,615.91**	**48,927.77**	**6,665.63**	**15,132.40**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency						
Qx(6)	6.39	12.28	9.24	**13.93**	5.95	**13.10**
p-value	0.381	0.056	0.161	**0.030**	0.429	**0.041**
Qxx(6)	**248.73**	**55.73**	**251.76**	**302.54**	2.52	**656.97**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	0.867	**0.000**
Bispectrum Test:						
Gaussianity	**15.68**	**4.13**	**3.13**	**21.22**	**5.22**	**4.55**
p-value	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**
Linearity	**13.26**	1.57	**3.39**	**19.02**	**3.95**	**3.81**
p-value	**0.000**	0.059	**0.000**	**0.000**	**0.000**	**0.000**
Joint Conditional Mean Test						
Joint Test	0.98	**2.36**	1.62	**7.82**	1.15	**3.68**
p-value	0.453	**0.016**	0.113	**0.000**	0.283	**0.000**
Trend	0.00	0.18	0.68	**10.61**	1.20	0.00
p-value	0.991	0.676	0.411	**0.001**	0.274	0.987
Linearity	**5.02**	**5.05**	**4.59**	**42.89**	1.29	**24.62**
p-value	**0.025**	**0.025**	**0.032**	**0.000**	0.201	**0.000**
A/C	0.40	**2.33**	1.20	2.03	0.93	0.85
p-value	0.879	**0.030**	0.301	0.059	0.474	0.530
Joint Conditional Variance Test						
Joint Test	**31.06**	**10.00**	**34.36**	**38.41**	1.71	**125.22**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	0.091	**0.000**
Trend	**59.05**	0.02	0.55	**9.03**	2.39	0.37
p-value	**0.000**	0.882	0.457	**0.003**	0.122	0.541
Static HS.	**8.33**	**30.97**	**62.60**	**7.31**	**8.78**	**290.24**
p-value	**0.004**	**0.000**	**0.000**	**0.007**	**0.003**	**0.000**
Dyn. HS.	**9.86**	**12.49**	**12.31**	**16.19**	0.30	**4.95**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	0.938	**0.000**
Windowed Tests for Stability (wl=125, th=0.01)						
No. of Windows	25	22	22	23	22	22
% Sig.Win.	24.00%	4.55%	9.09%	21.74%	0.00%	4.55%
% Sig. C	16.00%	0.00%	0.00%	4.35%	0.00%	0.00%
% Sig. H	12.00%	4.55%	9.09%	21.74%	0.00%	4.55%

Table 7.10
Results for the STAR Model (Cont.)

Stock:	1103	1209	1441	1908	2010
Mean (Autoregressive) Parameters:					
β_0	0.0547	0.0523	-0.0586	0.0555	-0.0610
t-stat.	3.38	3.07	-6.21	4.21	-2.06
β_1	0.0623	0.1616	0.1067	0.1158	0.1070
t-stat.	3.96	11.63	4.93	10.67	3.69
β_2	-0.0224	0.0203	0.0659	0.0153	0.0640
t-stat.	-1.21	1.04	2.69	1.03	2.92
β_3	0.0891	0.0775	0.1271	0.0941	0.0680
t-stat.	6.27	4.61	5.29	8.13	3.83
β_4				0.0164	-0.0039
t-stat.				0.97	-0.20
β_5				0.0342	-0.0587
t-stat.				3.01	-2.22
Variance Parameters:					
n (fixed)	10	6	19	5	13
σ^2	3.725	3.633	9.910	3.487	7.324
t-stat.	32.77	28.32	24.91	32.04	22.18
Q_11	0.1006	0.1679	0.0529	0.2016	0.0768
t-stat.	33.13	28.42	24.05	27.39	21.31
Q_21	-0.0057	-0.0270	-0.0060	-0.0212	-0.0079
t-stat.	-2.75	-7.59	-4.28	-5.44	-3.59
Q_22	0.1012	0.1721	0.0528	0.2054	0.0784
t-stat.	28.39	28.02	24.26	28.93	21.38
Q_31	0.0022	-0.0040	-0.0035	-0.0032	-0.0050
t-stat.	1.04	-1.08	-2.52	-0.83	-2.24
Q_32	-0.0054	-0.0236	-0.0060	-0.0187	-0.0078
t-stat.	-2.59	-6.51	-4.35	-4.77	-3.40
Q_33	0.1004	0.1704	0.0526	0.2048	0.0783
t-stat.	28.39	27.80	21.92	28.70	20.66
Q_41	-0.0093	-0.0126	-0.0071	-0.0196	-0.0059
t-stat.	-4.35	-3.50	-5.21	-5.00	-2.69
Q_42	0.0030	-0.0039	-0.0032	-0.0009	-0.0035
t-stat.	1.41	-1.07	-2.35	-0.23	-1.57
Q_43	-0.0048	-0.0226	-0.0058	-0.0182	-0.0079
t-stat.	-2.31	-6.22	-4.03	-4.63	-3.42
Q_44	0.1007	0.1670	0.0528	0.2045	0.0783
t-stat.	30.30	27.40	21.72	27.07	21.36

