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Modeling Nonlinear Dynamics in NASDAQ Stock Returns.

Salil Kumar Sarkar
Louisiana State University and Agricultural & Mechanical College

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Sarkar, Salil Kumar, Ph.D.

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U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

MODELING NONLINEAR DYNAMICS IN NASDAQ STOCK RETURNS

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by
Salil Kumar Sarkar
B.S., Electrical Engineering, IIT, Kanpur, India, 1977
MBA, Northeast Louisiana University, 1987
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This dissertation is dedicated to my parents, sister, brother and Ruma.

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TABLE OF CONTENTS

LIST OF TABLES

ABSTRACT

This dissertation investigates the nonlinear dynamics of the returns generation process of individual stocks listed on national market system from national association of security dealers automated quotation system (NASDAQ/NMS) and compares them to a similar sample from New York Stock Exchange (NYSE). One of the most prominent tools that has emerged for characterizing nonlinear processes is the Autoregressive Conditional Heteroscedasticity (ARCH) model, and its various extensions, the most significant being the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. From the stocks listed on the Center for Research in Security Prices (CRSP) tapes, a group of NASDAQ/NMS and NYSE stocks are chosen for the analysis. Weekly data for the years 1982 to 1988 are used for this study. Various forms of existing GARCH models are applied on the same data set with conditional error distributions of normal, Student-t, power exponential and mixed jump-diffusion process. Although attempts at exploring the relative merits of the models have been made on the foreign exchange market, no such study exists for individual stock returns. The performance of each model is evaluated by several diagnostics on the respective error distributions and evaluation of log likelihood values.

In a simulation study on non-nested testing GARCH-PE is found to be more flexible as compared to GARCH-T. Only 36% stocks of the given sample from each market can be modeled using GARCH. However, on forming portfolios, three out of four can be modeled using GARCH.

CHAPTER 1

INTRODUCTION

The distribution of speculative price changes has intrigued researchers for several decades. Knowledge about probabilistic properties of stock returns not only helps in understanding the returns processes themselves, but also validates or invalidates several other theories, such as mean-variance portfolio theory of Markowitz (1959) and the Capital Asset Pricing Model of Sharpe (1964), Mossin (1966), and Lintner (1965). An important assumption in all these theories is that stock price changes have a normal distribution. Though the initial study on the subject dates back to the turn of the century, it has picked up momentum only in the past three decades. Like most sciences, the literature shows an evolutionary pattern, as past knowledge is used to design more sophisticated models.

The initial assumption of stock price changes being independent, identically distributed random variables, has evolved showing evidence that the stock price changes are neither independent nor identically distributed. Most of the linear models have failed and current research reports the existence of nonlinear dependence. Moreover, dynamic or time varying parameters are found to perform better than the traditional linear time series models. Earlier documentation of time dependent variance has led to the class of

autoregressive conditional heteroscedasticity (ARCH) models. Both ARCH and the generalized autoregressive conditional heteroscedasticity (GARCH) models have been used on foreign exchange data or on stock indices. Moreover, in these models the choice of the conditional distribution of the innovations process has given extensive flexibility to the unconditional distribution.

The purpose of this dissertation is to study the nonlinear dynamics of individual stocks listed on the national market system (NMS) in the national association of securities dealers automated quotation (NASDAQ) system. Thus, the most actively traded stocks listed on the NASDAQ are used for the study. Subsequently, the stocks are put together as portfolios of different sizes and their nonlinear dynamics studied. A GARCH model is characterized by a combination of variance equation and conditional distribution. Linear GARCH models with conditional distributions such as, normal, Student-t, power exponential, and mixture of jump-diffusion processes are applied to the same set of weekly returns from selected NMS stocks, as well as a similar set of NYSE stocks for comparison.

The relative explanatory power of these models are studied by diagnostic tests on their standardized error distributions. The robustness of three additional tests used for testing non-nested models, Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Kullback-

Leibler Information Criterion (KLIC) are investigated by conducting a simulation study. The results from this simulation are subsequently used to pick the best GARCH model. Apart from the knowledge of the marginal density, and the respective GARCH parameters, this dissertation also studies a particular combination of the parameters called persistence of variance, or the half life of the process. It is already documented that individual stocks as well as stock indices show considerable persistence. Hence, this dissertation tries to understand the effect of diversification on persistence. While Chapter 2 gives a review of related literature, Chapter 3 contains a description of the data, their basic statistics and preliminary analysis. The model estimation on basic stocks along with simulation study for non-nested testing are given in Chapter 4, Chapter 5 covers the estimation results and Chapter 6 gives the conclusions and suggestions for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter covers the extant literature on time series analysis as applied to stock return data. The first half covers the theory of time series analysis and the differences between linear and nonlinear models. Subsequently, the theory is applied to stock returns and both linear as well as nonlinear models of stock returns are studied.

THEORY OF TIME SERIES ANALYSIS

To study the theory of time series analysis, it is useful to define and understand some terms, such as "white noise" and "strict white noise" used in this literature.

Let the stochastic process $\{x_t\}$, have a mean m, and covariance c_s given by $m = E[x_t]$, and $c_s = E[x_{t+s}x_t] - m^2$ respectively. The process is said to be second order or weakly stationary if m and c_s do not depend on time t. If $c_s = 0$ for all positive s and $c_0 < \infty$, then the process is called "white noise". Thus the process is "white noise" if x_{t+s} and x_t are uncorrelated over time. However, it is important to realize that whiteness implies second order independence and not statistical independence between the terms of the series, unless the process is Gaussian and consequently, completely described by the first two moments. A zero autocorrelation does not necessarily mean that the probability distribution of

x_{t+s} is independent of x_t, even if $\{x_t\}$ has identical unconditional distribution. If x_{t+s} and x_t are statistically independent, then the process is called "strict white noise". The distribution of $\{x_t^2\}$ is extremely useful in diagnostics of strict white noise. If the process $\{x_t\}$ is strict white noise then $\{x_t^2\}$ is also strict white noise.

LINEAR MODELS

The principal objective of all forms of time series models is to understand the distributional properties of a sequence of observations generated over time. The unit of time may vary depending upon the system under study. It may be a year, in case of sunspots, a week or day for stock returns, or a fraction of a second in case of radio waves. Thus if the series $\{ X_t \; ; \; t = 0, \pm 1, \pm 2, \ldots \}$ is the observation in discrete time, say weekly stock returns, the function can be stated as the identification of the function h, such that,

$$h(\ldots, X_{t-2}, X_{t-1}, X_t, X_{t+1}, X_{t+2}, \ldots) = \epsilon_t, \tag{2.1}$$

where ϵ_t is a zero mean, constant variance 'white noise', i.e.

$E\{ \epsilon_t \} = 0$,

$E\{ \epsilon_t \epsilon_s \} = 0$ for all s not equal to t, and

$E\{ \epsilon_t^2 \} = \sigma^2$.

In practice, X_t depends on past values only, thereby modifying the function to

$$(2.2) \qquad h(X_t, X_{t-1}, X_{t-2}, \ldots) = \epsilon_t.$$

Under the assumption that X_t can be expressed implicitly in terms of ϵ_t, ϵ_{t-1}, ϵ_{t-2}, .. , the function becomes

$$(2.3) \qquad X_t = f(\epsilon_t, \epsilon_{t-1}, \epsilon_{t-2}, \ldots).$$

Further, expanding f about the vector $\mathbf{0}$ = (0, 0, ..), gives the equation

$$(2.4) \qquad X_t = \sum_{u=0}^{\infty} g_u \epsilon_{t-u} + \sum_{u=0}^{\infty}\sum_{v=0}^{\infty} g_{uv}\epsilon_{t-u}\epsilon_{t-v} + \sum_{u=0}^{\infty}\sum_{v=0}^{\infty}\sum_{w=0}^{\infty} g_{uvw}\epsilon_{t-u}\epsilon_{t-v}\epsilon_{t-w} + \ldots\ldots + ,$$

where $f(0) = 0$, and

$$\left[g_u = \frac{\partial f}{\partial \epsilon_{t-u}}\right]_0 .$$

This expansion is called a Volterra series and was used by Wiener (1958) while considering a nonlinear physical system. If higher order derivatives g_{uv}, g_{uvw}, ... , = 0, the model simplifies to

(2.5) $$X_t = \sum_{u=0}^{\infty} g_u \epsilon_{t-u}$$

This is the traditional definition of the "linear model". However, in this model complete probabilistic properties of X_t are based upon the assumptions of the first two moments of ϵ_t. Thus, in statistical terms, properties of $\{X_t\}$ are not clear if $\{\epsilon_t\}$ is non-Gaussian.

NONLINEAR MODELS

Suppose the process η_t, is defined by

(2.6) $$\eta_t = e_t + \beta e_{t-1} e_{t-2},$$

where $\{e_t\}$ is strict white noise, i.e. $E(e_t) = 0$, $E(e_t^2) = \sigma^2$, $E(e_t e_s) = 0$ for all t not equal to s, and $\{e_t\}$ is statistically independent. The parameter ß can take on any non-zero value.

The moments of η_t are $E(\eta_t) = 0$, $E(\eta_t \eta_{t-1}) = 0$, and $E(\eta_t^2) = \sigma^2$, and thus fit the innovations process of any linear process. However, the process may have finite higher moments, e.g., $E(\eta_t \eta_{t-1} \eta_{t-2}) = \beta\sigma^4$. As explained by Priestley (1981), if a process η_t is obtained as the residual from a more general model, all conventional "linear models" would fail to detect the existence of higher moments in the residuals. Hence, the higher order terms of the Volterra series could be used to

devise nonlinear models to improve the predictors of the original series.

The problem with the general form of Volterra series is that it is impossible to estimate efficiently an infinite set of parameters from a finite set of observations. There are two approaches to solve the problem. Either assume that the Fourier transforms of the sequence $\{g_u\}$, $\{g_{uv}\}$, ... possess certain smoothness properties or that each of these transforms have known functional form with finite number of parameters.

The second approach is used in one of the most prominent tools that has emerged for characterizing nonlinear models -- the autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982). This model has been generalized to GARCH by Bollerslev (1986). A GARCH model is characterized by a conditional distribution. Additional flexibility is achieved by conditional distributions such as normal, Student-t, power exponential and mixed jump-diffusion process. Normal distribution has been extensively used to study the nonlinear dynamics of asset prices.

Types of Nonlinearities

A nonlinear process may be further analyzed by differentiating between the two major types of nonlinearities -- additive or multiplicative nonlinearity. The Hsieh (1989b) test is used for differentiating between additive and multiplicative nonlinearity.

Let $\{u_t\}$ be white noise but not strict white noise. If the given series has both linear and nonlinear dependence with its own lags, the linear dependence can be filtered by regressing it on the significant lags and taking the errors as $\{u_t\}$. Two types of nonlinear dependence in $\{u_t\}$ can be distinguished as follows:

Additive dependence:

$$(2.7) \qquad u_t=v_t+f(X_{t-1},\ldots,X_{t-k},u_{t-1},\ldots,u_{t-k})$$

Multiplicative dependence:

$$(2.8) \qquad u_t=v_t f(X_{t-1},\ldots,X_{t-k},u_{t-1},\ldots,u_{t-k})$$

where f(.) is any arbitrary nonlinear function of $x_{t-1},\ldots,x_{t-k}$ and $u_{t-1},\ldots,u_{t-k}$ for some finite k and $\{v_t\}$ is iid random variables with zero mean independent of $\{x_t\}$ and $\{u_t\}$.

Additive dependence implies that the nonlinearity occurs through the mean of the process. Similarly, multiplicative dependence implies that the nonlinearity occurs through the variance of the process. A GARCH process is used to model multiplicative nonlinearity. The statistical dependence in $\{u_t^2\}$ persists in case of additive as well as multiplicative nonlinearity. Consequently, $\{u_t^2\}$ is correlated with its own lags under either situation of additive or multiplicative nonlinearity. The discrimination between additive and

multiplicative nonlinearity is done using the expectation operator on u_t. Multiplicative dependence implies that

$$E[u_t | X_{t-1}, \ldots, X_{t-k}, u_{t-1}, \ldots, u_{t-k}] = 0 \tag{2.9}$$

and additive dependence implies that

$$E[u_t | X_{t-1}, \ldots, X_{t-k}, u_{t-1}, \ldots, u_{t-k}] \neq 0 \tag{2.10}$$

Under the null hypothesis of multiplicative nonlinearity the test is implemented by estimating the third order moment ρ_{uuu} (i,j) for some i,j > 0 by

$$r_{uuu}(i,j) = \frac{\left[\frac{1}{T}\sum u_t u_{t-i} u_{t-j}\right]}{\left[\frac{1}{T}\sum u_t^2\right]^{1.5}}. \tag{2.11}$$

As shown in Hsieh (1989b), $\sqrt{T}\ [\ (1/T)\ \Sigma\ u_t\ u_{t-i}\ u_{t-j}\ ]$ is asymptotically normally distributed, with zero mean. The variance of this asymptotic distribution can be consistently estimated by

$$\sigma_r^2 = \frac{\left[\frac{1}{T}\sum u_t^2 u_{t-i}^2 u_{t-j}^2\right]}{\left[\frac{1}{T}\sum u_t^2\right]^3}. \tag{2.12}$$

Therefore, the asymptotic property of $\sqrt{T}\ [\ (1/T)\ \Sigma\ u_t\ u_{t-i}\ u_{t-j}\ ]$ is used to discriminate between additive and multiplicative nonlinearity. It gives an a priori indication

of the applicability of GARCH to the given time series as GARCH is not suitable for modeling additive nonlinearity and such models are beyond the scope of this dissertation.

MODELS OF STOCK RETURNS

The linear and nonlinear models of stock returns are summarized in table 2.1 and discussed in the following sections. This topic has been extensively researched in the past few decades. The table is not an exhaustive but a representative list of the relevant papers on the subject.

LINEAR MODELS

The earliest theories of Bachelier (1900) and Osborne (1959) assume the price of an asset to be the summation of all available information, which is assumed to be independently and identically distributed. Since the stock market is a conglomeration of individual buyers and sellers, the exchange price fully reflects the equilibrium evaluation of all available information. Any deviation from the equilibrium is arbitraged away by the market. In such a market system, arrival of new information causes a price change. The price of a stock may reflect information about the firm, industry, or the economy as a whole. Consequently, a shift in price may be caused by information that may or may not be firm specific. Moreover, the same information may be interpreted differently by the market participants. Thus there is no a priori reason

to believe that the price changes will not be temporally independent and identically distributed.

Several security valuation models are developed based upon this specific distributional assumption of stock returns. Moreover, any empirical test of the model is either a joint hypothesis of the model and the distribution, or is conditional upon the assumption of normality. Therefore, understanding the properties of the underlying distribution is crucial to the validity of these theoretical and empirical results.

This theoretical model of Bachelier (1900) and Osborne (1959), which became a major building block for most of the subsequent valuation models, did not receive much support at either theoretical or empirical front. Samuelson (1973) points out that the Bachelier process has several major economic flaws. For example, according to this process, there is a positive probability for the stock price to be negative, which is economically impossible due to the limited liability of the stockholders. Similarly, there is a positive probability that an option may be worth more than the underlying asset. Consequently, earlier assumption of arithmetic Brownian motion is replaced by geometric Brownian motion to circumvent these problems. This implies that the logarithm of price relatives follow a normal process rather than the individual price changes.

At the empirical front, contrary to being Gaussian, actual distributions of price changes are found to be significantly peaked with fat tails, a phenomenon called leptokurtosis. A satisfactory model for stock returns must have a probability distribution similar to the observed distribution. The outliers are numerous, and excluding them takes away much of the significance from any tests carried out on the remainder of the data. Mandelbrot (1963) and Fama (1965a) put forward a hypothesis that realized security returns follow a symmetric stable Paretian distribution. These types of distributions can have finite, as well as, infinite variance.

One of the parameters of this symmetric distribution is the characteristic exponent α. Alpha is a measure of the height of the extreme tail areas of the distribution. The attraction of this distribution is that it is stable under addition; i.e., the sum of independent stable variables, each with the same α, is a stable variable with the same value of α. The permissible range of α is $0 < \alpha \leq 2$. A stable distribution possesses absolute moments of all orders $k < \alpha$; i.e., $E(|x|^k) < \infty$. Consequently, the mean and variance do not exist for $0 < \alpha < 1$. Mandelbrot (1963) suggested that as sample size increases the sample mean stabilizes but the sample variance does not. Thus a stable model with $1 < \alpha < 2$ could be used for stock returns. Under the special case of $\alpha = 2$, the relevant distribution is normal or Gaussian, while α

= 1 results in Cauchy distribution. The distribution has infinite variance for $0 < \alpha < 2$ and the variance is finite only in the extreme case of $\alpha = 2$.

To test the stable Paretian distribution empirically, Fama (1965a) estimated the characteristic exponent α for 30 securities and found α to be consistently less than two. Blattberg and Gonedes (1974) find that Student-t distribution gives a better fit to U.S. stock returns data than the stable distribution. Hagerman (1978) shows that estimates of α steadily increase from about 1.5 for daily returns to about 1.9 for returns measured over 35 days. Consequently, any statistical technique that requires a finite second moment is invalid.

Several important models of asset pricing in finance are built upon the assumption of finite variance. These include the mean-variance portfolio theory of Markowitz (1959) and the Capital Asset Pricing Model of Sharpe (1964), Mossin (1966) and Lintner (1965). Subsequent to his finding that stock returns follow a stable Paretian distribution, Fama (1965b) proposed a portfolio model taking into account these distributional characteristics. Fama's model requires that the distributions of the stock returns be symmetric and have the same characteristic exponent α. In theory, normal distribution is a member of the stable Paretian family, with the case of $\alpha = 2$. Thus, the Fama model should be a more general case of the Sharpe diagonal model and perform better

with actual data. However, the findings of Frankfurter and Lamoureux (1987) are to the contrary. They simulate two sets of "real world" data using actual stock returns data. One set conforms to the Gaussian distribution, while the other is a stable Paretian distribution. Using these two sets, efficient frontiers are generated under both assumptions of parametric environments. They find that the Gaussian assumption is preferable to the general stable distribution. It is interesting to note that a unique member of the general stable distribution turns out to be more robust in parameter estimations as compared to the general model, although the actual stock returns are known not to follow the normal distribution. One plausible reason behind this anomaly may be that actual stock returns being neither normal nor stable, the efficient frontiers calculated using these assumptions turn out to be inconsistent.

Subsequent research is focused on the notion of infinite variance. Akgiray and Booth (1988, 1989) study the tail shapes of 200 U.S. stocks and 50 German stocks. The tails of the return distributions are found to be thinner than those of infinite variance stable Paretian distributions and suggest a stochastic process characterized by finite variance distributions. Applying Cootner's (1964) technique of sample variance approaching population variance, as sample size increases, Perry (1983) rejects the hypothesis that security returns have infinite variance. He further concludes that the

variance is finite but "changes over time in a complex fashion (p. 220)".

Several other researchers have put forward a constant mean, changing variance normal distribution model for stock returns. The random variable x_t, then has the conditional distribution

$$(2.7) \qquad x_t \mid z_t \sim N(\mu, f(z_t)).$$

The non-constant variance $f(z_t)$ can be perceived to be conditional upon z_t. Researchers have attributed different meanings to z_t, and consequently various functional forms of $f(z_t)$ have been suggested. z_t could measure the number of new pieces of information with $f(z_t) = A + Bz_t$, $A \geq 0$, $B > 0$ in the models using information (Beckers 1981). While Granger and Morgenstern (1970), and Rogalski (1978) also use trading volume as the conditioning variable, Tauchen and Pitts (1983) suggest a joint distribution of returns and volume, conditional upon the amount of new information and the number of traders in the market. Another explanation for leptokurtosis -- mixture of distributions, initially rejected by Fama (1965a), drew considerable attention afterwards.

Akgiray and Booth (1987) compare the mixed jump-diffusion process with a finite mixture of distributions on weekly and monthly data using 200 stocks randomly selected from the CRSP data base. Their findings show that a mixed jump-diffusion

process gives a better fit to the data. Press (1967) pursues the mixture of normal distributions using a Poisson process as the mixing variable. Using 10 stocks from Dow Jones Industrial Average, he finds that a mixed distribution function gives a better fit to the empirical data.