Table 7.10
Results for the STAR Model (Cont.)

Stock:	1103	1209	1441	1908	2010
Variance Parameters (cont.):					
Q_51				-0.0035	0.0005
t-stat.				-0.89	0.22
Q_52				-0.0186	-0.0057
t-stat.				-4.71	-2.54
Q_53				0.0004	-0.0028
t-stat.				0.10	-1.22
Q_54				-0.0167	-0.0076
t-stat.				-4.26	-3.33
Q_55				0.2030	0.0774
t-stat.				26.36	21.50
Q_61				-0.0076	0.0042
t-stat.				-1.96	1.86
Q_62				-0.0030	0.0007
t-stat.				-0.78	0.29
Q_63				-0.0181	-0.0057
t-stat.				-4.59	-2.55
Q_64				0.0014	-0.0034
t-stat.				0.36	-1.50
Q_65				-0.0149	-0.0084
t-stat.				-3.81	-3.64
Q_66				0.1988	0.0762
t-stat.				27.90	21.55

Table 7.10
Results for the STAR Model (Cont.)

Stock:	1103	1209	1441	1908	2010
Misspecification Tests:					
(significant results are highlighted)					
No. of Obs.	2579	2572	900	2580	856
Skewness	-0.163	-0.081	-0.048	-0.557	-0.078
Kurtosis	1.295	2.221	0.807	5.956	0.940
S-K Test	**191.45**	**530.74**	**24.66**	**3,937.17**	**32.14**
p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency					
Qx(6)	1.54	11.05	7.20	9.25	4.51
p-value	0.957	0.087	0.303	0.160	0.608
Qxx(6)	**21.37**	**42.82**	10.25	6.69	6.42
p-value	**0.002**	**0.000**	0.115	0.350	0.378
Bispectrum Test:					
Gaussianity	**4.39**	**6.77**	1.25	**3.63**	1.14
p-value	**0.000**	**0.000**	0.105	**0.000**	0.127
Linearity	**5.25**	**5.00**	0.20	**3.40**	-0.05
p-value	**0.000**	**0.000**	0.421	**0.000**	0.520
Joint Conditional Mean Test					
Joint Test	0.71	1.63	1.11	1.19	0.57
p-value	0.681	0.112	0.356	0.303	0.800
Trend	0.49	0.09	0.13	0.98	0.71
p-value	0.486	0.764	0.716	0.323	0.398
Linearity	1.54	0.03	0.01	0.16	0.15
p-value	0.215	0.871	0.916	0.691	0.696
A/C	0.67	**2.15**	1.44	1.39	0.65
p-value	0.678	**0.045**	0.196	0.213	0.694
Joint Conditional Variance Test					
Joint Test	**12.49**	**14.47**	**2.42**	**2.10**	1.83
p-value	**0.000**	**0.000**	**0.014**	**0.032**	0.069
Trend	**51.40**	**70.47**	**6.42**	**10.43**	0.06
p-value	**0.000**	**0.000**	**0.011**	**0.001**	0.802
Static HS.	**21.01**	**6.16**	0.05	0.01	**7.66**
p-value	**0.000**	**0.013**	0.831	0.937	**0.006**
Dyn. HS.	0.65	0.75	**2.53**	0.93	1.25
p-value	0.691	0.610	**0.020**	0.469	0.280
Windowed Tests for Stability					
(wl=125, th=0.01)					
No. of Windows	20	20	7	20	6
% Sig.Win.	10.00%	15.00%	0.00%	5.00%	0.00%
% Sig. C	5.00%	5.00%	0.00%	0.00%	0.00%
% Sig. H	10.00%	10.00%	0.00%	5.00%	0.00%

Table 7.11
STAR Models Results for the Pre-Filtered Returns

Series:	Taiex	1103	1209	1908
Mean (Autoregressive) Parameters:				
β_0	0.0762	-0.0183	0.0657	0.0114
t-stat.	8.06	-1.16	5.57	0.81
β_1	-0.0080	0.0068	-0.0235	-0.0079
t-stat.	-0.49	0.71	-1.91	-0.52
β_2	0.0093	-0.0127	0.0117	0.0106
t-stat.	0.67	-0.70	0.68	0.75
β_3	0.0976	0.0763	0.0835	0.0863
t-stat.	6.66	6.86	7.00	7.90
β_4	0.0624		0.0200	0.0213
t-stat.	3.87		1.68	1.32
β_5			0.0105	0.0356
t-stat.			0.76	2.47
β_6			0.0342	
t-stat.			2.22	
Variance Parameters:				
n (fixed)	7	10	6	5
σ^2	1.401	3.916	3.574	3.758
t-stat.	33.11	35.39	35.85	33.59
Q_11	0.1435	0.1006	0.1674	0.2011
t-stat.	30.40	36.58	31.14	29.57
Q_21	0.0010	-0.0002	0.0043	0.0038
t-stat.	0.43	-0.09	1.44	1.03
Q_22	0.1432	0.1006	0.1677	0.2030
t-stat.	30.53	35.02	30.45	28.82
Q_31	-0.0021	0.0012	-0.0008	-0.0022
t-stat.	-0.93	0.62	-0.26	-0.60
Q_32	0.0011	0.0003	0.0066	0.0061
t-stat.	0.47	0.19	2.19	1.65
Q_33	0.1421	0.1001	0.1680	0.2034
t-stat.	29.63	31.75	31.32	32.23
Q_41	-0.0153	-0.0081	-0.0132	-0.0179
t-stat.	-6.54	-4.36	-4.41	-4.87
Q_42	-0.0015	0.0020	-0.0005	-0.0019
t-stat.	-0.66	1.09	-0.17	-0.52
Q_43	0.0027	0.0009	0.0065	0.0064
t-stat.	1.15	0.46	2.13	1.73
Q_44	0.1434	0.1004	0.1691	0.2023
t-stat.	30.46	30.21	30.89	31.35

Table 7.11
STAR Models Results for the Pre-Filtered Returns (Cont.)