NONLINEAR MODELS

Fama (1965a) and Mandelbrot (1963) in their seminal papers also observe that large price changes are generally followed by changes of similar signs. This led researchers such as Greene and Fielitz (1977), Aydogan and Booth (1988) and Lo (1989) to the persistence of variance models of stock returns. Greene and Fielitz (1977) performed R/S (ratio of sample sequential range to sample standard deviation) analysis on 200 NYSE stocks and reported long term dependence in returns. However, Aydogan and Booth (1988) comment that R/S analysis is a potentially useful technique but conclusions drawn from its application must be conditioned on the validity of its underlying assumptions. They further show that in the case of common stock returns either long term dependence is not prevalent or that it is too small to be accurately measured by rescaled range analysis. Subsequent analysis of stock returns data is focused on a varying conditional variance while assuming the unconditional variance to remain constant.

One of the most prominent tools that has emerged for characterizing such changing variances is the Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982), and its various extensions, the most significant being the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model of Bollerslev (1986). The GARCH model has been found to fit returns data of U.S as well as international stocks. Some examples on U.S. data are Bollerslev (1987), Akgiray (1989), Lamoureux and Lastrapes (1990) and Hatem (1990). Akgiray, Booth and Loistl (1989), Booth, Hatem and Mustafa (1990) and Booth et al. (1991) respectively found GARCH models fit returns data on German and Finnish stocks as well.

In summary, various linear and nonlinear models have been suggested for the returns generation process. Moreover, evidence of nonlinear dependence has been found in stock returns of both large, as well as small stock exchanges. Regardless of the reason for the existence of this nonlinear dependence, a common way of modeling it is through the use of GARCH models. However, most studies have been conducted on indices rather than individual stocks. The type of GARCH model that fits the data has been found to differ depending upon exchange, or over time. The variations in institutional structures in the trading process make theoretical modeling quite complex and as a result tend to cloud any inferences that may be derived from their application. Present empirical

evidence raises a number of questions concerning the nature and structure of returns data. The specific areas that this paper wishes to address are discussed in the following chapters.

TABLE 2.1

MODELS OF STOCK RETURNS

LINEAR MODELS	
Bachelier (1900)	arithmetic brownian motion
Osborne (1959)	arithmetic brownian motion
Samuelson (1973)	geometric brownian motion
Mandelbrot (1963)	stable Paretian
Fama (1965a)	stable Paretian (empirical)
Press (1967)	mixture of normal distributions
Tauchen and Pitts (1983)	return and volume evolve jointly
Perry (1983)	variance changes over time
Akgiray and Booth (1987)	mixed jump-diffusion process
NONLINEAR MODELS	
Bollerslev (1987)	GARCH (1,1)/Student-t
Jorion (1988)	ARCH (1,1)/mixed jump-diffusion
Akgiray (1989)	GARCH (1,1)/normal
Akgiray et al. (1989)	GARCH (1,1)/normal
Lamoureux & Lastrapes (1990)	GARCH (1,1)/normal with volume
Booth et al. (1990)	GARCH (1,1)/normal with BDS
Booth et al. (1991)	GARCH (1,1)/power exponential
Hatem (1990)	GARCH (1,1)/power exponential
Lin & Rozeff (1991)	GARCH (1,1)/normal with high-low spread

CHAPTER 3

PRELIMINARY DISTRIBUTIONAL AND DESCRIPTIVE ANALYSIS

As discussed in the previous chapter, most nonlinear modeling has been carried out on stock indices, rather than individual stocks, and the models differ depending upon the stock exchange under study. This paper investigates the nonlinear dependence of individual stock returns, and the effects, if any, by forming portfolios.

DATA DESCRIPTION

The data for this research are taken from the over the counter (OTC) market. The main reason is the marked difference between the various types of financial markets. Secondly, the primary exchange markets such as the NYSE are extensively researched, while the knowledge is considerably less about the other types of markets. To contrast the stochastic process of NASDAQ/NMS stocks with NYSE stocks, all the GARCH models are also applied on a sample of stocks of similar size selected from NYSE.

MARKET MICROSTRUCTURE

The OTC market differs from the exchange markets in several ways. The OTC market is a dealer market, while the

exchange is an agency/auction market[1]. Moreover, the OTC dealers compete with each other to keep markets fair, orderly, and liquid. The information flow in the two markets are also quite different. The exchange markets have consolidated order flow and floor information. The OTC markets deal directly with the customers and also maintain close contact with the firms. There is much more freedom with higher emphasis on competition in the OTC market as compared to the trading restrictions of the exchange markets. The most notable distinction between the two market types is the structure of the market making system. Tinic (1972) finds that the dealer cost per share, for providing services, is lower when there is greater competition. Reinganum (1990) investigates the influence of market microstructure of NASDAQ and NYSE on liquidity premiums. He finds that for small firms the average returns of NYSE securities exceed the average returns of NASDAQ securities. Moreover, this return differential persists after controlling for risk, liquidity-related variables and size.

The introduction of National Association of Securities Dealers' Automated Quotation System (NASDAQ) in 1971 has had a tremendous impact on the efficiency of the over the counter markets. The intensified competition between the NASDAQ and exchange markets is attributable to the markedly improved

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[1]Specialist in exchange market serve the function of a dealer.

quality of the OTC market in recent years. In 1982, the National Market System (NMS) was established for the most prominent NASDAQ issues. A Computer Assisted Execution System has been installed to include all NASDAQ issues in 1985. Moreover, in the same year, National Association of Securities Dealers (NASD) introduced its Equity Audit Trail, an automated, on line system that monitors trading activity in the NASDAQ market. This surveillance facility provides an integrated data base of second-by-second trade data, both quotes and transactions for all NASDAQ securities.

The NASDAQ/NMS now provides a clear alternative to the stock exchange markets and strong competition for listings and the order flow. Hasbrouck and Schwartz (1988) using a parameter called market efficiency coefficient (MEC) study price behavior of different stock markets. The MEC is a net measure of positive and negative autocorrelation in returns. Their findings suggest that the price behavior is similar on the two exchange markets, but appears to differ appreciably between the exchanges and the NASDAQ/NMS markets. In earlier years a firm typically traded first as OTC, gradually maturing to AMEX as it gained greater strength and visibility, and finally, after attaining full stature and maturity become listed in NYSE. Now, an increasing number of firms are remaining on the OTC in the belief that the competitive dealer market is a good market for their stocks and that the services

provided by the exchanges are not worth the listing costs involved.

Market professionals, academicians and regulators share a fundamental belief in competition and in the efficiency of a free-market system. Much of the recent change in the underlying structure of the securities markets has therefore been designed to strengthen competition within the system. This is clearly the case with the Congressionally mandated removal, in 1975, of fixed minimum brokerage commissions. In the 1975 Securities Acts Amendments, Congress established the dual objectives of increasing competition in the securities markets and of achieving a national market system (NMS). Congress set forth five goals for a NMS to achieve: (1) the economically efficient execution of transactions; (2) fair competition among brokers, dealers and markets; (3) broad availability of information with respect to quotations and transactions; (4) the practicability of executing investors' orders in the best market; and (5) an opportunity for investors' orders to meet without the participation of a dealer. Beyond this, Congress did not specifically define what the NMS would be; rather, it left the task of implementing the objectives of a NMS largely to the Securities and Exchange Commission (SEC).

The results of these changes are found mainly in the resounding success of the OTC markets through improvements in its NASDAQ system. The competition between the exchanges and

the OTC market is not primarily competition for the order flow itself. Rather it is competition for corporate listings. It is the corporations themselves that have increasingly chosen NASDAQ market over an exchange listing. The reasons for this are varied. Some companies cite the reporting requirements of the exchanges; others note the additional fees imposed by the exchanges. However, one of the important reasons may be that the companies are responding to the quality of the market that they feel they can obtain by having multiple dealers active in their securities as opposed to a single specialist.

A multiple-dealer system without perfect intermarket linkages must, to some extent, be a fragmented system. Therefore, the success of NASDAQ might suggest that good intermarket linkages are all that are needed to overcome the problems that might attend market fragmentation. However, the difference between the NASDAQ market and the exchange markets involves more than a multiple dealer market versus a consolidated market with a single specialist. Various rules and principles differ between the two alternative market systems. For instance, NASDAQ market makers have far greater freedom to choose the stocks they wish to trade; NASDAQ dealers are not constrained by an elaborate system of trading rules and market surveillance; NASDAQ market makers are allowed to have direct contact with their customers; NASDAQ market makers deal in both primary and secondary issues; public order flow is a greater source of liquidity in the

exchange markets; the consolidation of the public order flow on the exchange markets provides an informational advantage that the NASDAQ dealers do not have.

These differences have an important bearing in understanding the returns generation process in the two markets. Securities market is an amalgamation of two distinct markets and hence two different prices are established: an execution or service fee and the underlying price of the securities themselves. However, the provision of trading services necessarily accompanies the exchange of securities. Thus there is a conflict that is fundamental to the organization of the market: competition for the provision of trading services can adversely affect the quality of competition for pricing the securities that are traded. As a result, a trade-off exists between tighter pricing of shares and more competitive pricing of trading services. Consequently, security analysis is more frequent and more intensive for larger issues. Any news bit that would have a given percentage price impact would have a greater total monetary impact for securities of larger total market value. When security analysis is undertaken more frequently, orders to trade will clearly reflect more up-to-date information. Effectively, each news bit will remain in "inventory" for a shorter time before it is acted upon. To the extent that security analysis generates useful information, more intensive analysis ought to increase the homogeneity of investor

expectations. Thus, with homogeneous expectations, price adjustment delays are shorter. The reason is two fold: (1) any trader who agrees with the market assessment of security values would be less apt to seek a trade after he eventually does reassess his portfolio holding in a security and (2) any given trade will have a smaller impact on security price the more elastic the market's demand for the security.

A national market system that resulted in the consolidation of all orders for a particular security would maximize the extent to which public orders provide liquidity and immediacy of execution. This would help to ensure that trades are executed at reasonable prices. Pooling orders increases the effective thickness of the market. Cohen et al. (1986) find that in thicker markets: (1) bid-ask spreads are expected to be smaller; (2) market prices are expected to be less volatile; and (3) price adjustment delays are expected to be shorter, which implies weaker autocorrelation coefficients.

However, consolidation in a single marketplace might reduce competition in the market for marketability services. Thus such a unified marketplace might seemingly conflict with the goals of economically efficient execution of transactions and fair competition among brokers, dealers and markets. Part of the problem lies in the fact that the goals set forth by the Congress are not compatible. The empirical implications of these differences are studied in the following sections and chapters.

STATISTICAL ANALYSIS

The population of stocks in CRSP NASDAQ/NMS and NYSE tapes are ordered by market value of their equity and split into three groups respectively. The stocks are ordered by size to investigate size effect, if any. Eight stocks are selected at random from each of the six groups, giving a total of 48 stocks, of which 24 stocks are from NASDAQ/NMS and 24 from NYSE for comparison. Daily data for the years 1982 to 1988 from CRSP tapes are used to generate weekly data at the end of each Wednesday using the built in compounding function COMPND in CRSP sample programs. The program judiciously takes care of missing data and error conditions.

The parameter 'market value of equity' or size for each firm on NASDAQ/NMS and NYSE is calculated by multiplying the number of stocks outstanding by the closing price of each stock, both as of the end of 1988. Subsequently, the firms on the respective tapes are ordered by size. There are 986 NASDAQ/NMS stocks with good data, with a mean size of $178 million and variance of $17821 million; the largest firm being $5470 million. The corresponding figures on NYSE are 1080 stocks with a mean size of $3693 million and variance of $83434040 million with the largest firm being $780050 million. The NYSE tape has some outliers that increase the variance enormously. The fifth largest firm on NYSE has a size of $94520 million. Since the study is focused on NASDAQ/NMS, the distribution of stocks on the NASDAQ/NMS tape is used as the

basis of selection. On this tape 33% stocks are smaller than $25.6 million and 66% are smaller than $120.09 million. As such, the total population is split in three groups using the cut off points of $25 million and $120 million respectively. The firms on NYSE are split in three groups using the same benchmark after discarding the firms larger than $5470 million. The NYSE population goes down to 980 which is 90.7 percentile of the original distribution. Thus the individual groups on the two respective tapes are comparable by size. Eight stocks are chosen at random from each group, leading to 24 stocks from NASDAQ/NMS and an equal number from NYSE. To study the effect of size on portfolio, four equal weighted portfolios are made, three from each respective group and the fourth having all the stocks. The portfolios are named 'P1', 'P2', 'P3' and 'ALL'. Thus there are a total 48 stocks and eight portfolios in the study. Table 3.1.A and 3.1.B give a list of these stocks and portfolios from NASDAQ and NYSE respectively.

Since NASDAQ went through a major technological sophistication in the year 1985, the study checks for structural shift, if any, in the returns generation process. This is achieved by using an indicator variable for the pre- and post 1985 era. Each firm is checked for structural shift in mean and variance. A dummy variable is used to indicate pre- and post 1985 and the returns and squared returns are used as proxies for mean and variance respectively. The

returns and squared returns are regressed on the dummy variable. A significant coefficient for the dummy variable denotes a structural shift. Most coefficients are insignificant and for the three NASDAQ/NMS stocks with significant coefficients, the absolute values are very small. As such, further modeling is done assuming no shift.

For the NASDAQ/NMS stocks and portfolios, tables A.3.A.1 to A.3.A.7 in Appendix A, give the basic statistics of the returns such as, mean, variance, kurtosis, skewness, equiprobable χ^2 test for normality, and Hsieh test for discrimination between additive and multiplicative dependence. Similar figures for NYSE stocks and portfolios are also given in Appendix A in tables A.3.B.1 to A.3.B.7. The figures reported under Hsieh test is the number of times the null hypothesis of multiplicative nonlinearity was rejected out of a lag matrix of I = 10, J = 10. It should be noted that the test will reject multiplicative nonlinearity, only when it is applied to linearly filtered data. In this dissertation, the test is applied to weekly returns with linear as well as nonlinear dependence. If a return series has linear as well as nonlinear dependence and the Hsieh test for the series is also significant, the GARCH model that follows in the subsequent chapters will actually be the test for multiplicative nonlinearity.

Autocorrelations of basic returns and their squares are calculated in an attempt to identify linear and nonlinear

dependence. Any significant autocorrelation in returns indicates linear dependence, while that of their squares denotes nonlinear dependence. Other methods often used to identify nonlinear dependence are Fisher's kappa and Ljung-Box Q statistics. Ljung-Box statistics Q_x and Q_{xx} are calculated for 36 lags to check for dependence. One of the assumptions in the development of the Ljung-Box statistics is that innovations are normally distributed. However, Ljung and Box (1978) do check the sensitivity of the test to departures from normality. They apply the statistic on double exponential and uniform distributions. The results agree closely with those obtained under normality assumption. Thus, the Ljung-Box statistic is robust enough to detect nonlinearities in non-normal distributions as well.

Table 3.2 gives a distribution of the type of dependence in NASDAQ and NYSE stocks and their respective portfolios. It is interesting to note that 14 NASDAQ stocks show both linear as well as nonlinear dependence while the corresponding figure for NYSE is eight. Moreover, just one NASDAQ stock is statistically independent and the comparable figure on NYSE is five. Thus, it is observed that NASDAQ stocks show more dependence than NYSE stocks. However, on forming portfolios, both NASDAQ as well as NYSE show both linear and nonlinear dependence.

Two NASDAQ stocks (S4 and S6) show a mean significantly different from 0 at 5% level and none are significant at 1%

level. On the contrary, five NYSE stocks (S7, S11, S21, S23 and S24) have significant mean at 5% level among which three (S11, S21 and S23) are significant at 1% level. Thus more NYSE stocks have significant mean than NASDAQ stocks. It may be either a market effect or a sample effect rather than a size effect as the stocks from the two markets have comparable size. However, none of the portfolios have significant means.

All the NYSE and NASDAQ stocks and portfolios have statistically significant kurtosis at the 1% level. Both NASDAQ and NYSE have 18 stocks with significant skewness. However, in NASDAQ five stocks with insignificant skewness are from the group of stocks with largest size. The six stocks with insignificant skewness are S15, S19, S20, S21, S22 and S23 for NASDAQ and S3, S5, S11, S18, S21 and S22 for NYSE. The standard errors of skewness and kurtosis are taken as $\sqrt{(6/n)}$ and $\sqrt{(24/n)}$ respectively where n is the sample size.

All stocks and portfolios are checked for normality using equiprobable chi-square goodness of fit test with 25 degrees of freedom. It is interesting to note that for most stocks the chi-square value reduces as the firm size increases and null hypothesis of normality can not be rejected for stocks S22, S23 and S24 for NYSE and NASDAQ. All NASDAQ portfolios show significant departures from normality at the 1% level. Among NYSE portfolios three are significant at 5% level out of which two are at 1% level.

The Hsieh (1989b) test is performed to discriminate between additive and multiplicative nonlinearity, the null hypothesis being multiplicative nonlinearity. A 10 by 10 lag structure is used for this test for third moment and the number of times the null is rejected is reported in Appendix A in tables A.3.A.1 to A.3.A.7 for NASDAQ and A.3.B.1 to A.3.B.7 for NYSE. Since the number of relevant cells is 55, (due to symmetrical matrix) a statistical significance level can be evaluated by taking the number of rejections of null as proportion of 55. Thus a cell entry of three or more is significant at the 5% level. Both NASDAQ and NYSE have eight stocks each that fail the Hsieh test. The stock numbers for NASDAQ are 4, 6, 9, 10, 14, 18, 19, 22 and portfolios 'P2', 'P3' and 'ALL'. The corresponding numbers for NYSE are 4, 8, 10, 11, 13, 19, 21, 23 and portfolio 'P3'. However, since the test is not applied to linearly filtered data, one can not reject the null hypothesis on the basis of this test alone as linear dependence is found in several stocks. Moreover, both types, additive as well as multiplicative nonlinearities are evident in the autocorrelation and Q_{xx} statistics of squared returns. Thus, Hsieh test in conjunction with autocorrelation and Q statistics on returns and squared returns should be used for the hypothesis testing for differentiation between additive and multiplicative nonlinearity. A GARCH model is suitable for stocks with nonlinear dependence but insignificant Hsieh test. For example, NASDAQ stocks S4 and

S19 have significant Hsieh test and Q_x but insignificant Q_{xx}. As such, these two stocks are not a good candidate for GARCH. Again NASDAQ stocks S6 and S14 have significant Hsieh test, insignificant Q_x but significant Q_{xx}. These two stocks may have additive nonlinearity and may not be explained by GARCH. However, it is difficult to comment about NASDAQ stocks S9, S10, S18 and S22 as all these have significant Hsieh test, Q_x and Q_{xx}. The null hypothesis of multiplicative nonlinearity may not be rejected in these stocks as there is significant linear dependence.

In summary, it is found that weekly returns from NASDAQ and NYSE stocks as well as their respective portfolios, may have any type of dependence or no dependence at all. Most of them have significant skewness but all have high kurtosis. Some large stocks from both markets that tend to be symmetric, are also found to conform to normality as per equiprobable chi-square goodness of fit test. It is also observed that portfolios in general show both linear as well as nonlinear dependence. Probably stock indices are better explained by GARCH due to this reason. Regarding differences between NASDAQ and NYSE, there does seem to be a difference in the nonlinear dependence between the two types of stocks as more NYSE stocks are statistically independent than NASDAQ stocks.

TABLE 3.1.A

NAMES OF NASDAQ FIRMS USED IN STUDY

Stock	Group	Cusip	Name
1	1	58514510	Megadata Corp.
2	1	40412510	H C C Inds Inc.
3	1	65730510	North Atlantic Inds Inc.
4	1	31381910	Federal Screw Wks
5	1	71658310	Petroleum Equip Tools Co.
6	1	85979110	Sterner Ltg Sys Inc.
7	1	10480210	Brae Corp
8	1	84761510	Spectrum Ctl Inc.
9	2	31164810	Farr Co.
10	2	50182320	Lob Corp.
11	2	53517110	Lindberg Corp.
12	2	43641610	Holmes Limited D H
13	2	33753110	First Western Finl Corp.
14	2	82774210	Silver King Mines Inc.
15	2	85362610	Standard Microsystems Corp.
16	2	28519110	Electro Nucleonics Inc.
17	3	71956710	Piccadilly Cafeterias Inc.
18	3	45878210	Intermec Corp.
19	3	19089310	Cobe Labs Inc.
20	3	21852510	Cordis Corp.
21	3	90957210	United Banks Colo Inc.
22	3	00190310	Ask Computer Sys Inc.
23	3	22743010	Cross & Trecker Corp.
24	3	48248010	KLA Instrs. Corp.

Portfolio 'P1' contains all the stocks in Group 1
Portfolio 'P2' contains all the stocks in Group 2
Portfolio 'P3' contains all the stocks in Group 3
Portfolio 'ALL' contains all the stocks

TABLE 3.1.B

NAMES OF NYSE FIRMS USED IN STUDY

Stock	Group	Cusip	Name
1	1	36161410	G F Corp.
2	1	86426110	Suave Shoe Corp.
3	1	44041610	Horizon Corp.
4	1	29358020	Ensource Inc.
5	1	62873510	N B I inc.
6	1	19337810	Coleco Inds. Inc.
7	1	88826610	Titan Corp.
8	1	53191120	Lifetime Corp.
9	2	37935240	Global Marine Inc.
10	2	12060910	Bunker Hill Income Secs. Inc.
11	2	28252010	1838 Bd-Deb Trading Fd.
12	2	11522310	Brown & Sharpe Mfg. Co.
13	2	37291210	Geo Intl. Corp.
14	2	30423120	Fairfield Communities Inc.
15	2	71461110	Perry Drug Stores Inc.
16	2	61533910	Mony Real Estate Investors
17	3	84546710	Southwestern Energy Co.
18	3	26147110	Dravo Corp.
19	3	63654010	National Intergroup Inc.
20	3	72348410	Pinnacle West Capital Corp.
21	3	39006410	Great Atlantic & Pacific Tea
22	3	69846210	Panhandle Eastn Corp.
23	3	37576610	Gillette Co.
24	3	89418010	Travelers Corp.

Portfolio 'P1' contains all the stocks in Group 1
Portfolio 'P2' contains all the stocks in Group 2
Portfolio 'P3' contains all the stocks in Group 3
Portfolio 'ALL' contains all the stocks

TABLE 3.2

DEPENDENCE DETAILS OF STOCKS AND PORTFOLIOS

Type	Linear Only (5%/1%)	Nonlinear Only (5%/1%)	Both (5%/1%)	Independent	Total
Stocks					
NASDAQ	6 / 5	3 / 1	14 / 12	1	24
NYSE	5 / 4	6 / 5	8 / 5	5	24
Portfolios					
NASDAQ			4 / 4		4
NYSE			4 / 4		4

CHAPTER 4

MODEL ESTIMATION

In the previous chapter statistical properties of weekly returns of NASDAQ, NYSE stocks and their respective portfolios are studied. Apart from their basic statistics such as mean, variance, etc. the preliminary diagnostics on the returns did give an insight into their dependence structure, if any, and to the type of dependence, such as linear, additive nonlinear, multiplicative nonlinear or a combination of these. The purpose of this chapter is to study their dynamics in more depth and the flexibility of the GARCH model of Engle (1982) and Bollerslev (1986) is exploited in the process. The sign pattern or dependence that Fama (1965a) observed in the returns distribution can be mathematically modeled using the ARCH model credited to Engle (1982). In a typical ARCH process the conditional variance is dependent on past values of the random variable. An ARCH process uses a linear lag structure, while Bollerslev (1986) generalized it to a more flexible lag structure in the GARCH process. Additional flexibility is introduced into both these models by the choice of the underlying distribution. Various distributions such as, normal, Student-t, power exponential, or mixed jump-diffusion process, have been assumed by researchers in the past. Although the purpose of ARCH or GARCH is to remove nonlinear dependence, its removal does not necessarily imply

that any particular conditional distribution F(.) is the true one. This is because distributional shape may be partially determined by factors other than ARCH or GARCH effects.

MODEL SPECIFICATION

Applying the model to stock returns, the GARCH (p,q) process can be described as follows:

$$R_t | \Omega_{t-1} \sim F(\mu, h_t),$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j},$$

$$\text{(4.1)} \qquad e_t = R_t - \mu,$$

where p > 0 and q $\geq$ 0 and the parameters satisfy the conditions

$\alpha_0 > 0$, α_i, $\beta_j \geq 0$, i= 1, ... , p, j = 1, ... , q. $F(\mu, h_t)$ is the conditional distribution of the returns variable R_t, with mean μ and conditional variance h_t.

The GARCH model can be augmented to handle linear dependence. An augmented AR(m)-GARCH(p,q) process can be stated as:

$$R_t | \Omega_{t-1} \sim F(\mu_t, h_t),$$

$$\mu_t = \phi_0 + \sum_{k=1}^{m} \phi_k R_{t-k},$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j},$$

$$(4.2) \qquad e_t = R_t - \mu_t,$$

where m is the order of linear dependence.

The unconditional mean and variance of the AR(m)-GARCH (p,q) process are constant, but the conditional mean and variance are dependent on functional form F(.) of the underlying conditional distribution and the variance equation. Consequently, additional flexibility is achieved by combining different types of conditional distributions with different variance equations. Since the variance equation in the above model is linear, it is also called linear or standard GARCH. The empirical distribution of variables generated by GARCH processes are heavy tailed, compared to the normal distribution. However, no general expression for the distribution function is available. To estimate the parameters of a AR(m)-GARCH (p,q) process, it is necessary to specify the order (m,p,q) of the process and the conditional distribution function F(.). Bollerslev, et al. (1990) report that in most applications p = q = 1 has been found to suffice. The order of m can be ascertained from the empirical characteristics of the returns data. Generally m = 1 is used if data has significant linear dependence. Moreover, the linear variance equation has been more extensively researched than the nonlinear equation credited to Nelson (1991).

The functional form F(·) has been assumed to be normal by several researchers, such as Akgiray (1989), Akgiray, Booth and Loistl (1989), and Lamoureux and Lastrapes (1990). Akgiray (1989) finds that daily returns of CRSP value weighted and equal weighted indices can not be modeled as linear white noise processes as they exhibit significant levels of second order dependence. His GARCH (1,1) model with a conditional normal distribution fits the data very satisfactorily. Akgiray, Booth, and Loistl (1989) find the overall behavior of daily observations for DAX index of 30 German blue chip stocks, adjusted for possible autocorrelation and day-of-the-week effects, is able to be well explained by a AR(1)-GARCH(1,1) process, with conditional normal. Their study is focused around the October 1987 crash, by splitting the data into pre-, during-, and post-crash periods. Since the GARCH parameters take on different values within these respective periods, it supports the notion of a different stochastic process in each of the three periods. In fact the GARCH model is found to fit better during the pre-, and post-crash periods as compared to actual crash period. Their study suggests that the October 1987 crash temporarily changed the way returns are generated in the German stock market. Lamoureux and Lastrapes (1990) observe the presence of GARCH effects in the U.S. stock market. While the economic interpretation of the GARCH effect is still in its infancy, Lamoureux and Lastrapes (1990) try to explain the GARCH effect by a proxy for information. They

suggest that returns generation is a linear process in economic time, but when observed in calendar time, it becomes a higher order process. They try to support their hypothesis, by using trading volume as a proxy for economic time which is supposed to be determined by information flow. Lin and Rozeff (1991) use high-low spread as the proxy for information flow to explain GARCH effect in the 30 stocks in Dow Jones Industrial Average and the S&P 500 index over the 1988-89 period. Comparing high-low spread to trading volume, they suggest that the relationship between high-low spread and volatility is more defined while the functional form between trading volume and volatility is unknown.

Though the unconditional distribution, in a GARCH with conditional normal has a higher kurtosis than normal, it may not capture the entire leptokurtosis of the returns distribution. Bollerslev (1987) suggested the use of standardized Student-t distribution as the conditional distribution. This distribution has fatter tails than the normal, but converges to normal as the degrees of freedom increases. Booth, et al. (1991), and Hatem (1990) have found that power exponential distribution fits stock returns data better than either normal or Student-t. Booth, et al. (1991) report presence of linear and nonlinear dependence in Finnish stock returns by using linear GARCH models with three types of conditional distributions -- normal, Student-t, and the power exponential. Their findings suggest that an AR(2)-GARCH (1,1)

model with a power exponential conditional distribution, which is characterized by an autoregressive mean, represents the data better than any of the other models. However, while using German stocks Booth, Hatem and Mustafa (1990) find a normal distribution fit the data. Thus, the type of model as well as the conditional distribution is found to differ depending on the exchange.

While most of the other studies deal with daily or weekly data, Hatem (1990) studies the nonlinear dependence in intradaily stock prices. He applies the GARCH model to ten minute, and thirty minute data, with conditional distributions such as normal, Student-t and power exponential. His findings suggest that the power exponential provides a better fit to the data than either normal or Student-t.

Jorion (1988) compares diffusion process, mixed jump-diffusion process and ARCH with mixed jump-diffusion process (ARCH-MJ) as the conditional distribution for CRSP value weighted index on monthly and weekly data. Thus, his study is a comparison of linear and nonlinear models. The jump parameters for neither monthly nor weekly data are significant. However, he reports better overall fit for the unconditional mixed jump-diffusion model using Schwarz Information Criterion (SIC). Though the ARCH-MJ models fail for CRSP index, this dissertation will investigate the explanatory power of such a model for individual stocks on NASDAQ and NYSE.

This dissertation attempts to study the relative strengths or weaknesses of the models by applying normal (N), the Student-t (T), the power exponential (PE), and mixed jump-diffusion process (MJ) as conditional distributions on the same data. The AR(1)-GARCH(1,1) process can be stated as:

$$R_t | \Omega_{t-1} \sim F(\mu_t, h_t),$$

$$\mu_t = \phi_0 + \phi_1 R_{t-1},$$

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1},$$

$$e_t = R_t - \mu_t. \tag{4.3}$$

The conditional density function F(.) for the first three in respective order are:

$$N(\mu_t, h_t) = \frac{1}{\sqrt{2\pi h_t}} \exp\left[\frac{-e_t^2}{2h_t}\right], \tag{4.4}$$

$$T(\mu_t, h_t, d) = \frac{\Gamma\left[\frac{(d+1)}{2}\right]}{\Gamma\left[\frac{d}{2}\right]} \frac{1}{\sqrt{h_t(d-2)\pi}} \left[1 + \frac{e_t^2}{h_t(d-2)}\right]^{-(d+1)/2}, \quad d>2, \tag{4.5}$$

$$PE(\mu_t, h_t, d) = \frac{\frac{d}{2}\sqrt{\Gamma\left[\frac{3}{d}\right]}}{\left[\Gamma\left[\frac{1}{d}\right]\right]^{\frac{3}{2}}} \frac{1}{\sqrt{h_t}} \exp\left[-\left[\frac{\Gamma\left[\frac{3}{d}\right]}{\Gamma\left[\frac{1}{d}\right]}\right]^{\frac{d}{2}} \left|\frac{e_t}{\sqrt{h_t}}\right|^d\right], \quad 2 \ge d \ge 1, \tag{4.6}$$

where μ_t is the mean, h_t the conditional variance, d the degrees of freedom, and e_t the innovation process.

The mixed jump-diffusion process is used to model discontinuities in the returns distribution. The conditional density function for mixed jump-diffusion process is given by

$$(4.7) \qquad MJ(\mu_t, h_t, n_t, Y_t) = \mu_t + \sqrt{h_t}\, z + \sum_{i=1}^{n_t} \ln Y_i ,$$

where z is standard normal, n_t is the actual number of jumps and Y_i is the jump size.

Maximum likelihood estimates of the unknown parameters are based on the sum of the conditional log likelihoods for each model. The parameters of the respective models are calculated using the numerical optimization algorithm of Berndt, Hall, Hall, and Hausman (1974). The advantage of this algorithm is that the hessian for the information matrix is approximated using the first derivatives of the likelihood function. Thus there is no need to calculate the second derivative of the function. Optimum parameter estimates that give the highest log likelihood value for each model are obtained through an iterative process.

MODEL SELECTION

There are two ways of measuring the performance of a model. A model may be considered best if it meets the

underlying assumptions or it may be considered best if it is able to forecast accurately irrespective of the assumptions. The former criterion is used in this dissertation. When there are several models satisfying the underlying assumptions, it leads to the problem of selecting the best model. There are three alternative methods available for testing a model. The first two -- model parameters and diagnostics on residuals, are applicable for testing each individual model and the last one -- valuation of log likelihood function, is used on competing models to select the best one. Moreover, it is essential that the model is valid before applying the tests on its residuals or log likelihood value. Thus, the model selection procedure involves the sequential process of selecting the models with valid parameters, checking their standardized residuals for underlying assumptions and applying the valuation of log likelihood function tests on the competing models for picking the best one.

MODEL PARAMETERS

For a model to be satisfactory, it must have significant parameters. Assuming an AR(1)-GARCH(1,1) model, the unconditional variance[2] of errors σ_e^2 as well as that of returns σ_R^2 can be calculated using the following formula.

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[2]Bollerslev (1986) derives the unconditional moments for GARCH.

(4.8) $$\sigma_e^2 = \frac{\alpha_0}{1-\alpha_1-\beta_1};$$

(4.9) $$\sigma_R^2 = \frac{\sigma_e^2}{1-\phi_1^2}.$$

A valid GARCH model must have finite positive unconditional variance σ_e^2 and σ_R^2. This implies that the coefficient α_0 should be significantly greater than zero and the sum of α_1 and β_1 be less than one. The individual significance levels of α_0, α_1 and β_1 are given by the estimation process. Hence, a model is not valid if it has an insignificant α_0. Moreover, parameter estimates of the original distribution such as unconditional variance σ_R^2, as calculated from the model should not differ drastically from the empirical estimate.

Having established that the model is a valid one with significant parameters and meeting the diagnostics on standardized residuals, it is possible to calculate a measure of persistence, called half life (HL) of the process. Half life is calculated using the parameter estimates of the model and is given as:

(4.10) $$HL = \left[\frac{-\log(2)}{\log(\alpha_1+\beta_1)}\right]+1.$$

A half life can be defined as the time period required to dissipate away half the total impact from a particular shock. Thus a half life of four with weekly data suggests that the

persistence level becomes half the initial value after approximately a month.

DIAGNOSTICS OF RESIDUALS

Another measure of the performance of a particular model is obtained by testing the standardized residuals. Since all the models have at least one linear term, the residuals have zero mean and a variance of σ_e^2 after standardization. They should also conform to the underlying assumptions such as the conditional distribution of the model. An equiprobable χ^2 goodness of fit test is used for checking the distributional assumption. The model should also be successful in taking out the dependence from the returns. Consequently, the residuals should not have any linear or nonlinear dependence. Any significant autocorrelation or Q statistic in the residual or squared residual implies dependence and obviously a bad model.

VALUATION OF LOG LIKELIHOOD FUNCTION

The method of maximum likelihood chooses the values of the unknown parameters that maximizes the probability of drawing the actual sample from the specified GARCH process. Thus the likelihood function is a function of parameters given the sample observations. It is mathematically identical to the joint probability density function of the sample, but it is interpreted as a function of the unknown parameters instead of the values of the variables, which are assumed to be known.

In practice, the parameter estimations are performed on the log of the likelihood function.

Each model has a log likelihood value that is maximized through an iterative process. Apart from being the maxima, this value may not mean much for a particular model. However, it is useful for comparing competing models. The tests based upon likelihood function value can be put in two groups -- nested models (AIC, SIC and LR) and non-nested models (KLIC).

Nested Models

One of the earliest attempt at model selection using maximum likelihood value was made by Akaike (1974) through AIC. The maximum likelihood estimates (MLE) under regularity conditions are asymptotically efficient. Thus, the likelihood function tends to be sensitive to deviation of model parameters from the true values. Assume that x_1, x_2, ..., x_N are the N independent observations of a random variable with probability density function g(x). If a parametric family of density functions if given by $f(x|\theta)$ with a vector parameter θ, the average log likelihood is given by

$$(4.11) \qquad \frac{1}{N}\sum_{i=1}^{N} ln f(x_i|\theta) .$$

As N is increased indefinitely, this average tends to the following integral with probability one.

$$(4.12) \qquad S(g;f(\cdot|\theta)) = \int g(x) \ln f(x|\theta)\, dx,$$

where the existence of the integral is assumed. From the efficiency of MLE it can be seen that the mean log likelihood $S(g;f(\cdot|\theta))$ must be sensitive to any small deviation of $f(x|\theta)$ from $g(x)$. This difference is given by

$$(4.13) \qquad I(g;f(\cdot|\theta)) = S(g;g) - S(g;f(\cdot|\theta)).$$

The difference $I(g;f(\cdot|\theta))$ is known as the Kullback-Leibler mean information for the discrimination between $g(x)$ and $f(x|\theta)$ and takes positive value unless $f(x|\theta) = g(x)$ holds almost everywhere. One of the most important characteristics of $S(g;f(\cdot|\theta))$ is that its natural estimate, the average log likelihood (4.11) can be obtained without the knowledge of $g(x)$. Thus the model with minimum $EI(\theta_0;\hat{\theta})$ will be closest to the actual distribution. Further assuming θ to be sufficiently close to the actual parameters θ_0 and using an approximation for $\Delta\theta$, the AIC is defined as the difference between the log likelihood value and the number of parameters given by

$$(4.14) \qquad AIC = \ln L(\hat{\theta};x) - K,$$

where $\ln L(\hat{\theta};\ x)$ is the log likelihood value at the maximum likelihood estimate and K the number of parameters. A bias is

introduced when the MLE is used as the parameter estimate and the number of parameters K is used to offset the bias. The best model is selected by choosing the one with highest AIC value.

A modification of AIC was suggested by Schwarz (1978) through Schwarz Information Criterion (SIC). According to SIC, the problem of selecting one of a number of models is treated by finding its Bayes solution and evaluating the leading terms of the asymptotic expansion. Assuming an a priori probability of the true model being K and an a priori conditional distribution of the parameters given that K is the true model, Schwarz suggested choosing the a posteriori most probable model. In SIC the log likelihood value is corrected for both, sample size as well as the number of parameters. The model selection is based upon choosing the model with lowest value of SIC, which is given by

$$SIC = -2\,lnL(\hat{\theta};x) + (lnN)K, \tag{4.15}$$

where $lnL(\hat{\theta};x)$ is the log likelihood value at the maximum likelihood estimate, N the sample size and K the number of parameters. SIC has received a lot of criticism for being a Bayesian approach. In the absence of discriminatory prior information, a Bayesian approach reduces to comparison of log likelihoods. Moreover, a Bayesian approach assumes that the models under consideration exhaust all possibilities. Therefore, under these assumptions SIC corrects the likelihood

function for both sample size and the number of parameters. Both the models AIC and SIC are derived using iid observations for nested linear models. Moreover, for AIC the MLE of the parameters should be sufficiently close to actual parameters for the approximation of their difference to be valid.

In spite of these limitations of AIC and SIC they are used for testing of nonlinear non-nested models by several researchers such as Jorion (1988), Hsieh (1989a) and Nelson (1991).

Both these tests, SIC and its predecessor AIC are counting mechanisms and lack the power of a statistical test. One statistical test often used in testing nested hypothesis is the likelihood ratio (LR) test (Judge, et al. (1985)).

The LR test procedure compares the maximum value of the likelihood function under the assumption that the null hypothesis is correct to the maximum value of the unrestricted likelihood function. The null hypothesis can be thought of as reducing or restricting the set of possible values for the parameters. This reduced set of possible values restricts the maximum value that the likelihood function can take. The LR test is given by

$$(4.16) \qquad LR = 2\,[\,lnL_1(\hat{\theta}_1;x) - lnL_2(\hat{\theta}_2;x)\,] \overset{d}{\rightarrow} \chi^2_{K_1 - K_2} \quad K_1 > K_2,$$

where $lnL_1(\hat{\theta}_1;x)$ and $lnL_2(\hat{\theta}_2;x)$ are the log likelihood values of the nested models with K_1 and K_2 parameters respectively.

Lütkepohl (1985) does a simulation study using AIC, SIC and LR on nested linear autoregressive models and finds SIC to be a better performer than either AIC or LR. The poor performance of LR indicates that for small samples the actual distribution of the considered test statistics is not very well approximated by their asymptotic χ^2 distribution.

Non-nested Models

Although Student-t, power exponential, or mixed jump-diffusion process can be compared to normality as each of them are nested individually, it is difficult to compare them among themselves because they are non-nested. Unfortunately, the literature on testing of non-nested models in econometrics is still in its infancy. Pesaran and Deaton (1978), and Davidson and MacKinnon (1981) derive test statistics for non-nested models, including nonlinear models, but the distribution of errors in all these models are assumed to be normal. The distribution of errors in the non-nested GARCH models for comparison such as GARCH-T and GARCH-PE are not normal by hypothesis.