Series:	Taiex	1103	1209	1908
Variance Parameters (cont.):				
Q_51	-0.0085		-0.0031	-0.0047
t-stat.	-3.63		-1.02	-1.30
Q_52	-0.0141		-0.0130	-0.0175
t-stat.	-6.04		-4.30	-4.75
Q_53	-0.0005		-0.0011	-0.0002
t-stat.	-0.23		-0.36	-0.04
Q_54	0.0045		0.0068	0.0079
t-stat.	1.95		2.25	2.13
Q_55	0.1434		0.1678	0.2009
t-stat.	31.23		29.10	31.93
Q_61			-0.0013	-0.0077
t-stat.			-0.45	-2.10
Q_62			-0.0023	-0.0039
t-stat.			-0.76	-1.05
Q_63			-0.0133	-0.0165
t-stat.			-4.40	-4.48
Q_64			-0.0006	0.0029
t-stat.			-0.20	0.80
Q_65			0.0077	0.0092
t-stat.			2.54	2.51
Q_66			0.1679	0.1975
t-stat.			30.44	34.36
Q_71			-0.0046	
t-stat.			-1.54	
Q_72			-0.0021	
t-stat.			-0.71	
Q_73			-0.0016	
t-stat.			-0.53	
Q_74			-0.0130	
t-stat.			-4.31	
Q_75			-0.0001	
t-stat.			-0.03	
Q_76			0.0073	
t-stat.			2.42	
Q_77			0.1664	
t-stat.			29.33	

Table 7.11
STAR Models Results for the Pre-Filtered Returns (Cont.)

Series:	Taiex	1103	1209	1908
Misspecification Tests:				
(significant results are highlighted)				
No. of Obs.	3142	2579	2572	2580
Skewness	-0.150	0.020	-0.047	-0.353
Kurtosis	4.263	3.886	4.957	9.299
S-K Test	**219.80**	**84.13**	**409.16**	**4,299.52**
p-value	**0.000**	**0.000**	**0.000**	**0.000**
Tests for Serial Dependency				
Qx(6)	4.77	4.74	**14.13**	4.40
p-value	0.573	0.578	**0.028**	0.623
Qxx(6)	**210.85**	**16.17**	**47.04**	5.26
p-value	**0.000**	**0.013**	**0.000**	0.511
Bispectrum Test:				
Gaussianity	**15.28**	**4.01**	**5.16**	**4.05**
p-value	**0.000**	**0.000**	**0.000**	**0.000**
Linearity	**16.17**	**3.53**	**3.68**	**2.69**
p-value	**0.000**	**0.000**	**0.000**	**0.004**
Joint Conditional Mean Test				
Joint Test	0.99	0.87	1.30	1.26
p-value	0.445	0.544	0.238	0.259
Trend	3.45	3.08	0.03	1.50
p-value	0.063	0.080	0.873	0.220
Linearity	0.07	1.02	0.14	0.35
p-value	0.792	0.313	0.709	0.553
A/C	0.60	0.54	1.71	1.35
p-value	0.730	0.775	0.115	0.231
Joint Conditional Variance Test				
Joint Test	**40.00**	**8.57**	**13.60**	**2.28**
p-value	**0.000**	**0.000**	**0.000**	**0.020**
Trend	**62.86**	**38.63**	**57.90**	**5.46**
p-value	**0.000**	**0.000**	**0.000**	**0.020**
Static HS.	**87.09**	**9.41**	**4.16**	**6.89**
p-value	**0.000**	**0.002**	**0.041**	**0.009**
Dyn. HS.	**3.63**	0.57	**3.27**	0.54
p-value	**0.001**	0.752	**0.003**	0.777
Windowed Tests for Stability				
(wl=125, th=0.01)				
No. of Windows	25	20	20	20
% Sig.Win.	12.00%	5.00%	20.00%	5.00%
% Sig. C	4.00%	5.00%	5.00%	0.00%
% Sig. H	12.00%	0.00%	15.00%	5.00%

Table 7.12
Significant Day-of-the-Week Effects by Model Specification

Series	Linear	GARCH	GARCH-t	STAR
Taiex	-	-M	-M	n.a.
DJIA	-	-	-	n.a.
FT-30	-M,+F	-M,+F	-M,+F	n.a.
Nikkei	-M,-T	+W,+S	(-T),+W,+S	n.a.
HSI	-M	-M	-M	n.a.
STI	-M,(-T)	-M,+F	-M,(+W)	n.a.
1103	-	(+F)	(-T)	n.a.
1209	-	(-M)	(-M)	n.a.
1417	-	(+S)	(+S)	n.a.
1439	-	-	n.a.	n.a.
1441	-	-M,(+S)	(-M),+S	n.a.
1706	-W	-	n.a.	n.a.
1801	+S	+S	n.a.	n.a.
1908	-	+S	-	n.a.
2010	-	-M	-	n.a.
2101	-	(-M)	n.a.	n.a.
2312	-	-	n.a.	n.a.
2603	-	-	n.a.	n.a.

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 7.13
Significant Autocorrelation Effects by Model Specification

Series	Linear	GARCH	GARCH-t	STAR
Taiex	1,3	1,3,4	1,3,4	1,3,4
DJIA	2,4,5	4	-	1,6
FT-30	1,4	1	1	1
Nikkei	1,2,6	1	1	1
HSI	3	1,3,5	1,3,5	1,3,5
STI	1,2	1,6,7	1,6	1,2,5,6,7
1103	1,2,3	1,3	3	1,3
1209	1,3	1,3,4,6	1,3	1,3
1417	1,3	-	-	n.a.
1439	1,3	1	n.a.	n.a.
1441	1,2,3	1,3	3	1,2,3
1706	1,3	1,3	n.a.	n.a.
1801	1,3	1,3	n.a.	n.a.
1908	1,3	1,3	1,3	1,3,5
2010	1,2,3,5	1	-	1,2,3,5
2101	1,2,3,4,5	1,3,4,6	n.a.	n.a.
2312	1,3,5	1,3,5	n.a.	n.a.
2603	1,3	1,3	n.a.	n.a.

Table 7.14
Significant Misspecification Tests by Model Specification

Series	GARCH	GARCH-t	STAR
Taiex	SK,JV(T)	SK	SK,Q_{xx},B(G,L),JV(T,S,D)
DJIA	SK	SK	SK,Q_{xx},B(G),JM(L,A), JV(S,D)
FT-30	SK,JM(L)	SK,Q_{xx},JM(L,A),JV(D)	SK,Q_{xx},B(G,L),JV(S,D)
Nikkei	SK,JV(T,S,D)	SK,B(G,L),JM(L),JV(T,S,D)	SK,Q_x,Q_{xx},B(G,L),JM(T,L), JV(T,S,D)
HSI	SK,Q_{xx},B(G,L), JM(L,A),JV(S,D)	SK,Q_{xx},B(G,L),JM(A),JV(S,D)	SK,B(G,L)
STI	SK,Q_x,B(G),JM(A)	SK,B(G),JM(A)	SK,Q_x,Q_{xx},B(G,L),JM(L), JV(S,D)
1103	SK	SK	SK,Q_{xx},B(G,L),JV(T,S)
1209	SK	SK	SK,Q_{xx},B(G,L),JV(T,S)
1417	SK	SK	n.a.
1439	SK,JV(T,D)	n.a.	n.a.
1441	SK	SK,JM(A)	SK,JV(T,D)
1706	SK,Q_{xx},JV(D)	n.a.	n.a.
1801	Q_{xx},JV(T,D)	n.a.	n.a.
1908	SK,B(G,L)	SK	SK,B(G,L),JV(T)
2010	SK,Q_{xx},JV(D)	SK,Q_{xx}	SK
2101	SK,Q_{xx},JM(L,A), JV(T,D)	n.a.	n.a.
2312	-	n.a.	n.a.
2603	-	n.a.	n.a.

Key: SK is the Bera-Jarque Skewness-Kurtosis Test; B(G,L) represents the Gaussianity and Linearity components, respectively, of the Bispectrum Test; JM(T,L,A) represents the Trend, Linearity, and Autocorrelation components, respectively, of the Joint Conditional Mean Test; while JV(T,S,D) stands for the Trend, Static Heteroskedasticity, and Dynamic Heteroskedasticity components of the Joint Conditional Variance Test.