Another approach to test non-nested models is suggested by Vuong (1989). It is based on the asymptotic properties of the likelihood ratio of the two models. Thus, the various competing models need to be compared in pairs. The Kullback-Leibler (1951) Information Criterion (KLIC) measures the distance between two distributions. The test can be used for

nested, non-nested or overlapping models. If F_θ and G_γ are the two conditional distributions of Y_t given Z_t, the test calculates their likelihood ratio and subsequently normalizes it. This normalized likelihood ratio converges in distribution to a standard normal. Since the likelihood function is dependent on number of parameters, Vuong suggests modifying it using either Akaike (1974) or Schwarz (1978) information criteria. The likelihood ratio is normalized by dividing it by its standard deviation and the square root of sample size. A simulation is done to study the behavior of AIC, SIC and KLIC test under dependent observations and non-nested hypothesis testing.

The details of Vuong's application of KLIC test are as follows. Let X_t be a mx1 observed random vector partitioned as $X_t=(Y_t, Z_t)$ where Y_t and Z_t are 1 and k dimensional vectors with m=1+k. Under the assumptions and regularity conditions (X_t being iid with continuous conditional density function and twice continuously differentiable log likelihood function) given in Vuong (1989) let two competing parametric families of conditional distributions F_θ and G_γ be defined such that

$$F_\theta \equiv \{F_{Y|Z}(\theta),\, \theta \epsilon \Theta\}, \qquad G_\gamma \equiv \{G_{Y|Z}(\gamma),\, \gamma \epsilon \Gamma\}.$$

The relationship between the two competing models F_θ and G_γ may be nested, overlapping or non-nested. At the maximum likelihood estimate (MLE) $\hat{\theta}_n$ for the conditional model F_θ the conditional log likelihood function is given by

$$(4.17) \qquad L_n^f(\hat{\theta}_n) = \sum_{t=1}^{n} \ln f(Y_t | Z_t; \hat{\theta}_n),$$

where n is the sample size. Similarly, the log likelihood function for the conditional model G_γ is given by

$$(4.18) \qquad L_n^g(\hat{\gamma}_n) = \sum_{t=1}^{n} \ln g(Y_t | Z_t; \hat{\gamma}_n).$$

The likelihood ratio (LR) statistic for the model F_θ against the model G_γ is given by

$$(4.19) \qquad LR_n(\hat{\theta}_n, \hat{\gamma}_n) = [L_n^f(\hat{\theta}_n) - L_n^g(\hat{\gamma}_n)] = \sum_{t=1}^{n} \ln \frac{f(Y_t | Z_t; \hat{\theta}_n)}{g(Y_t | Z_t; \hat{\gamma}_n)}.$$

Assume $h^\circ(\cdot|\cdot)$ as the true conditional density of Y_t given Z_t. The minimum KLIC that measures the distance between true distribution and a specified model, say F_θ is given by

$$(4.20) \qquad KLIC(H^\circ_{Y|Z}; F_\theta) \equiv E^\circ[\ln h^\circ(Y_t | Z_t)] - E^\circ[\ln f(Y_t | Z_t)].$$

From Jensen's inequality this KLIC measure is always non-negative and is equal to zero if and only if F_θ is correctly specified.

Extending this concept, given a pair of competing models, it is natural to select the model that is closest to the true conditional distribution. Using the KLIC measure of distance, the competing hypothesis and definitions can be stated as:

$$(4.21) \qquad H_0 : E^\circ \left[ln \frac{f(Y_t|Z_t;\theta)}{g(Y_t|Z_t;\gamma)} \right] = 0,$$

meaning that F_θ and G_γ are equivalent, against

$$(4.22) \qquad H_f : E^\circ \left[ln \frac{f(Y_t|Z_t;\theta)}{g(Y_t|Z_t;\gamma)} \right] > 0,$$

meaning that F_θ is better than G_γ, or

$$(4.23) \qquad H_g : E^\circ \left[ln \frac{f(Y_t|Z_t;\theta)}{g(Y_t|Z_t;\gamma)} \right] < 0,$$

meaning F_θ is worse than G_γ.

If F_θ and G_γ are strictly non-nested, then

(i) under H_0: $n^{-1/2}\ LR_n\ (\hat{\theta}_n, \hat{\gamma}_n)\ /\ \hat{\omega}_n \xrightarrow{d} N(0,1)$,

(ii) under H_f: $n^{-1/2}\ LR_n\ (\hat{\theta}_n, \hat{\gamma}_n)\ /\ \hat{\omega}_n \to +\infty$,

(iii) under H_g: $n^{-1/2}\ LR_n\ (\hat{\theta}_n, \hat{\gamma}_n)\ /\ \hat{\omega}_n \to -\infty$,

where n is the sample size and $\hat{\omega}_n^2$ denote the variance of

$$ln \left[\frac{f(Y_t|Z_t;\hat{\theta}_n)}{g(Y_t|Z_t;\hat{\gamma}_n)} \right],$$

given by

$$(4.24) \qquad \hat{\omega}_n^2 \equiv \frac{1}{n} \sum_{t=1}^{n} \left[ln \frac{f(Y_t|Z_t;\hat{\theta}_n)}{g(Y_t|Z_t;\hat{\gamma}_n)} \right]^2 - \left[\frac{1}{n} \sum_{t=1}^{n} ln \frac{f(Y_t|Z_t;\hat{\theta}_n)}{g(Y_t|Z_t;\hat{\gamma}_n)} \right]^2 .$$

SIMULATIONS

The power of AIC, SIC, LR and KLIC in selecting the best model under non-nested and nested situations is tested using simulations. As such, 1000 repetitive GARCH processes each with 350 observations are simulated. The number of observations is 350 as there are only 352 returns for actual stocks in the previous chapter and one of the uses for the simulation is to pick the best model from the competing ones for the stocks and portfolios under study. Moreover, the parameters for the simulation are obtained from averaging the parameters for the respective models estimated from the 24 NASDAQ stocks[3]. Hence, four GARCH models (without any linear terms) with conditional distributions of normal, Student-t, power exponential and mixed jump-diffusion processes, respectively, are simulated with 1000 repetitions of 350 observations each. A random number from a uniform (0,1) distribution is drawn. Subsequently, the inverse distribution function for N, T and PE with zero mean, unit variance (for T and PE the degrees of freedom are obtained from averaging the NASDAQ parameters) is calculated. The conditional variance is calculated using the variance equation and the observation is scaled accordingly. For the MJ simulation, a poisson distribution is used for simulating the timing of the jumps while their magnitude is derived randomly from a standard normal distribution. Subsequently, GARCH models with

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[3]See Chapter 5 for parameter estimates.

conditional distributions of normal, Student-t, power exponential and mixed jump-diffusion are run on each of these data sets. The intermediate log likelihood values of the last iterations are stored. Thus for each simulation there are four GARCH outputs. The outputs for a particular simulation are taken in pairs and AIC, SIC, LR (if applicable) and KLIC tests are applied. The results are given in tables 4.2.1 through 4.5.3. Table 4.1 gives the decision rule for interpreting the KLIC tests.

SIMULATED GARCH NORMAL

Tables 4.2.1 to 4.2.3 give the results of application of different GARCH models taken in pairs, with the underlying distribution being simulated GARCH normal. According to table 4.2.1, KLIC is unable to decide between normal, Student-t and power exponential. However, each of these outperform the mixed jump-diffusion process when paired with the latter. Consequently, one should select the simpler model i.e. the model with fewer number of parameters -- normal. The contrasting of normal with Student-t or power exponential becomes more clear in the likelihood ratio tests in table 4.2.3 as these are nested comparisons. GARCH-N turns out to be distinctly better than GARCH-T, GARCH-PE or GARCH-MJ. AIC as well as SIC give similar results with SIC favoring normal more than AIC, primarily because the penalty imposed by SIC is higher than that imposed by AIC.

The results of the non-nested comparison of GARCH-T with GARCH-PE are interesting. KLIC is unable to decide between the two but SIC, one of the commonly used non-nested testing criterion, favors GARCH-PE to GARCH-T by 84.9:15.1. The ideal situation is 50:50 as the true underlying distribution is GARCH-N, which is neither GARCH-T nor GARCH-PE. Since both GARCH-T and GARCH-PE have equal number of parameters the results from AIC do not differ from those of SIC. Of course, LR being a test for nested hypothesis is not applicable in this instance.

Thus, it seems under the situation of simulated GARCH-N, a GARCH-PE is able to explain the variations better than GARCH-T. This result is supported by SIC as well as AIC and KLIC does not provide any information to the contrary.

SIMULATED GARCH STUDENT-T

Tables 4.3.1 to 4.3.3 give the results of the fitted models in pairs when the underlying distribution is simulated GARCH-T. As in the previous case, each of the models GARCH-N, GARCH-T and GARCH-PE individually outperform GARCH-MJ using KLIC, SIC or AIC. When compared to normal, both GARCH-T and GARCH-PE outperform normal but power exponential outperforms more than Student-t using KLIC, SIC, AIC or LR. Moreover, comparing GARCH-PE and GARCH-T using KLIC the picture is unclear at the 5% level, but at 1% level PE dominates T 36:0. However, the picture reverses if SIC or AIC is used, as T

outperforms PE 71.3:28.7. There are of course 287 times that PE performs better than T using these tests.

Given contradictory results from KLIC and SIC, the results of KLIC are preferable as KLIC is more suitable for non-nested hypothesis testing and it is a statistical test rather than a counting mechanism.

SIMULATED GARCH POWER EXPONENTIAL

Tables 4.4.1 to 4.4.3 give the results of the four GARCH models when applied on simulated GARCH-PE. Once again mixed jump-diffusion process is outperformed by all the other models using any of the four tests AIC, SIC, LR and KLIC. Moreover, when GARCH-N is compared with GARCH-T or GARCH-PE, it is GARCH-PE that is dominant using any of the tests. Using KLIC at 5% level GARCH-T to GARCH-N is 12:4.4 and GARCH-PE to GARCH-N is 56.6:0.5. Applying the decision rule the picture is unclear between GARCH-T and GARCH-N but GARCH-PE is undoubtedly superior to GARCH-N. Using KLIC at 1% level the corresponding figures are 4.8:0 and 16:0 that shows both GARCH-T and GARCH-PE are superior to GARCH-N. The direct comparison between GARCH-T and GARCH-PE is decisive at 1% as well as 5% level of KLIC. At 5% level GARCH-PE is better than GARCH-T by 45.8:0.1 and at 1% level the figure is 19.4:0.

The overall pattern does not change in case of AIC, SIC or LR. The AIC figures for GARCH-T and GARCH-PE when compared to GARCH-N are 58.1:41.9 and 92:8; the corresponding SIC

figures are 47.9:52.1 and 86:14 and the 5% LR figures are 52.6:47.4 and 89.4:10.6. The SIC figures for direct comparison between GARCH-PE and GARCH-T are 97.3:2.7.

Thus, when the underlying distribution is simulated GARCH-PE, it is correctly identified by GARCH-PE, irrespective of the testing method used. However, when comparing GARCH-T and GARCH-N, KLIC is indecisive at 5% level but favors GARCH-T at 1% level. The same comparison using SIC leads to contradictory result favoring GARCH-N over GARCH-T, though by a very narrow margin.

SIMULATED GARCH MIXED JUMP-DIFFUSION PROCESS

The tables 4.5.1 to 4.5.3 give the results when the underlying distribution is simulated mixed jump-diffusion process. These results on the surface appear uninteresting but when compared to the unconditional mixed jump-diffusion process are quite interesting. None of the comparisons between GARCH-T, GARCH-PE and GARCH-N are decisive using KLIC at either 5% or 1% level. However, each of these are individually favored to GARCH-MJ using any of the four tests. All the three other tests, AIC, SIC and LR respectively favor GARCH-N when it is compared with GARCH-T or GARCH-PE albeit by a narrow margin.

Akgiray and Booth (1987) find the mixed jump-diffusion process to be a satisfactory model in explaining the returns generation of 200 stocks. However, the unconditional jump

effect is completely captured by GARCH with smooth distributions such as N or PE. As such, GARCH with conditional MJ is a poor performer in explaining stock returns. Similar findings are reported in Jorion (1988) as well.

IDEAL SELECTION CRITERION

The summary figures for nested and non-nested testing using the simulation are given in table 4.6.1. AIC and SIC are derived as iid nested tests but used under non-nested non iid situations and KLIC is applicable for both nested as well as non-nested situations. Thus, the performance of AIC, SIC and KLIC are analyzed for both nested and non-nested situations. LR being a nested test exclusively is not covered under non-nested testing. For the non-nested case PE is compared to T, while for the nested case T and PE are individually compared to N for the different underlying distributions.

There is non mathematical difference in the results of AIC and SIC under the non-nested case. All the tests favor PE under simulated N as well as PE. However, under simulated T, the ratio of PE:T as given by AIC and SIC is 28.7:71.3, and that given by KLIC is 3.6:0. The performance of AIC and SIC under N and T is also quite different than that under PE. The margin of error for all the tests under simulated PE (AIC/SIC = 2.7%, KLIC = 0%) is within acceptable statistical limits.

However, error levels of AIC/SIC under simulated N and T (15.1% and 28.7%) are considerably high. KLIC is the only decisive test giving statistically acceptable errors under all the different types of simulations. It leans towards PE for simulated N, T and PE. However, the KLIC results of 0.1:0 under simulated N is not statistically significant. Thus under simulated N, KLIC is unable to differentiate between PE and T, but under simulated T and PE, KLIC identifies the distribution as PE.

In the nested comparisons under simulated N all the tests LR, AIC, SIC and KLIC are able to identify it as N at statistically significant levels. The order of significance is KLIC, LR, SIC and AIC[4] The error levels of LR, AIC and SIC under simulated T and PE are statistically high. Only KLIC gives statistically significant results and they favor PE for simulated T as well as PE. Thus, KLIC is the only test that gives statistically significant results under different underlying distributions for nested and non-nested comparisons.

In summary, the GARCH-PE process seems to be the most flexible as it is able to explain most of the variations irrespective of the underlying simulation process. It is a fat tailed distribution and for similar parameters has a higher peak than Student-t. The total range of the power

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[4] The actual results given by KLIC for T:N or PE:N under simulated N is 0:0 for both. However, the model with less parameters (N) is preferred.

exponential distribution is much wider than either Student-t or normal. The power exponential distribution can span platokurtic as well as leptokurtic distributions but Student-t is a fat tailed distribution as compared to normal. While normal is a special case of both, peaked distributions such as double exponential is a special case of power exponential only. Presumably this wide range makes power exponential relatively robust to underlying distributions.

Several models along with several testing criterion are suggested in the previous sections. The method of selecting the best model is a two step procedure. The first stage is to select the valid models for a particular stock or portfolio based upon the significance of parameter estimates. Subsequently, the residuals are checked for satisfaction of underlying assumptions. They should conform to the respective distributional assumptions and should not show any linear or nonlinear dependence. This leads to the competing models for a stock or portfolio. The diagnostics on the standardized residuals give the χ^2 goodness of fit test for the underlying distribution. Having identified the underlying distribution, the likelihood ratio test can be applied if the distribution is N and it is a nested comparison. If the comparison is between T and PE and the underlying distribution is either one of these, according to simulation results PE is more robust as compared to T.

TABLE 4.1

DECISION RULE FOR KLIC TEST

Second Distribution ⇓ \ First Distribution ⇒	N	T	PE
T	A B C D		
PE			
MJ			

A Number of stocks having KLIC values < -1.96 (5%)

B Number of stocks having KLIC values > +1.96 (5%)

C Number of stocks having KLIC values < -2.576 (1%)

D Number of stocks having KLIC values > +2.576 (1%)

A > 2.5 AND B < 2.5 ⇒ Second distribution better (5%)

A < 2.5 AND B < 2.5 ⇒ Both distributions equally good (5%)

A < 2.5 AND B > 2.5 ⇒ First distribution better (5%)

A > 2.5 AND B > 2.5 ⇒ Unable to decide (5%)

C > 0.5 AND D < 0.5 ⇒ Second distribution better (1%)

C < 0.5 AND D < 0.5 ⇒ Both distributions equally good; (1%)

C < 0.5 AND D > 0.5 ⇒ First distribution better (1%)

C > 0.5 AND D > 0.5 ⇒ Unable to decide (1%)

TABLE 4.2.1

KLIC TEST

SIMULATED DISTRIBUTION: GARCH NORMAL

Second Distribution ⇓ / First Distribution ⇒	N	T	PE
T	0.0 0.0 0.0 0.0		
PE	0.2 0.0 0.0 0.0	0.2 0.0 0.1 0.0	
MJ	0.0 100.0 0.0 0.0	0.0 100.0 0.0 0.0	0.0 100.0 0.0 0.0

TABLE 4.2.2

AKAIKE INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH NORMAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		95.5	94.2	100.0
T	4.5		15.1	100.0
PE	5.8	84.9		100.0
MJ	0.0	0.0	0.0	

SCHWARZ INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH NORMAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		99.8	99.2	100.0
T	0.2		15.1	100.0
PE	8.0	84.9		100.0
MJ	0.0	0.0	0.0	

TABLE 4.2.3

LIKELIHOOD RATIO TEST (5%)

SIMULATED DISTRIBUTION: GARCH NORMAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		98.9	98.4	100.0
T	1.1			
PE	1.6			
MJ	0.0			

LIKELIHOOD RATIO TEST (1%)

SIMULATED DISTRIBUTION: GARCH NORMAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		99.8	99.6	100.0
T	0.2			
PE	0.4			
MJ	0.0			

TABLE 4.3.1

KLIC TEST

SIMULATED DISTRIBUTION: GARCH STUDENT-T

Second Distribution ⇓ / First Distribution ⇒	N		T		PE	
T	52.0	2.8				
	20.9	0.0				
PE	67.0	0.1	5.2	4.7		
	37.0	0.0	3.6	0.0		
MJ	0.0	100.0	0.0	100.0	0.0	100.0
	0.0	0.0	0.0	0.0	0.0	0.0

TABLE 4.3.2

AKAIKE INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH STUDENT-T

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		8.4	3.8	100.0
T	91.6		71.3	100.0
PE	96.2	28.7		100.0
MJ	0.0	0.0	0.0	

SCHWARZ INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH STUDENT-T

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		11.0	6.5	100.0
T	89.0		71.3	100.0
PE	93.5	28.7		100.0
MJ	0.0	0.0	0.0	

TABLE 4.3.3

LIKELIHOOD RATIO TEST (5%)

SIMULATED DISTRIBUTION: GARCH STUDENT-T

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		9.6	4.7	100.0
T	90.4			
PE	95.3			
MJ	0.0			

LIKELIHOOD RATIO TEST (1%)

SIMULATED DISTRIBUTION: GARCH STUDENT-T

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		11.9	6.8	100.0
T	88.1			
PE	93.2			
MJ	0.0			

TABLE 4.4.1

KLIC TEST

SIMULATED DISTRIBUTION: GARCH POWER EXPONENTIAL

First Distribution ⇒ Second Distribution ⇓	N		T		PE	
T	12.0	4.4				
	4.8	0.0				
PE	56.6	5.0	45.8	0.1		
	16.0	0.0	19.4	0.0		
MJ	0.0	100.0	0.0	100.0	0.0	100.0
	0.0	0.0	0.0	0.0	0.0	0.0

TABLE 4.4.2

AKAIKE INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH POWER EXPONENTIAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		41.9	8.0	100.0
T	58.1		2.7	100.0
PE	92.0	97.3		100.0
MJ	0.0	0.0	0.0	

SCHWARZ INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH POWER EXPONENTIAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		52.1	14.0	100.0
T	47.9		2.7	100.0
PE	86.0	97.3		100.0
MJ	0.0	0.0	0.0	

TABLE 4.4.3

LIKELIHOOD RATIO TEST (5%)

SIMULATED DISTRIBUTION: GARCH POWER EXPONENTIAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		47.4	10.6	100.0
T	52.6			
PE	89.4			
MJ	0.0			

LIKELIHOOD RATIO TEST (1%)

SIMULATED DISTRIBUTION: GARCH POWER EXPONENTIAL

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		53.7	14.7	100.0
T	46.3			
PE	85.3			
MJ	0.0			

TABLE 4.5.1

KLIC TEST

SIMULATED DISTRIBUTION: GARCH MIXED JUMP-DIFFUSION

First Distribution ⇒ Second Distribution ⇓	N		T		PE	
T	1.0	0.0				
	0.2	0.0				
PE	0.5	0.0	0.0	2.0		
	0.2	0.0	0.0	0.0		
MJ	0.0	100.0	0.0	100.0	0.0	100.0
	0.0	0.0	0.0	0.0	0.0	0.0

TABLE 4.5.2

AKAIKE INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH MIXED JUMP-DIFFUSION

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		60.7	79.0	100.0
T	39.3		49.6	100.0
PE	21.0	50.4		100.0
MJ	0.0	0.0	0.0	

SCHWARZ INFORMATION CRITERION

SIMULATED DISTRIBUTION: GARCH MIXED JUMP-DIFFUSION

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		75.6	93.9	100.0
T	24.4		49.6	100.0
PE	6.1	50.4		100.0
MJ	0.0	0.0	0.0	

TABLE 4.5.3

LIKELIHOOD RATIO TEST (5%)

SIMULATED DISTRIBUTION: GARCH MIXED JUMP-DIFFUSION

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		69.8	88.1	100.0
T	30.2			
PE	11.9			
MJ	0.0			

LIKELIHOOD RATIO TEST (1%)

SIMULATED DISTRIBUTION: GARCH MIXED JUMP-DIFFUSION

Figures in Row Indicate Preferred Distribution

	N	T	PE	MJ
N		77.4	95.2	100.0
T	22.6			
PE	4.8			
MJ	0.0			

TABLE 4.6

SIMULATION SUMMARY TABLE

NON-NESTED TESTING (PE:T)

	Type of Test ⇒		
	AIC	SIC	KLIC (1%)
Simulated Distribution ⇓			
GARCH-N	84.9:15.1	84.9:15.1	0.1:0.0
GARCH-T	28.7:71.3	28.7:71.3	3.6:0.0
GARCH-PE	97.3:2.7	97.3:2.7	19.4:0.0
GARCH-MJ	50.4:49.6	50.4:49.6	0.0:0.0

SIMULATION SUMMARY TABLE

NESTED TESTING

		LR (1%)	AIC	SIC	KLIC (1%)
N	T:N	0.2:99.8	4.5:95.5	0.2:99.8	0.0:10
	PE:N	0.4:99.6	5.8:94.2	0.8:99.2	0.0:100
T	T:N	88.1:11.9	91.6:8.4	89.0:11.0	20.9:0.0
	PE:N	93.2:6.8	96.2:3.8	93.5:6.5	37.0:0.0
PE	T:N	46.3:53.7	58.1:41.9	47.9:52.1	4.8:0.0
	PE:N	85.3:14.7	92.0:8.0	86.0:14.0	16.0:0.0
MJ	T:N	22.6:77.4	39.3:60.7	24.4:75.6	0.2:0.0
	PE:N	4.8:95.2	21.0:79.0	6.1:93.9	0.2:0.0

CHAPTER 5

ESTIMATION RESULTS

The typical nonlinearity modeled by GARCH is multiplicative nonlinearity but according to the diagnostics on returns several stocks did not have this type of nonlinearity. However, all the GARCH models GARCH-N, GARCH-T, GARCH-PE and GARCH-MJ after augmenting for linear dependence, if any, are applied to all the stocks and portfolios. The purpose is to find out the flexibility of the GARCH model. Consequently, there are different extent to which the models fit the data.

The parameter estimates are reported in Appendix B as tables B.5.A.1 to B.5.A.24 for the NASDAQ stocks and tables B.5.A.25 to B.5.A.28 for the NASDAQ portfolios. Similarly, the parameters for NYSE stocks and portfolios are also reported in Appendix B as tables B.5.B.1 to B.5.B.28. All the models have at least one linear term ϕ_0 that is the unconditional mean of the distribution. If the diagnostics on the returns show linear dependence, the models have an additional linear term ϕ_1. The linear and GARCH parameter estimates as well as the log likelihood values are reported for all the models. Several additional terms such as $\alpha_1 + \beta_1$, HL, σ_c^2, σ_R^2, AIC and SIC are reported if the model has a significant α_0 and at least one of the parameters either α_1 or β_1 is significant as well. The LR statistic of T or PE is also reported if either of these is valid along with the N.

The diagnostic tests on the standardized residuals are given in Appendix C as tables C.5.A.1 to C.5.A.28 for the NASDAQ stocks and portfolios. The corresponding tables for NYSE stocks and portfolios are given in Appendix C tables C.5.B.1 to C.5.B.28. These tables give the location and shape parameters such as mean, variance, skewness, kurtosis and equiprobable χ^2 value, and the dependence details on residuals and squared residuals such as autocorrelation and Ljung-Box Q statistics.

MODEL DISCUSSION

For a GARCH model to be valid it must have a finite positive unconditional variance σ_e^2 as calculated using 4.5. This implies that the coefficient α_0 should be significant and $\alpha_1+\beta_1 < 1$[5]. Since all the three parameters have to be non-negative, the significance is checked using a one tailed test. As such, models that satisfy this condition are identified for further analysis. Moreover, the models need to be classified as ARCH or GARCH depending on the level of significance of β_1. Tables 5.1.A and 5.1.B give an overview of the performance of the various competing models for NASDAQ and NYSE stocks and portfolios. Models that do not have an α_0 significant at least at the 5% level are not reported at all. Those with

[5]The individual significance of each of α_0, α_1 and β_1 is given by the model. The bounds for the standard error of $(\alpha_1+\beta_1)$ can be calculated using $\sigma^2(\alpha_1+\beta_1) = \sigma^2(\alpha_1) + \sigma^2(\beta_1) + 2\rho_{\alpha 1\beta 1}\sigma(\alpha_1)\sigma(\beta_1)$ for $\rho = \pm 1$.

significant α_0 are checked for the level of significance of α_1 as well as β_1 and the least significant level among the three is reported as the level of the model. If all the three parameters α_0, α_1 and β_1 are significant at the 1% level then the model is also given the same level of significance (**) and if any one of these are at 5% level, the model is given a conservative level of 5% (*). The models that have only β_1 as insignificant are reported as ARCH models. Those with insignificant α_1 are indicated accordingly. A very diverse picture appears when the models are analyzed in light of the preliminary statistics on returns and the diagnostics on the standardized residuals. It is interesting to note that GARCH-MJ does not have a single α_0 that is significant either for NASDAQ or for NYSE. The MJ distribution is found to perform satisfactory as an unconditional distribution in a linear model. However, GARCH with conditional distributions of T or N captures the unconditional MJ effect. Hence, MJ is a poor performer as a conditional distribution. These results are similar to ARCH-MJ of Jorion (1989). However, in most models the mixed jump-diffusion process is successful in eliminating the nonlinear dependence observed in the data.

NASDAQ Stocks

Based exclusively on model estimates, there are 5, 13 and 14 stocks without a valid model for N, T and PE respectively. Among the portfolios, there is only one (P3) that does not

have a valid T model. However, significant parameter estimates is just one of the methods in model selection. The standardized residuals of the models with valid parameter estimates are further checked for satisfaction of underlying assumptions. Among the stocks that have at least one valid model several can be discarded based upon error diagnostics. Stock numbers 1, 3, 6, 7, 11, 13, 14, 16, 17 and 22 had at least one valid model based upon parameter estimates but their standardized residuals do not meet the underlying assumptions. The residuals do not fit the equiprobable χ^2 goodness of fit test for the underlying distribution and in some cases (S6, S11 and S13) show linear and nonlinear dependence as well. There are five stocks (S5, S10, S12, S15 and S24) that have only one model that emerges best on applying the diagnostics on residuals. There are two stocks though (S2 and S8) that have more than one model satisfying the underlying conditions. Model selection for these stocks are done based upon the log likelihood value based tests. In all the cases, the competing models are nested and application of likelihood ratio test gives GARCH-PE for S2 and ARCH-PE for S8.

NASDAQ Portfolios

All the portfolios have at least one valid model based upon parameter estimates. Applying the diagnostics on residuals, none of the errors from 'P1' meet the underlying assumptions and the other three have competing models. The valid models

for 'P2' are T and PE, while that for 'P3' and 'ALL' are N and PE. The best model for 'P3' and 'ALL' are chosen on the basis of likelihood ratio tests as the competing models are nested. The best model for P3 is GARCH-N and that for ALL is GARCH-PE. Model selection for 'P2' is done on the basis of simulation for non-nested hypothesis testing. The χ^2 test on standardized residuals of P2 show that all the three models meet the underlying assumptions but applying the LR test both T and PE are found superior to N. This leads to non-nested testing between T and PE. Since the model meets the underlying distributional assumptions of PE, GARCH-PE is valid. Moreover, as found in the simulations GARCH-PE is more robust GARCH model than GARCH-T. Hence, GARCH-PE is chosen as the best model for portfolio 'P2'.

NYSE Stocks

Based upon parameter estimates, there are 5 stocks without a valid model for N and 14 stocks each without valid models for T and PE respectively. However, among the stocks that have at least one valid model, eleven can be discarded by applying the diagnostics on standardized residuals. Stock numbers 1, 2, 3, 5, 9, 10, 11, 15, 16 and 20 have at least one valid model based upon parameter estimates but their standardized residuals do not meet the underlying assumptions. The residuals do not fit the equiprobable χ^2 goodness of fit test for the underlying distribution. Among the valid stocks

six (S12, S13, S17, S19, S22 and S23) have only one model that emerges best on applying the diagnostics on residuals. There are three stocks though (S6, S18 and S24) that have more than one model satisfying the underlying conditions. Model selection for these stocks are done based upon the log likelihood value based tests. In all the cases, the competing models are nested and application of likelihood ratio test gives decisive results. The competing models for S6 and S18 are N and PE, while those for S24 are N and T. Hence, the competing models for these stocks are all nested. Applying the LR test GARCH-PE is the best model for S6 and S18, and GARCH-T is the best model for S24.

NYSE Portfolios

The portfolio models are quite similar for the two markets NASDAQ and NYSE. According to parameter estimates 'P1' has three valid models but on application of error diagnostics, none of the models meet their underlying assumptions. Among the other three portfolios, 'P2' and 'ALL' have nested competing models and 'P3' has just GARCH-N that satisfy the assumptions. The likelihood ratio test is applied to select the best models ARCH-PE and GARCH-PE from the competing ones for 'P2' and 'ALL'.

MODEL SUMMARY

Table 5.2 gives a summary of the best models selected for NASDAQ and NYSE stocks and portfolios. There are 15 stocks in each market that can not be modeled using GARCH. Out of the nine that can be modeled, more than half are PE. While each market has three N stocks, there are six PE stocks in NASDAQ and five in NYSE. There is only one GARCH-T in the total sample of stocks from the two markets. The pattern of conditional distribution among portfolios is identical in the two markets. Each has two PE, one N and portfolio 'P1' with no model.

The distribution of nonlinear models in the two markets are quite similar. More than half the stocks do not have a nonlinear model. However, on forming portfolios, each has more than one model with significant parameters but on applying the diagnostics on standardized residuals the models for 'P1' do not meet the underlying assumptions for both markets.

TABLE 5.1.A

MODEL SUMMARY FOR NASDAQ STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
1	** (ARCH)	* α_1 insig.	-	-	No valid model
2	**	*	*	-	GARCH-PE; HL=5.33 σ_R^2=0.0045
3	**	-	-	-	χ^2 (residuals) significant No valid model
4	-	-	-	-	No valid model
5	**	*	*	-	GARCH-PE; HL=17.77 σ_R^2=0.016
6	*	-	* α_1 insig.	- -	All χ^2 (residuals) significant No valid model
7	**	**	**	-	All χ^2 (residuals) significant No valid model
8	** (ARCH)	* (ARCH)	** (ARCH)	-	ARCH-PE; HL=1.72 σ_R^2=0.0048
9	-	-	-	-	No valid model

TABLE 5.1.A (CONTINUED)

MODEL SUMMARY FOR NASDAQ STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
10	** (ARCH)	* (ARCH)	* (ARCH)	-	ARCH-PE; HL=1.95 σ_R^2=0.0056
11	* (ARCH)	* (ARCH)	* (ARCH)	-	No valid model
12	** (ARCH)	**	*	-	GARCH-PE; HL=5.99 σ_R^2=0.0027
13	* (ARCH)	* (ARCH)	* (ARCH)	-	No valid model
14	**	-	-	-	No valid model
15	*	-	-	-	GARCH-N; HL=2.32 σ_R^2=0.0074
16	* (ARCH)	-	-	-	No valid model
17	-	* (ARCH)	-	-	No valid model
18	**	-	-	-	GARCH-N; HL=9.36 σ_R^2=0.0061

TABLE 5.1.A (CONTINUED)

MODEL SUMMARY FOR NASDAQ STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
19	* (ARCH)	–	–	–	No valid model
20	* (ARCH)	–	–	–	ARCH-N; HL=1.75 σ_R^2=0.0061
21	–	–	–	–	No valid model
22	*	–	–	–	No valid model
23	–	–	–	–	No valid model
24	** (ARCH)	**	** (ARCH)	– (ARCH)	ARCH-PE; HL=1.44 σ_R^2=0.007
Portfolios					
P1	**	**	** α_1 insig.	–	No valid model
P2	**	*	*	–	GARCH-PE; HL=4.00 σ_R^2=0.0013

TABLE 5.1.A (CONTINUED)

MODEL SUMMARY FOR NASDAQ STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Portfolios					
P3	**	-	** (ARCH)	-	GARCH-N; HL=2.34 σ_R^2=0.0016
ALL	**	*	*	-	GARCH-PE; HL=4.19 σ_R^2=0.0011

If all the three parameters α_0, α_1 and β_1 are significant at the 1% level then the model is also given the same level of significance (**) and if any one of these are at 5% level, the model is given a conservative level of 5% (*).

TABLE 5.1.B

MODEL SUMMARY FOR NYSE STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
1	** (ARCH)	** (ARCH)	** (ARCH)	-	No valid model
2	*	-	-	-	No valid model
3	**	-	-	-	No valid model
4	-	-	-	-	No valid model
5	** (ARCH)	* (ARCH)	* (ARCH)	-	No valid model
6	**	-	*	-	GARCH-PE; HL=9.13 σ_R^2=0.0181
7	-	-	-	-	No valid model
8	-	-	-	-	No valid model
9	*	** (ARCH)	**	-	No valid model
10	*	-	-	-	No valid model
11	*	-	-	-	No valid model

TABLE 5.1.B (CONTINUED)

MODEL SUMMARY FOR NYSE STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
12	** (ARCH)	* (ARCH)	* (ARCH)	-	ARCH-PE; HL=1.94 σ_R^2=0.0055
13	*	-	-	-	GARCH-N; HL=9.36 σ_R^2=0.0154
14	-	-	-	-	No valid model
15	** (ARCH)	-	-	-	No valid model
16	**	* α_1 insig.	**	-	No valid model
17	**	** (ARCH)	*	-	GARCH-PE; HL=2.66 σ_R^2=0.0034
18	**	*	*	-	GARCH-PE; HL=4.95 σ_R^2=0.0033
19	*	-	*	-	GARCH-PE; HL=4.78 σ_R^2=0.0041
20	** (ARCH)	** (ARCH)	* (ARCH)	-	No valid model

TABLE 5.1.B (CONTINUED)

MODEL SUMMARY FOR NYSE STOCKS & PORTFOLIOS

Num.	(N)	(T)	(PE)	(MJ)	Best Model/Comments
Stocks					
21	-	-	-	-	No valid model
22	**	*	-	-	GARCH-N; HL=7.13 σ_R^2=0.0023
23	**	-	-	-	GARCH-N; HL=3.94 σ_R^2=0.0032
24	*	*	-	-	GARCH-T; HL=5.99 σ_R^2=0.0015
Portfolios					
P1	**	*	*	-	No valid model
P2	* (ARCH)	*	* (ARCH)	- (ARCH)	ARCH-PE; HL=1.42 σ_R^2=0.0011
P3	*	-	-	-	GARCH-N; HL=7.40 σ_R^2=0.0097
ALL	**	*	*	-	GARCH-PE; HL=2.57 σ_R^2=0.0008

If all the three parameters α_0, α_1 and β_1 are significant at the 1% level then the model is also given the same level of significance (**) and if any one of these are at 5% level, the model is given a conservative level of 5% (*).

TABLE 5.2

SUMMARY TABLE FOR BEST MODELS

	NASDAQ	NYSE
Stocks		
PE	6	5
N	3	3
T	0	1
No Model	15	15
Total	24	24
Portfolios		
PE	2	2
N	1	1
T	0	0
No Model	1	1
Total	4	4

CHAPTER 6

SUMMARY AND DISCUSSION OF FUTURE RESEARCH

Several interesting conclusions can be drawn from this study. As highlighted in table 3.2 basic stocks show different types of dependence. They may be statistically independent, linearly dependent, nonlinearly dependent or both linear as well as nonlinearly dependent. Moreover, according to Hsieh test the nonlinear dependence may be classified as additive or multiplicative.

Comparing the two markets NASDAQ and NYSE the distribution of firms by the market value of equity is quite different. NASDAQ has a total of 986 firms with good data. The mean size (market value of equity) is $178 million, with the largest being $5470 million. NYSE has a total of 1080 firms with a mean of $3693 million. Firms larger than $5470 million on the NYSE are not considered in the study. Thus the NYSE population goes down to 980 which is 90.7 percentile of the original distribution. Subsequently, the cut off points for the three windows are marked as $25 million and $120 million as these are 33 and 66 percentile marks of NASDAQ firms. Consequently, samples of eight firms are drawn from each of the three windows of the two markets. These windows are named as groups one to three in tables 3.1.A and 3.1.B. Thus two sets of sample are drawn from two populations that are identical in size but differ in their market micro

structure. Any difference observed in these two groups of stocks should be due to the differences in their respective returns generation processes.

NON-NESTED HYPOTHESIS TESTING

A simulation study is done for selection of the best model when the alternative hypothesis are non-nested. Four GARCH processes with conditional distributions of N, T, PE and MJ are simulated with each having 1000 samples of 350 observations each. Model selection is done using AIC, SIC, LR and KLIC. These tests are based upon different assumptions. SIC is a modification of AIC and a Bayesian approach assuming all the possibilities are considered and that they have equal priors. While AIC and SIC are counting mechanisms, LR and KLIC are statistical tests. AIC, SIC and LR are applicable for nested linear hypothesis with iid observations only and KLIC, though suitable for either nested or non-nested hypothesis, requires observations to be iid. A GARCH process by definition does not have iid observations. Thus, the simulation tests the robustness of AIC, SIC and KLIC in non-nested nonlinear hypothesis testing.

The overall results indicate that GARCH-PE is the most flexible GARCH model robust to variations in the underlying conditional distribution. When the underlying distribution is not PE, GARCH-PE dominates the other models. Of course, when

the underlying distribution is PE, GARCH-PE continues to perform better than the other models.

In summary, KLIC augments the equiprobable χ^2 goodness of fit test on the standardized residuals. If the underlying distribution is PE, KLIC says GARCH-PE is better than any other model. If the underlying distribution is not PE, for example T, GARCH-PE is still found to perform better than the performance of GARCH-T with underlying PE.

There are several reasons that can be attributed to this phenomenon. It may be that the PE distribution is robust to variations as N is a special case of PE or as PE and T are members of Generalized-t. Moreover, PE can handle leptokurtosis as well as platokurtosis, while T is a thick tailed distribution. Not only does PE have a wider range than T, it can handle higher peakedness as compared to T, as double exponential is a special case of PE.

STOCKS

Though the inferences are drawn from a sample of 24 stocks and four portfolios per market, they seem to be indicative of the overall pattern. One of the initial difference is in the statistical dependence data already reported in table 3.2. NASDAQ stocks show more dependence than NYSE in this table. There are 14 NASDAQ stocks that have both linear and nonlinear dependence as compared to eight NYSE stocks. Again there are five NYSE stocks that are

statistically independent as compared to only one of NASDAQ. Thus in the continuum from statistically independent to nonlinear dependence, NYSE is skewed to the left and NASDAQ to the right. Most of the other basic statistics are quite similar. The kurtosis is significant for all stocks under study. There are six stocks on each that have significant skewness and eight that fail the Hsieh test. As reported earlier the Hsieh test results need to be analyzed in light of the dependence statistics such as autocorrelation or Ljung-Box Q statistics. The null hypothesis of multiplicative nonlinearity could be rejected for NASDAQ stocks S4, S6, S14 and S19. Consequently, a priori information is there that among those stocks showing nonlinear dependence GARCH may not be applicative for some that have additive nonlinearity. As seen from table 5.1.A these stocks do not have a valid GARCH model. Hsieh test is ambiguous on NASDAQ stocks S9, S10, S18 and S22 due to presence of linear dependence. It is observed from table 5.1.A that S10 and S18 do have valid nonlinear models. Thus the robustness of GARCH in modeling multiplicative nonlinear dependence is supported by preliminary diagnostics such as autocorrelations and Ljung-Box Q statistics on returns and returns square along with Hsieh test.

There are nine (36% of sample size) stocks from each market that can be modeled using GARCH or ARCH. The distribution of the nine nonlinear stocks is interesting. In

case of NASDAQ they are distributed evenly among the three windows with three in each. However, in case of NYSE there is just one (S6) from the first window, two (S12 and S13) from the second window and six (S17, S18, S19, S22, S23 and S24) from the third window. The half life (HL) of NASDAQ stocks range from 1.44 to 17.77. Moreover, 1.44 is for the largest stock in the sample and 17.77 for stock five that is from the first window. Probably due to longer memory, the half life of GARCH stocks are higher than that of ARCH stocks. The ARCH HL range from 1.44 to 1.95 and GARCH HL range from 2.32 to 17.77. There are four stocks in NASDAQ that are ARCH and five that are GARCH. The corresponding figures for NYSE are one ARCH and eight GARCH. Consequently, the average NYSE HL is higher than NASDAQ.

PORTFOLIOS

Though the individual stocks have varying degrees of dependence, all the portfolios show significant linear and nonlinear dependence. All the portfolios have insignificant mean. The variance of the largest portfolio 'ALL' is less than any of its constituent portfolio 'P1', 'P2' or 'P3' for both markets NASDAQ and NYSE. Moreover, while most stocks have positive skewness, the skewness of the portfolio moves from positive to negative as the size increases. The skewness for the NASDAQ portfolios 'P1' is positive, while that for 'P2' and 'ALL' are negative. Portfolio 'P3' has insignificant

skewness. Only one portfolio in NYSE, 'P2' has significant positive skewness, and the skewness for the others are all insignificant. Comparing portfolio 'ALL' between NASDAQ and NYSE, the NASDAQ portfolio has higher mean, variance, skewness but opposite sign, kurtosis, χ^2_{normal} and Hsieh test. While the linear and nonlinear dependence characteristics of the two portfolios are quite similar, NASDAQ 'ALL' is higher than NYSE 'ALL' in almost all basic statistical measures.

The nonlinear modeling of the two sets of portfolios are quite similar. Portfolio 'P1' of either market does not have a valid nonlinear model. Similarly, the conditional distributions for 'P2' is PE, 'P3' is N and 'ALL' is once again PE. The only difference in the two markets is that 'P2' is GARCH-PE in case of NASDAQ and ARCH-PE in case of NYSE. All the other nonlinear portfolio models are GARCH. Although the modeling may be different at the level of individual stocks, yet once the portfolios are formed the modeling becomes quite similar. The market characteristics seem to have a higher influence on the individual stocks than portfolios. Moreover, 'P1' is statistically different from 'P2' or 'P3', all of which have equal number of stocks. The only difference in these portfolios is in the selection of stocks. Portfolios of very small stocks, though showing significant linear as well as nonlinear dependence can not be efficiently modeled using GARCH. Another interesting observation is that the null hypothesis of multiplicative

nonlinearity cannot be rejected for both portfolios NASDAQ 'P1' and NYSE 'P1' and yet they can not be modeled using GARCH. Probably the main reason is that both the linear and nonlinear dependence are significant for considerable long lags and thus can not be modeled using GARCH.

SUGGESTIONS FOR FUTURE RESEARCH

In the simulation study, the number of observations could be increased from 350 to 1000 per sample. It is anticipated that a sample size of 1000 will eliminate small sample effects of estimation, if any, in the study.

The simulation study is done to resolve an ambiguous situation when two non-nested models turn out to be competing using the diagnostics on residuals. However, the results of the simulation are applied only for just one (NASDAQ portfolio 'P2') out of the 56 stocks and portfolios studied. In all remaining 55 cases the best model is chosen either on the basis of diagnostics on the standardized residuals or using nested hypothesis testing. However, the simulation study does give an insight into the flexibility of the GARCH-PE in case a situation of non-nested testing arises.

Future research could also probe into the reasons behind the dominance of PE over T by using them as special cases of Generalized-t. PE has a wider range than T as it can handle both leptokurtosis and platokurtosis and consequently robust to variations in the underlying distribution.

CONCLUSIONS

There are several contributions of this dissertation. It is the first time that nonlinear modeling has been attempted on individual stocks and the relative performance studied based upon diagnostics on returns, standardized residuals and non-nested simulation. Not all stocks have a GARCH effect but once they are put together in a portfolio and if the stocks are not the smallest ones in the market, the portfolio does have a GARCH effect. Moreover, MJ is not an appropriate conditional distribution for GARCH as evidenced by the performance of GARCH-MJ on the stocks, portfolios or under simulation. GARCH-PE is found to be the most flexible GARCH model robust to variations in the underlying distributions. Similar robustness of an empirical distribution over theoretical model has been found earlier by Frankfurter and Lamoureux (1987). They simulate two sets of stock returns data. One set conforms to the stable Paretian distribution, while the other is a Gaussian distribution. On forming efficient frontiers, they find that the Gaussian assumption is preferable to the general stable distribution. It is interesting to note that a unique member of the general stable distribution turns out to be more robust in parameter estimations as compared to the general model.

GARCH-PE has performed better than GARCH-T in earlier studies as well. Booth, et al. (1991), and Hatem (1990) have found that power exponential distribution fits stock returns

data better than either normal or Student-t. Booth, et al. (1991) suggest that an AR(2)-GARCH (1,1) model with a power exponential conditional distribution, represents the Finnish data better than any of the other models. However, while using German stocks Booth, Hatem and Mustafa (1990) find a normal distribution fit the data. Hatem (1990) studies the nonlinear dependence in intradaily stock prices. He applies the GARCH model to ten minute and thirty minute data. His findings also suggest that the power exponential provides a better fit to the data than either normal or Student-t.

The simulation study gives an additional insight into the flexibility of GARCH-PE and its superiority to GARCH-T. The two GARCH models that are able to explain most asset pricing data are GARCH-N and GARCH-PE. Since it is dominated by GARCH-PE in most cases, probably there is no justification in applying GARCH-T to asset pricing data.

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APPENDIX A

EMPIRICAL CHARACTERISTICS OF RETURNS

Table A.3.A.1
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 1	NASD 2	NASD 3	NASD 4
Location and Shape				
Returns				
Mean	0.00300	-0.00019	0.00217	0.00922*
Variance	0.01021	0.00557	0.00822	0.00468
Skewness	2.14137**	1.35553**	0.95488**	0.78521**
Kurtosis	11.90410**	6.26472**	3.64185**	2.03713**
χ^2_{normal}	143.813**	190.13**	118.601**	206.561**
Hsieh Test	1	0	2	4
Structure				
Returns	0.01340	-0.01521	-0.01469	0.01236
Returns^2	-0.01823	-0.00196	-0.00145	-0.00321**
Dependence				
Returns				
Autocorrelation:				
lag 1	0.25243**	0.33756**	0.26093**	0.21828**
lag 2	-0.01548	0.05036	-0.10192	0.01732
lag 3	-0.02189	-0.00379	-0.00091	0.00070
lag 4	-0.01316	0.05962	0.07962	0.01134
lag 5	0.02043	-0.06543	0.04545	0.04888
lag 6	-0.08423	-0.05493	-0.04647	-0.01520
Ljung-Box:				
Q(6)	25.72**	45.38**	31.75**	18.06**
Q(12)	37.70**	53.68**	38.93**	32.39**
Q(24)	45.49**	58.88**	58.19**	42.10*
Squared Returns				
Autocorrelation:				
lag 1	0.28521**	0.36817**	0.10957	0.08996
lag 2	0.00082	0.06579	0.01439	0.08891
lag 3	-0.01382	-0.02643	0.15872**	-0.02046
lag 4	0.01857	-0.03605	0.06619	-0.01940
lag 5	-0.00207	-0.00258	-0.01601	0.02756
lag 6	-0.00985	0.01249	0.03381	0.04911
Ljung-Box:				
Q(6)	29.19**	50.58**	15.45*	7.13
Q(12)	29.83**	56.91**	22.53*	14.78
Q(24)	35.70**	59.72**	33.86	33.07

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.A.2
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 5	NASD 6	NASD 7	NASD 8
Location and Shape				
Returns				
Mean	-0.00172	0.00845*	-0.00067	0.00056
Variance	0.01482	0.00439	0.00919	0.00475
Skewness	2.20820**	1.33956**	2.14425**	0.59909**
Kurtosis	11.163**	7.73182**	20.8569**	4.09425**
χ^2_{normal}	202.453**	128.657**	178.941**	180.924**
Hsieh Test	2	3	1	1
Structure				
Returns	0.01090	0.00188	-0.02071*	-0.00398
Returns^2	0.01221*	-0.00024	0.00561	0.00121
Dependence				
Returns				
Autocorrelation:				
lag 1	0.22250**	0.13888	-0.00607	0.21803**
lag 2	-0.06787	-0.09775	0.00011	0.03497
lag 3	0.06697	-0.01523	0.13362	-0.01084
lag 4	-0.00117	0.01297	0.13016	-0.07034
lag 5	-0.02641	-0.05702	-0.09859	0.00199
lag 6	0.05269	-0.03523	-0.01492	0.01657
Ljung-Box:				
Q(6)	22.13**	12.04	16.07*	19.28**
Q(12)	26.86**	16.55	17.52	25.35*
Q(24)	44.30**	27.62	29.06	35.71
Squared Returns				
Autocorrelation:				
lag 1	0.38295**	0.03254	0.13600	0.14203
lag 2	0.02625	0.20528**	0.03855	-0.01383
lag 3	0.16983**	-0.03853	0.03239	0.00856
lag 4	0.11475	-0.00829	0.09001	-0.02994
lag 5	0.02425	-0.04653	0.07142	-0.00258
lag 6	0.01554	-0.02215	0.02190	0.02756
Ljung-Box:				
Q(6)	67.81**	16.93*	12.41	7.87
Q(12)	74.95**	19.32	18.78	11.84
Q(24)	78.86**	28.37	20.63	25.22

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.A.3
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 9	NASD 10	NASD 11	NASD 12
Location and Shape				
Returns				
Mean	0.00682	0.00160	-0.00044	0.00358
Variance	0.00391	0.00552	0.00341	0.00347
Skewness	0.27708**	1.08242**	0.74154**	-0.30305**
Kurtosis	1.21455**	3.73345**	2.92061**	7.16546**
χ^2_{normal}	151.603**	119.309**	151.178**	103.02**
Hsieh Test	3	4	2	2
Structure				
Returns	-0.00189	-0.00693	0.00702	-0.00796
Returns^2	-0.00216**	0.00093	-0.00048	0.00037
Dependence				
Returns				
Autocorrelation:				
lag 1	0.11803	0.19664**	0.23417**	0.20913**
lag 2	0.03965	-0.00997	-0.11409	-0.05287
lag 3	-0.10687	0.00198	-0.04003	0.00180
lag 4	-0.00487	-0.02152	-0.11857	-0.05201
lag 5	0.05694	-0.04985	-0.11240	0.04978
lag 6	0.03173	0.00684	0.05401	-0.06264
Ljung-Box:				
Q(6)	11.15	14.88*	35.39**	19.85**
Q(12)	24.43*	18.27	47.62**	34.53**
Q(24)	45.98**	30.97	91.21**	46.89**
Squared Returns				
Autocorrelation:				
lag 1	0.13296	0.17419**	0.12284	0.28931**
lag 2	0.09924	-0.00357	0.03853	0.11778
lag 3	0.04556	0.00991	-0.05817	0.07113
lag 4	0.03694	-0.03457	-0.01708	0.00405
lag 5	-0.00168	-0.01021	0.02072	0.00800
lag 6	0.06438	0.01913	-0.06022	0.02230
Ljung-Box:				
Q(6)	12.54	11.44	8.68	36.77**
Q(12)	55.64**	15.15	11.15	38.81**
Q(24)	77.68**	50.06**	20.98	44.99**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.A.4
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 13	NASD 14	NASD 15	NASD 16
Location and Shape				
Returns				
Mean	0.00247	0.00419	0.00270	0.00585
Variance	0.00470	0.00764	0.00744	0.00770
Skewness	0.50626**	1.28638**	0.14314	0.52830**
Kurtosis	2.80326**	3.24642**	0.94517**	1.64135**
χ^2_{normal}	84.47**	96.363**	45.938**	43.388**
Hsieh Test	1	3	0	1
Structure				
Returns	0.001085	0.000651	-0.020311*	0.000945
Returns^2	-0.003994**	-0.001503	0.000194	-0.000390
Dependence				
Returns				
Autocorrelation:				
lag 1	0.10487	0.11675	0.15716**	0.07887
lag 2	0.01548	-0.04184	-0.04004	0.01282
lag 3	-0.08261	0.05129	0.02928	-0.00150
lag 4	-0.08587	-0.03339	0.02134	0.05103
lag 5	0.00909	-0.07095	0.06800	0.04066
lag 6	0.05266	-0.01746	-0.01213	-0.01744
Ljung-Box:				
Q(6)	10.12	8.74	11.55	3.91
Q(12)	30.89**	18.37	18.30	5.28
Q(24)	63.23**	34.18	27.02	12.73
Squared Returns				
Autocorrelation:				
lag 1	0.00319	0.03550	0.16204**	0.09199
lag 2	0.01152	0.00084	0.09904	0.00808
lag 3	0.05225	0.14293	-0.03367	0.02332
lag 4	0.03927	0.03916	0.05419	-0.01031
lag 5	0.01905	0.02861	-0.01352	-0.01977
lag 6	0.02176	0.00041	0.00135	0.02965
Ljung-Box:				
Q(6)	1.88	8.61	14.38*	3.73
Q(12)	16.25	23.67*	16.55	7.59
Q(24)	49.83**	30.65	29.43	19.57

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.A.5
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 17	NASD 18	NASD 19	NASD 20
Location and Shape				
Returns				
Mean	0.00230	0.00682	0.00514	0.00738
Variance	0.00249	0.00536	0.00400	0.00619
Skewness	0.41595**	0.71149**	0.03552	0.10091
Kurtosis	1.38657**	3.34708**	1.64282**	0.74635**
χ^2_{normal}	55.994**	49.479**	70.584**	28.516
Hsieh Test	0	7	3	2
Structure				
Returns	-0.002337	-0.008917	0.009050	-0.005360
Returns^2	-0.000176	-0.001937	-0.000326	-0.000820
Dependence				
Returns				
Autocorrelation:				
lag 1	0.19823**	0.15023	0.18499**	0.11692
lag 2	-0.01259	-0.08142	0.02106	-0.07527
lag 3	-0.01450	-0.03599	-0.02544	0.02677
lag 4	-0.01572	0.08231	-0.06448	0.03536
lag 5	0.01831	0.05432	-0.04343	0.01889
lag 6	-0.04899	0.09868	0.04222	0.06157
Ljung-Box:				
Q(6)	15.20*	17.88**	15.39*	9.09
Q(12)	37.36**	26.33*	25.91*	13.59
Q(24)	43.45**	32.72	33.08	26.63
Squared Returns				
Autocorrelation:				
lag 1	0.09232	0.15435	0.10411	0.13168
lag 2	-0.01525	0.02633	-0.03327	0.14329
lag 3	-0.06410	0.04752	-0.01001	0.06829
lag 4	0.03759	0.09939	-0.05549	0.01121
lag 5	-0.05665	0.04269	-0.04601	-0.02567
lag 6	-0.01282	0.06638	-0.04425	-0.02630
Ljung-Box:				
Q(6)	6.31	15.33*	6.86	15.70*
Q(12)	17.31	19.80	11.23	17.67
Q(24)	34.46	27.47	23.83	23.92

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.A.6
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NASD 21	NASD 22	NASD 23	NASD 24
Location and Shape				
Returns				
Mean	0.00023	0.00557	0.00134	0.00719
Variance	0.00187	0.00668	0.00428	0.00654
Skewness	-0.09136	-0.14400	0.14294	0.67330**
Kurtosis	1.64431**	2.06843**	0.74440**	1.35899**
χ^2_{normal}	50.045**	36.164	36.589	36.448
Hsieh Test	1	7	2	2
Structure				
Returns	-0.004736	-0.004691	-0.008477	-0.015565
Returns^2	0.000231	0.002814*	-0.001480	0.00005
Dependence				
Returns				
Autocorreletaion:				
lag 1	0.24129**	0.01661	0.20889**	0.22405**
lag 2	-0.13150	-0.10323	-0.01747	-0.09727
lag 3	-0.05469	0.00798	-0.03219	-0.00174
lag 4	-0.02225	-0.06452	0.00222	-0.04767
lag 5	0.01148	-0.02425	0.01861	0.01848
lag 6	0.01775	0.10952	0.01763	-0.01221
Ljung-Box:				
Q(6)	28.31**	9.96	16.25*	22.24**
Q(12)	34.67**	16.08	27.94**	28.84**
Q(24)	47.11**	39.00*	53.66**	48.90**
Squared Returns				
Autocorreletaion:				
lag 1	0.07733	0.1008	0.21667**	0.21931**
lag 2	0.02580	0.136	-0.0017	0.00249
lag 3	0.05168	0.03945	-0.03726	0.09110
lag 4	0.17197**	0.046	-0.05337	-0.01465
lag 5	0.10666	0.02131	-0.03679	-0.04319
lag 6	0.08870	0.07195	0.02643	0.02268
Ljung-Box:				
Q(6)	20.88**	13.57*	18.97**	21.03**
Q(12)	26.44**	18.53	20.31	22.40*
Q(24)	46.16**	26.59	30.47	31.37

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, and the Q-statistics for various lags. For the autocorrelatin coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error.

Table A.3.A.7
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)
NASDAQ Portfolios

Statistics	P1	P2	P3	ALL
Location and Shape				
Returns				
Mean	0.00260	0.00334	0.00450	0.00348
Variance	0.00180	0.00140	0.00155	0.00114
Skewness	0.56569**	-0.45574**	-0.22133	-0.44737**
Kurtosis	4.74829**	5.37143**	3.13324**	6.29159*
χ^2_{normal}	55.711**	44.096*	43.105*	49.620**
Hsieh Test	1	5	5	9
Dependence				
Returns				
Autocorreletaion:				
lag 1	0.37344**	0.23278**	0.25428**	0.36440**
lag 2	0.07079	0.01332	-0.02843	0.07021
lag 3	0.11340	0.08196	0.04441	0.12397
lag 4	0.14393	-0.01766	-0.01484	0.06499
lag 5	0.02940	0.02750	0.03522	0.05422
lag 6	-0.03701	0.08459	0.11305	0.08130
Ljung-Box:				
Q(6)	64.29**	24.73**	29.15**	59.50**
Q(12)	69.87**	28.52**	32.08**	61.35**
Q(24)	93.26**	43.11*	48.71**	76.23**
Squared Returns				
Autocorreletaion:				
lag 1	0.25676**	0.40018**	0.18543**	0.36507**
lag 2	0.00454	0.07486	0.10736	0.08573
lag 3	0.07995	0.00986	0.01142	0.05112
lag 4	0.03185	0.01990	-0.03593	0.02703
lag 5	-0.03158	0.00650	-0.03011	-0.02007
lag 6	-0.04591	0.02427	0.04227	-0.00100
Ljung-Box:				
Q(6)	27.25**	59.42**	17.84**	51.42**
Q(12)	82.87**	62.03**	28.57**	54.65**
Q(24)	89.82**	64.40**	33.87	57.17**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, and the Q-statistics for various lags. For the autocorrelatin coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error.

Table A.3.B.1
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 1	NYSE 2	NYSE 3	NYSE 4
Location and Shape				
Returns				
Mean	0.00133	0.00080	-0.00109	-0.00370
Variance	0.00629	0.00484	0.00536	0.00666
Skewness	0.51980**	0.86663**	-0.09498	2.16904**
Kurtosis	2.39830**	4.00101**	3.13725**	14.4004**
χ^2_{normal}	271.15**	200.187**	217.467**	505.853**
Hsieh Test	0	0	1	6
Structure				
Returns	-0.0106	0.010590	0.008168	0.002283
Returns^2	0.0025	0.001268	0.000954	0.001760
Dependence				
Returns				
Autocorrelation:				
lag 1	0.13466**	0.02671	0.02667	0.08518
lag 2	-0.03868	-0.07470	-0.11675	0.03092
lag 3	0.03964	-0.02052	-0.03860	-0.00521
lag 4	0.02325	-0.02174	-0.04397	-0.04422
lag 5	-0.01635	-0.03803	0.04920	0.00555
lag 6	-0.00691	-0.01458	0.06291	-0.00387
Ljung-Box:				
Q(6)	7.86	3.16	8.65	3.65
Q(12)	12.45	12.30	13.13	9.12
Q(24)	20.08	30.54	30.64	19.37
Squared Returns				
Autocorrelation:				
lag 1	0.18180**	0.03134	0.05813	-0.01030
lag 2	0.00927	-0.00033	0.07506	0.00327
lag 3	0.03708	-0.01353	0.06215	0.00154
lag 4	0.00454	0.11989	-0.04521	-0.01738
lag 5	0.01347	0.00979	0.07408	0.03326
lag 6	-0.03993	0.08642	0.11246	-0.02443
Ljung-Box:				
Q(6)	12.94*	8.31	11.88	0.76
Q(12)	23.81*	9.51	28.06**	2.79
Q(24)	31.28	19.87	32.70	4.13

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.2
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 5	NYSE 6	NYSE 7	NYSE 8
Location and Shape				
Returns				
Mean	-0.00664	0.00137	0.00348*	0.01083
Variance	0.00695	0.01084	0.00611	0.01895
Skewness	0.08452	0.81979**	0.81760**	1.88367**
Kurtosis	1.68412**	3.50846**	3.05177**	9.43938**
χ^2_{normal}	68.459**	52.17**	199.479**	318.459**
Hsieh Test	2	0	0	4
Structure				
Returns	-0.009672	-0.030217**	-0.002465	0.029533*
Returns^2	0.002051	-0.008782**	-0.000320	0.009261
Dependence				
Returns				
Autocorrelation:				
lag 1	0.14214	0.23824**	0.15563**	0.16375**
lag 2	-0.01874	0.03890	0.00137	0.08230
lag 3	-0.00198	0.10593	0.00171	0.00501
lag 4	-0.03557	0.10817	0.02376	-0.00750
lag 5	0.01284	0.02580	0.13564	0.00350
lag 6	-0.00705	-0.05578	0.14970	-0.03816
Ljung-Box:				
Q(6)	7.76	30.33**	23.54**	12.52
Q(12)	10.86	32.86**	34.40**	15.11
Q(24)	26.97	57.76**	44.69**	30.87
Squared Returns				
Autocorrelation:				
lag 1	0.36391**	0.09302	0.09207	-0.01117
lag 2	0.16163**	0.12248	-0.04826	0.04601
lag 3	0.07697	0.12637	-0.02638	-0.00913
lag 4	0.01434	0.08228	-0.05486	0.03538
lag 5	0.03448	0.07814	0.09719	-0.02153
lag 6	-0.01751	0.04470	0.08208	0.00140
Ljung-Box:				
Q(6)	59.21**	19.50**	11.01	1.45
Q(12)	61.30**	27.14**	12.23	1.92
Q(24)	82.04**	36.66*	16.32	6.30

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.3
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 9	NYSE 10	NYSE 11	NYSE 12
Location and Shape				
Returns				
Mean	-0.00221	0.00461	0.00376**	0.00241
Variance	0.01231	0.00042	0.00063	0.00330
Skewness	0.50768**	0.46664**	0.38930	0.73655**
Kurtosis	2.31439**	4.39797**	0.79088**	2.11966**
χ^2_{normal}	314.493**	295.09**	169.309**	53.303**
Hsieh Test	2	8	6	3
Structure				
Returns	0.000649	-0.003330	-0.002790	-0.000847
Returns^2	0.010171**	0.0	0.0	-0.000376
Dependence				
Returns				
Autocorrelation:				
lag 1	0.10396	0.14136	0.11397	0.16464**
lag 2	-0.03053	0.04274	0.02117	-0.01147
lag 3	-0.04613	0.03357	0.05641	0.01497
lag 4	-0.10589	-0.05502	-0.04409	0.00589
lag 5	-0.02369	0.03031	0.07351	-0.07231
lag 6	0.02837	0.05382	0.04134	0.00064
Ljung-Box:				
Q(6)	9.46	10.63	9.18	11.67
Q(12)	11.97	23.80*	16.13	15.02
Q(24)	31.11	34.56	26.51	30.29
Squared Returns				
Autocorrelation:				
lag 1	0.22522**	0.13327	0.05445	0.05586
lag 2	0.03429	0.02521	0.06287	0.01103
lag 3	0.02654	0.00147	0.00469	-0.02283
lag 4	0.08800	-0.05692	0.04270	-0.02945
lag 5	0.03827	-0.03265	0.07428	-0.02414
lag 6	0.03670	0.00148	-0.00963	0.03603
Ljung-Box:				
Q(6)	22.52**	8.10	5.15	2.33
Q(12)	25.75*	14.67	9.22	12.75
Q(24)	41.85*	25.43	23.07	22.90

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.4
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 13	NYSE 14	NYSE 15	NYSE 16
Location and Shape				
Returns				
Mean	0.00128	0.00513	0.00331	0.00364
Variance	0.00869	0.00495	0.00357	0.00132
Skewness	1.09811**	0.89218**	0.48560**	2.67458**
Kurtosis	3.14331**	2.82345**	2.72975	22.0033**
χ^2_{normal}	120.3**	68.74**	38.714	510.385**
Hsieh Test	5	0	2	0
Structure				
Returns	0.01701	-0.013603	-0.012664*	-0.002908
Returns^2	0.001477	0.0	-0.000918	-0.001532*
Dependence				
Returns				
Autocorrelation:				
lag 1	0.17677**	0.19315**	0.18497**	0.14017
lag 2	-0.03369	0.01435	-0.03398	0.04409
lag 3	-0.06237	-0.01635	0.05364	0.08382
lag 4	-0.04636	0.10568	0.07574	-0.00192
lag 5	0.06900	0.03507	-0.01309	-0.06338
lag 6	0.10016	-0.00149	0.06956	0.01163
Ljung-Box:				
Q(6)	19.02**	17.90**	17.49**	11.70
Q(12)	25.31*	29.61**	25.06**	17.68
Q(24)	36.87*	49.76**	37.36*	28.50
Squared Returns				
Autocorrelation:				
lag 1	0.17985**	0.03289	0.06376	0.00389
lag 2	0.07018	0.03003	0.03002	0.01322
lag 3	0.11133	-0.03367	0.00949	0.03222
lag 4	0.07197	0.08894	-0.01233	-0.01320
lag 5	0.11832	0.13094	-0.06088	-0.00744
lag 6	0.16396	-0.06441	-0.04493	-0.00834
Ljung-Box:				
Q(6)	34.32**	11.63	3.92	0.55
Q(12)	45.68**	14.44	10.14	23.75*
Q(24)	62.72**	23.61	36.76*	24.48

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.5
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 17	NYSE 18	NYSE 19	NYSE 20
Location and Shape				
Returns				
Mean	0.00319	0.00400	0.00124	0.00222
Variance	0.00327	0.00390	0.00395	0.00119
Skewness	0.70412**	0.26725	0.78422**	-0.58928**
Kurtosis	3.24680**	13.85600**	2.72666**	4.04743**
χ^2_{normal}	43.813**	118.176**	61.235**	46.363**
Hsieh Test	0	2	4	1
Structure				
Returns	-0.006297	0.006698	-0.004544	-0.003085*
Returns^2	-0.002508**	0.001865	-0.000262	-0.000108
Dependence				
Returns				
Autocorrelation:				
lag 1	0.11670	0.08729	0.03764	0.11948
lag 2	0.03759	-0.24731**	-0.03488	-0.07429
lag 3	-0.04290	0.00999	0.00950	0.07816
lag 4	0.01076	0.07165	0.03283	-0.02844
lag 5	-0.05316	0.07476	-0.07166	0.01927
lag 6	0.05480	-0.00750	0.02743	0.10348
Ljung-Box:				
Q(6)	8.16	28.46**	3.48	13.53*
Q(12)	15.36	51.43**	8.74	15.09
Q(24)	26.06	58.38**	16.56	29.84
Squared Returns				
Autocorrelation:				
lag 1	0.17759**	0.13760	0.20674**	0.27128**
lag 2	0.21045**	0.45975**	0.07239	-0.00310
lag 3	0.03291	0.03490	0.03700	0.02631
lag 4	0.07799	0.06472	0.06297	-0.00605
lag 5	-0.00894	0.06484	-0.00015	-0.01125
lag 6	0.06134	0.04700	0.02575	0.02854
Ljung-Box:				
Q(6)	31.00**	86.46**	19.24**	26.80**
Q(12)	62.41**	91.95**	45.49**	27.15**
Q(24)	73.52**	92.24**	55.07**	28.64

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.6
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)

Statistics	NYSE 21	NYSE 22	NYSE 23	NYSE 24
Location and Shape				
Returns				
Mean	0.01162**	0.00483	0.00711**	0.00458*
Variance	0.00300	0.00238	0.00260	0.00163
Skewness	0.17982	0.25123	0.44461**	0.91759**
Kurtosis	1.64722**	1.73235**	7.89539**	3.19683**
χ^2_{normal}	60.527**	26.533	39.422	34.46
Hsieh Test	5	1	3	1
Structure				
Returns	-0.003678	0.003786	0.005409	-0.0037
Returns^2	-0.001055	-0.000460	0.002251*	-0.0016**
Dependence				
Returns				
Autocorreletaion:				
lag 1	-0.00883	0.08711	0.12204	0.09002
lag 2	-0.01715	-0.02084	-0.13302	-0.03417
lag 3	-0.06566	-0.13249	0.04016	0.16022**
lag 4	-0.10814	-0.05821	0.00391	0.01616
lag 5	0.07469	-0.01018	-0.03936	-0.00249
lag 6	0.07596	0.03035	0.03366	-0.00369
Ljung-Box:				
Q(6)	9.97	10.73	13.17*	12.59
Q(12)	25.10*	17.94	16.97	18.91
Q(24)	32.50	27.23	28.48	28.98
Squared Returns				
Autocorreletaion:				
lag 1	-0.02317	0.05429	0.28815**	0.28989**
lag 2	0.03799	0.07750	0.14423	0.15126**
lag 3	0.04402	0.02937	0.10748	0.06310
lag 4	-0.01029	-0.03943	0.01408	0.00385
lag 5	0.01271	0.10439	0.00346	0.03235
lag 6	0.14371	0.09443	0.00638	0.01227
Ljung-Box:				
Q(6)	8.95	11.21	41.21**	39.95**
Q(12)	19.94	17.57	48.87**	46.08**
Q(24)	26.58	23.09	55.97**	55.15**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelatin coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. Hsieh test gives the number of cells with significant third moments in a (10,10) lag structure.

Table A.3.B.7
Empirical Characteristics of Returns
(Weekly Returns from 1982-88; n=353)
NYSE Portfolios

Statistics	P1	P2	P3	ALL
<u>Location and Shape</u>				
<u>Returns</u>				
Mean	0.00080	0.00274	0.00485	0.00280
Variance	0.00204	0.00110	0.00086	0.00085
Skewness	0.02572	0.89924**	-0.20606	0.01459
Kurtosis	2.63886**	2.97100**	7.32508**	5.00681**
χ^2_{normal}	41.122**	33.190	61.093**	39.139*
Hsieh Test	2	0	3	2
<u>Dependence</u>				
<u>Returns</u>				
Autocorreletaion:				
lag 1	0.32218**	0.23416**	0.13474	0.35662**
lag 2	0.05842	-0.02918	-0.12751	0.02892
lag 3	0.02967	0.00914	-0.02760	0.02834
lag 4	0.01358	0.05375	-0.02181	0.01582
lag 5	0.04937	-0.02468	0.01046	0.03513
lag 6	0.05583	0.03539	0.09187	0.08626
Ljung-Box:				
Q(6)	40.56**	21.56**	15.80*	49.08**
Q(12)	41.56**	26.12*	20.46	53.09**
Q(24)	51.31**	37.56*	28.61	58.41**
<u>Squared Returns</u>				
Autocorreletaion:				
lag 1	0.35712**	0.14550	0.07376	0.29964**
lag 2	0.17313*	-0.03707	0.27834**	0.14248
lag 3	0.01405	0.06116	0.03276	0.04549
lag 4	-0.00753	0.12416	0.00683	-0.01080
lag 5	0.01789	-0.01810	-0.01863	-0.00531
lag 6	0.08108	-0.02480	0.08557	0.03123
Ljung-Box:				
Q(6)	58.69**	15.24*	32.77**	40.36**
Q(12)	59.94**	41.64**	37.88**	44.68**
Q(24)	71.49**	51.03**	42.70*	47.66**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, and the Q-statistics for various lags. For the autocorrelatin coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error.

APPENDIX B

MODEL ESTIMATES OF RETURNS

Table B.5.A.1
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 1

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.57399	-0.86684	-0.87295	0.57400
		(0.70368)	(0.39373)	(0.35982)	(1.92158)
$\varnothing_1$		0.26971**	0.19093**	0.20954**	0.26970*
		(0.11004)	(0.05008)	(0.04808)	(0.13483)
α_0	x10^3	9.67213**	2.80395*	7.05254**	9.70000
		(1.78439)	(1.69271)	(2.15942)	(1991.41841)
α_1		0.71042**	0.15377	0.19056	0.71040*
		(0.22453)	(0.11019)	(0.16464)	(0.31923)
β_1		0.00000	0.55108**	0.00763	0.00000
		(0.13352)	(0.23262)	(0.26010)	(0.17461)
1/d			0.27513	0.96774	0.00035
			(0.04856)	(0.06140)	(0.23906)
λ					0.00035
					(0.23906)
μ	x10^1				0.00210
					(0.02180)
δ^2					0.00032
					(0.22019)
L(θ)	x10^{-3}	0.30924	0.37156	0.36364	-29.41973
$\alpha_1+\beta_1$		0.71042	0.70485		
HL		3.02737	2.98173		
σ_e^2	x10^1	0.33401	0.09500		
σ_R^2	x10^1	0.36021	0.09860		
AIC		304.24	365.56		
SIC		-589.16	-707.94		
LR			124.64**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.2
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 2

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.00771	-0.43832	-0.36973	-0.00800
		(0.38357)	(0.31217)	(0.31652)	(5.82885)
$\varnothing_1$		0.34115**	0.28142**	0.29307**	0.34200**
		(0.05956)	(0.05344)	(0.05362)	(0.09149)
α_0	x10^3	0.55581**	0.51756*	0.61041*	0.60000
		(0.21514)	(0.29840)	(0.27449)	(1.43745)
α_1		0.75908**	0.14391*	0.10882*	0.07590
		(0.03035)	(0.07151)	(0.05375)	(0.05331)
β_1		0.80886**	0.76390**	0.74327**	0.80890**
		(0.06390)	(0.09499)	(0.09593)	(0.13596)
1/d			0.23173**	0.74154**	0.00010
			(0.00012)	(0.05259)	(0.00324)
λ					0.00010
					(0.00324)
μ	x10^1				0.00200
					(0.06537)
δ^2					0.00030
					(0.00076)
L(θ)	x10^{-3}	0.44575	0.48382	0.47517	-33.25680
$\alpha_1+\beta_1$		0.88477	0.90781	0.85209	
HL		6.66181	8.16623	5.33059	
σ_e^2	x10^1	0.04824	0.05614	0.04127	
σ_R^2	x10^1	0.05459	0.06097	0.04515	
AIC		440.75	477.82	469.17	
SIC		-862.18	-932.46	-915.16	
LR			76.14**	58.84**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.3
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 3

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.07855	-0.25770	-0.06467	-0.08000
		(0.44586)	(0.39744)	(0.34621)	(1.79685)
$\varnothing_1$		0.29770**	0.23470**	0.22108**	0.29770**
		(0.06478)	(0.05499)	(0.04843)	(0.08268)
α_0	x10^3	1.09800**	0.74760	0.68356	1.10000
		(0.43219)	(0.52535)	(0.50951)	(8.17741)
α_1		0.20770**	0.132900*	0.13691*	0.20770**
		(0.05439)	(0.06466)	(0.06788)	(0.08922)
β_1		0.67750**	0.79700**	0.78403**	0.67750**
		(0.08419)	(0.09751)	(0.10882)	(0.12548)
1/d			0.23300**	0.89251**	0.00015
			(0.06499)	(0.08623)	(0.00378)
λ					0.00015
					(0.00378)
μ	x10^1				0.00100
					(0.02056)
δ^2					0.00020
					(0.00280)
L(θ)	x10^{-3}	0.37252	0.39117	0.39241	-32.02682
$\alpha_1+\beta_1$		0.88520			
HL		6.68425			
σ_e^2	x10^1	0.09564			
σ_R^2	x10^1	0.10495			
AIC		367.52			
SIC		-715.72			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.4
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 4

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	0.83482**	0.13633	0.21719	0.83000
		(0.32156)	(0.29539)	(0.31998)	(3.14050)
$\varnothing_1$		0.17705**	0.19007**	0.14895**	0.17700*
		(0.05014)	(0.04510)	(0.04906)	(0.07639)
α_0	$x10^3$	0.07605	0.11376	0.09504	0.08000
		(0.05953)	(0.10884)	(0.09482)	(0.28596)
α_1		0.05321**	0.05494*	0.05248*	0.05320
		(0.02211)	(0.03301)	(0.03111)	(0.04340)
β_1		0.92930**	0.91942**	0.92572**	0.92900**
		(0.02836)	(0.04670)	(0.04352)	(0.05868)
1/d			0.22705**	0.75478**	0.00012
			(0.00138)	(0.01862)	(0.00273)
λ					0.00012
					(0.00273)
μ	$x10^1$				0.00170
					(0.03590)
δ^2					0.00021
					(0.00040)
$L(\theta)$	$x10^{-3}$	0.46193	0.46947	0.47065	-32.61558

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.5
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 5

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.94698 (0.49819)	-1.35896 (0.43677)	-1.12754 (0.39180)	-0.95000 (1.88915)
$\varnothing_1$		0.20868** (0.06195)	0.16120** (0.05292)	0.17628** (0.04902)	0.20870** (0.07003)
α_0	x10^3	0.38445** (0.13402)	0.88414* (0.47804)	0.62754* (0.34829)	0.40000 (1.86324)
α_1		0.17495** (0.02807)	0.19020** (0.07572)	0.17543** (0.05891)	0.17490** (0.03453)
β_1		0.81338** (0.02141)	0.76838** (0.06122)	0.78407** (0.05421)	0.81340** (0.03131)
1/d			0.26538** (0.02455)	0.90711** (0.09346)	0.00022 (0.00278)
λ					0.00022 (0.00278)
μ	x10^1				0.00700 (0.02194)
δ^2					0.00010 (0.00111)
L(θ)	x10^{-3}	0.30906	0.32657	0.32779	-30.89123
$\alpha_1+\beta_1$		0.98833	0.95857	0.95950	
HL		60.04614	17.38316	17.76565	
σ_e^2	x10^1	0.32942	0.21343	0.15495	
σ_R^2	x10^1	0.34442	0.21912	0.15992	
AIC		304.06	320.57	321.79	
SIC		-588.80	-617.96	-620.40	
LR			35.02**	37.46**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.6
GARCH(1,1) Estimates of NASDAQ Stock 6

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	0.89303**	0.11850	-0.00010	0.89000
		(0.36097)	(0.29435)	(0.28144)	(1.91212)
α_0	$x10^3$	2.09452**	2.39400	2.10348*	2.09000
		(0.64128)	(1.83744)	(1.21965)	(28.13440)
α_1		0.15772**	0.08559	0.10783	0.15770*
		(0.06221)	(0.08043)	(0.08042)	(0.08272)
β_1		0.36184*	0.37355	0.36213	0.36180
		(0.18983)	(0.44388)	(0.35472)	(0.25953)
1/d			0.27000**	0.88201**	0.00010
			(0.05782)	(0.01639)	(0.00536)
λ					0.00010
					(0.00536)
μ	$X10^1$				0.00010
					(0.02090)
δ^2					0.00010
					(0.00490)
$L(\theta)$	$X10^{-3}$	0.46787	0.49748	0.49526	-33.19594
$\alpha_1+\beta_1$		0.51956		0.46996	
HL		2.05861		1.91794	
σ_e^2	$X10^1$	0.04360		0.03969	
σ_R^2	$X10^1$	0.04360		0.03969	
AIC		463.87		490.26	
SIC		-912.27		-961.19	
LR				54.78**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.A.7
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 7

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.24528	-0.73377	-0.00043	-0.25000
		(0.40237)	(0.33938)	(0.31058)	(2.94549)
$\varnothing_1$		0.00152	0.02785	0.00003	0.00150
		(0.07986)	(0.06237)	(0.05391)	(0.14108)
α_0	x10^3	1.88510**	1.77051**	1.76000**	1.90000
		(0.35899)	(0.73653)	(0.71597)	(38.86366)
α_1		0.38317**	0.36512**	0.36120**	0.38320**
		(0.05814)	(0.13201)	(0.12340)	(0.10685)
β_1		0.42689**	0.47302**	0.45760**	0.42690*
		(0.06504)	(0.13339)	(0.13946)	(0.19220)
1/d			0.26251**	0.98300**	0.00011
			(0.02748)	(0.08545)	(0.00153)
λ					0.00011
					(0.00154)
μ	x10^1				0.00410
					(0.03505)
δ^2					0.00072
					(0.00755)
L(θ)	x10^{-3}	0.38454	0.41129	0.40896	-32.93516
$\alpha_1+\beta_1$		0.81006	0.83814	0.81880	
HL		4.29055	4.92554	4.46720	
σ_e^2	x10^1	0.09925	0.10938	0.09713	
σ_R^2	x10^1	0.09925	0.10947	0.09713	
AIC		379.54	405.29	402.96	
SIC		-739.76	-787.40	-782.74	
LR			53.50**	48.84**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.8
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 8

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.17475	-0.31711	-0.26488	-0.17000
		(0.30625)	(0.29267)	(0.25989)	(1.39937)
$\varnothing_1$		0.18322**	0.19866**	0.11056*	0.18320*
		(0.06949)	(0.05673)	(0.05580)	(0.09532)
α_0	x10^3	2.42587**	2.40300**	2.93059**	2.40000
		(0.48554)	(0.99658)	(0.81837)	(141.07061)
α_1		0.37526**	0.28820*	0.33661**	0.37530*
		(0.08885)	(0.13481)	(0.14169)	(0.16180)
β_1		0.14881	0.22466	0.04284	0.14880
		(0.12126)	(0.23484)	(0.16697)	(0.19768)
1/d			0.24489**	0.91584**	0.00025
			(0.03846)	(0.09107)	(0.02764)
λ					0.00025
					(0.02764)
μ	x10^1				0.00110
					(0.01707)
δ^2					0.00017
					(0.01837)
L(θ)	x10^{-3}	0.46470	0.48606	0.48492	-30.32493
$\alpha_1+\beta_1$		0.52406	0.51285	0.37946	
HL		2.07274	2.03801	1.71531	
σ_e^2	x10^1	0.05097	0.04933	0.04723	
σ_R^2	x10^1	0.05274	0.05135	0.04781	
AIC		459.70	480.06	478.92	
SIC		-900.08	-936.94	-934.66	
LR			42.72**	40.44**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.9
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 9

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	0.55362*	0.38560	0.38780	0.55300
		(0.32596)	(0.28183)	(0.28408)	(2.47232)
$\varnothing_1$		0.09853*	0.09976*	0.10427*	0.09850
		(0.05444)	(0.05262)	(0.05290)	(0.06691)
α_0	$x10^3$	0.14110	0.27275	0.21824	0.14000
		(0.10056)	(0.19930)	(0.17091)	(0.48699)
α_1		0.07123**	0.14302*	0.11006*	0.07120*
		(0.02665)	(0.07105)	(0.05647)	(0.04249)
β_1		0.89242**	0.80722**	0.83940**	0.89200**
		(0.04422)	(0.07984)	(0.07621)	(0.06788)
1/d			0.20748*	0.75966**	0.00010
			(0.10058)	(0.08438)	(0.00264)
λ					0.00010
					(0.00264)
μ	$x10^1$				0.00010
					(0.02761)
δ^2					0.00010
					(0.00045)
$L(\theta)$	$x10^{-3}$	0.48809	0.49649	0.49789	-33.18617

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.10
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 10

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.00434 (0.39199)	-0.50772 (0.34092)	-0.52789 (0.31752)	-0.00400 (2.79746)
$\varnothing_1$		0.19222** (0.06275)	0.16413** (0.05809)	0.14141** (0.05565)	0.19220* (0.08960)
α_0	x10^3	3.40677** (0.97313)	2.55947** (0.94353)	2.83336** (1.11080)	3.40000 (93.61290)
α_1		0.22581** (0.06748)	0.32415* (0.14422)	0.28532* (0.12714)	0.22580* (0.12723)
β_1		0.13860 (0.20952)	0.25718 (0.21348)	0.19507 (0.25077)	0.13860 (0.35980)
1/d			0.20148** (0.00029)	0.82819** (0.05500)	0.00015 (0.00961)
λ					0.00015 (0.00961)
μ	x10^1				0.00110 (0.03157)
δ^2					0.00022 (0.01204)
L(θ)	x10^{-3}	0.43286	0.45055	0.44795	-31.89104
$\alpha_1+\beta_1$		0.36441	0.58133	0.48038	
HL		1.68664	2.27783	1.94541	
σ_e^2	x10^1	0.05360	0.06113	0.05453	
σ_R^2	x10^1	0.05566	0.06283	0.05564	
AIC		427.86	444.55	441.95	
SIC		-836.40	-865.92	-860.72	
LR			35.38**	30.18**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.11
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 11

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	-0.12445 (0.32472)	-0.41342 (0.28058)	-0.32000 (0.26240)	-0.12000 (6.55083)
$\varnothing_1$		0.24384** (0.05838)	0.18693** (0.05804)	0.19930** (0.05402)	0.24380* (0.10709)
α_0	$x10^3$	1.97407** (0.80322)	2.21397** (0.80137)	1.76000** (0.67895)	1.90000 (30.37037)
α_1		0.10674* (0.05563)	0.27762* (0.15472)	0.18490* (0.10215)	0.10670 (0.13740)
β_1		0.28072 (0.27297)	0.17481 (0.22353)	0.23120 (0.25267)	0.28070 (0.74447)
1/d			0.23422** (0.00017)	0.77000** (0.06537)	0.00034 (0.01225)
λ					0.00034 (0.01225)
μ	$x10^1$				0.00220 (0.07218)
δ^2					0.00033 (0.00468)
$L(\theta)$	$x10^{-3}$	0.51366	0.53719	0.53474	-29.29342
$\alpha_1+\beta_1$		0.38745	0.45243	0.41610	
HL		1.73104	1.87394	1.79052	
σ_e^2	$x10^1$	0.03223	0.04043	0.03014	
σ_R^2	$x10^1$	0.03427	0.04190	0.03139	
AIC		508.66	531.19	528.74	
SIC		-998.00	-1039.20	1034.30	
LR			47.06**	42.16**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.12
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 12

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.39809	0.07000	0.16167	0.39800
		(0.24883)	(0.21710)	(0.22853)	(1.17829)
$\varnothing_1$		0.19367**	0.21550**	0.21262**	0.19370*
		(0.06410)	(0.06009)	(0.05296)	(0.11508)
α_0	x10^3	1.51427**	0.80000**	0.33700*	1.50000
		(0.31728)	(0.26699)	(0.15833)	(82.69922)
α_1		0.40228**	0.42490**	0.14820**	0.40230*
		(0.09210)	(0.14803)	(0.04346)	(0.20322)
β_1		0.20524	0.39810**	0.72200**	0.20520
		(0.13934)	(0.12762)	(0.07972)	(0.27799)
1/d			0.23700**	0.74000**	0.00013
			(0.04272)	(0.04158)	(0.00659)
λ					0.00013
					(0.00660)
μ	x10^1				0.00120
					(0.01591)
δ^2					0.00024
					(0.01157)
L(θ)	x10^{-3}	0.52915	0.57045	0.55799	-32.28634
$\alpha_1+\beta_1$		0.60752	0.82300	0.87020	
HL		2.39084	4.55827	5.98552	
σ_ϵ^2	x10^1	0.03858	0.04520	0.02596	
σ_R^2	x10^1	0.04009	0.04740	0.02719	
AIC		524.15	564.45	551.99	
SIC		-1028.98	-1105.72	-1080.80	
LR			82.60**	57.68**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.13
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 13

Statistics		(N)	(T)	(PE)	(MJ)
$\emptyset_0$	x10^2	-0.11194	-0.41200	-0.30762	-0.41200
		(0.32490)	(0.28071)	(0.25614)	(2.84947)
$\emptyset_1$		0.24423**	0.18690**	0.18869**	0.18690
		(0.05833)	(0.05809)	(0.05382)	(0.12031)
α_0	x10^3	1.89426*	2.20000**	1.70179**	2.20000
		(0.85269)	(0.80712)	(0.59881)	(52.21380)
α_1		0.10315*	0.27700*	0.20075*	0.27700
		(0.05421)	(0.15457)	(0.10492)	(0.19814)
β_1		0.31007	0.18000	0.21952	0.18000
		(0.28685)	(0.22613)	(0.22920)	(0.30181)
1/d			0.23400**	0.77593**	0.00011
			(0.05980)	(0.00006)	(0.00450)
λ					0.00011
					(0.00450)
μ	x10^1				0.00120
					(0.03106)
δ^2					0.00023
					(0.00706)
L(θ)	x10^{-3}	0.51365	0.53716	0.53471	-32.85504
$\alpha_1+\beta_1$		0.41322	0.45700	0.42028	
HL		1.78431	1.88516	1.79962	
σ_e^2	x10^1	0.03228	0.04052	0.02936	
σ_R^2	x10^1	0.03433	0.04198	0.03044	
AIC		508.65	531.16	528.71	
SIC		-997.98	-1039.14	-1034.24	
LR			47.02**	42.12**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.14
GARCH(1,1) Estimates of NASDAQ Stock 14

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	0.31941	-0.92888	-0.74469	0.31900
		(0.50685)	(0.35898)	(0.34523)	(2.63924)
α_0	$x10^3$	1.07502**	1.55672	1.19385	1.08000
		(0.43381)	(1.13819)	(0.86129)	(6.54329)
α_1		0.09404**	0.13169	0.09234	0.09400
		(0.03569)	(0.08914)	(0.06192)	(0.04906)
β_1		0.76815**	0.69723**	0.74251**	0.76800
		(0.07220)	(0.16155)	(0.14926)	(0.11015)
1/d			0.30359**	0.93876**	0.00060
			(0.04037)	(0.03450)	(0.01467)
λ					0.00060
					(0.01467)
μ	$x10^1$				0.00190
					(0.02992)
δ^2					0.00017
					(0.00310)
$L(\theta)$	$x10^{-3}$	0.36571	0.39805	0.39197	-27.73268
$\alpha_1+\beta_1$		0.86220			
HL		5.67482			
σ_e^2	$x10^1$	0.07801			
σ_R^2	$x10^1$	0.07801			
AIC		361.71			
SIC		-707.95			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.A.15
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 15

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.32596	0.25000	-0.16000	0.32600
		(0.45783)	(0.38131)	(0.39679)	(3.73389)
$\varnothing_1$		0.18077**	0.15690**	0.12840**	0.18080**
		(0.05874)	(0.04962)	(0.05266)	(0.07536)
α_0	x10^3	2.93205*	0.80000	2.40000	2.90000
		(1.57010)	(0.77113)	(1.89349)	(15.36029)
α_1		0.14242*	0.12990*	0.13350	0.14240
		(0.06625)	(0.07597)	(0.08746)	(0.10205)
β_1		0.44971*	0.78430**	0.53000*	0.44970
		(0.24782)	(0.13469)	(0.31045)	(0.39704)
1/d			0.23300**	0.77000**	0.00015
			(0.08034)	(0.09149)	(0.00593)
λ					0.00015
					(0.00594)
μ	x10^1				0.00110
					(0.04157)
δ^2					0.00022
					(0.00305)
L(θ)	x10^{-3}	0.37311	0.36920	0.37369	-32.01260
$\alpha_1+\beta_1$		0.59213			
HL		2.32273			
σ_e^2	x10^1	0.07188			
σ_R^2	x10^1	0.07432			
AIC		368.11			
SIC		-716.90			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.16
GARCH(1,1) Estimates of NASDAQ Stock 16

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.56766 (0.48218)	0.19000 (0.46726)	-0.10106 (0.40323)	0.56800 (4.20096)
α_0 x10^2	0.68250* (0.30503)	0.27000 (0.20400)	0.50194 (0.43551)	0.68000 (858.05095)
α_1	0.11089* (0.05251)	0.08700* (0.04348)	0.09263 (0.06957)	0.11090 (0.09823)
β_1	0.00000 (0.41973)	0.53670* (0.30857)	0.25030 (0.60017)	0.00010 (0.53755)
1/d		0.05000* (0.02954)	0.83250** (0.02780)	0.00010 (0.95521)
λ				0.00010 (0.95521)
μ				0.00001 (0.00463)
δ^2				0.0001 (0.95448)
L(θ)	361.322	365.732	371.990	-33419.952
$\alpha_1+\beta_1$	0.16341			
HL	1.31518			
σ_e^2	0.00768			
σ_R^2	0.00768			
AIC	357.32			
SIC	-699.18			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.A.17
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 17

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.12226 (0.26402)	-0.9242 (0.22597)	-0.20423 (0.22665)	0.12000 (7.94689)
$\varnothing_1$		0.21198** (0.05849)	0.22443** (0.05355)	0.20748** (0.05390)	0.21200* (0.12092)
α_0	x10^2	0.20848** (0.06882)	0.19103** (0.06660)	0.18000** (0.06195)	0.21000 (26.38097)
α_1		0.09339 (0.05830)	0.24133* (0.14178)	0.18217 (0.11185)	0.09340 (0.17705)
β_1		0.03921 (0.29594)	0.09661 (0.22390)	0.08426 (0.26772)	0.03920 (1.40242)
1/d			0.25744** (0.00043)	0.80242** (0.00542)	0.00035 (0.03682)
λ					0.00035 (0.03682)
μ					0.00021 (0.00890)
δ^2					0.00032 (0.03055)
L(θ)		564.027	578.492	579.708	-29170.545
$\alpha_1+\beta_1$			0.33794		
HL			1.63890		
σ_e^2			0.00289		
σ_R^2			0.00304		
AIC			572.49		
SIC			-1121.80		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.18
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 18

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.45235	0.08103	0.17940	0.45200
		(0.33631)	(0.30503)	(0.32285)	(3.95506)
$\varnothing_1$		0.16094**	0.13128**	0.13186**	0.16090
		(0.06285)	(0.04987)	(0.05434)	(0.12273)
α_0	x10^2	0.04757**	0.02818	0.03676	0.04000
		(0.01940)	(0.02015)	(0.02374)	(0.56361)
α_1		0.16978**	0.10543*	0.12047*	0.16970
		(0.04066)	(0.04704)	(0.05277)	(0.14940)
β_1		0.75069**	0.84616**	0.80966**	0.75000**
		(0.06185)	(0.06900)	(0.08188)	(0.20528)
1/d			0.22524**	0.73299**	0.00011
			(0.00318)	(0.00427)	(0.00130)
λ					0.00011
					(0.00130)
μ					0.00041
					(0.00450)
δ^2					0.00072
					(0.00248)
L(θ)		442.311	452.674	452.934	-32892.430
$\alpha_1+\beta_1$		0.92047			
HL		9.36005			
σ_e^2		0.00598			
σ_R^2		0.00614			
AIC		437.31			
SIC		-855.30			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.19
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 19

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.40000	0.24310	0.12057	0.12000
		(0.33760)	(0.29494)	(0.29229)	(4.81769)
$\varnothing_1$		0.20070**	0.20070**	0.20541**	0.21200
		(0.05722)	(0.05233)	(0.05236)	(0.07661)
α_0	x10^2	0.32010**	0.32077*	0.30702*	0.21000
		(0.12901)	(0.15477)	(0.15204)	(27.66308)
α_1		0.11180*	0.14697	0.12428	0.09340
		(0.06061)	(0.10762)	(0.08979)	(0.11059)
β_1		0.06490	0.09687	0.06642	0.03920
		(0.33111)	(0.36628)	(0.40584)	(0.81015)
1/d			0.23104**	0.76820**	0.00035
			(0.00438)	(0.00645)	(0.03650)
λ					0.00035
					(0.03650)
μ					0.00021
					(0.00538)
δ^2					0.00032
					(0.03205)
L(θ)		481.013	494.017	493.770	-29212.6896
$\alpha_1+\beta_1$		0.1767			
HL		1.39990			
σ_e^2		0.00389			
σ_R^2		0.00405			
AIC		476.01			
SIC		-932.71			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.20
GARCH(1,1) Estimates of NASDAQ Stock 20

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.85573* (0.43285)	0.76282* (0.42483)	0.74117* (0.42610)	0.85600 (2.92463)
α_0 x10^2	0.36938** (0.13424)	0.37626* (0.19247)	0.36849* (0.16063)	0.36900 (10.08165)
α_1	0.14720* (0.07509)	0.13682 (0.09471)	0.14514 (0.09104)	0.14720 (0.11255)
β_1	0.25009 (0.25229)	0.24795 (0.33515)	0.25355 (0.30340)	0.25000 (0.36261)
1/d		0.04696 (0.04001)	0.56840** (0.04187)	0.00052 (0.04633)
λ				0.00052 (0.04633)
μ				0.00019 (0.00317)
δ^2				0.00017 (0.01486)
L(θ)	401.727	402.768	402.516	-28130.025
$\alpha_1+\beta_1$	0.39729			
HL	1.75090			
σ_e^2	0.00613			
σ_R^2	0.00613			
AIC	397.73			
SIC	-779.99			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.A.21
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 21

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.13242	0.04726	0.01070	0.13200
		(0.20140)	(0.19283)	(0.18334)	(4.07975)
$\varnothing_1$		0.28239**	0.24370**	0.23242**	0.28230**
		(0.05250)	(0.04683)	(0.04795)	(0.10671)
α_0	x10^2	0.01149	0.01016	0.00544	0.01000
		(0.00741)	(0.01075)	(0.00605)	(0.10450)
α_1		0.08853**	0.06365	0.06885*	0.08850
		(0.03416)	(0.04512)	(0.03971)	(0.10771)
β_1		0.84048**	0.88999**	0.89939**	0.84000**
		(0.06476)	(0.08052)	(0.06065)	(0.21614)
1/d			0.22951**	0.77501**	0.00015
			(0.08128)	(0.00308)	(0.00644)
λ					0.00015
					(0.00644)
μ					0.00011
					(0.00460)
δ^2					0.00022
					(0.00071)
L(θ)		627.655	631.825	634.652	-31765.105

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.22
GARCH(1,1) Estimates of NASDAQ Stock 22

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.60497 (0.42556)	0.50316 (0.38278)	0.40279 (0.38151)	0.60500 (3.34324)
α_0 x10^2	0.15795* (0.08985)	0.18018 (0.15278)	0.16551 (0.13874)	0.16000 (1.36490)
α_1	0.09138* (0.04478)	0.10386 (0.07791)	0.09268 (0.06762)	0.09138 (0.06719)
β_1	0.67099** (0.15728)	0.63480** (0.25919)	0.64986** (0.24886)	0.67100** (0.22112)
1/d		0.20260** (0.01234)	0.75386** (0.02441)	0.00013 (0.00719)
λ				0.00013 (0.00719)
μ				0.00011 (0.00374)
δ^2				0.00011 (0.00456)
L(θ)	389.428	399.550	398.229	-32400.911
$\alpha_1+\beta_1$	0.76237			
HL	3.55458			
σ_e^2	0.00665			
σ_R^2	0.00665			
AIC	385.43			
SIC	-755.39			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.A.23
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 23

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.67228	0.13554	-0.22845	-0.67000
		(0.37664)	(0.30222)	(0.30966)	(101.32935)
$\varnothing_1$		-0.03856	0.21077**	0.19786**	-0.03860
		(0.04704)	(0.04874)	(0.05184)	(0.11673)
α_0	x10^2	0.00000	0.07322	0.36090	0.01000
		(0.00956)	(0.08326)	(0.23111)	(0.01819)
α_1		0.00234	0.08905	0.14821	0.00230
		(0.00511)	(0.07353)	(0.10125)	(0.03196)
β_1		0.99709**	0.77011**	0.00000	0.99000**
		(0.02402)	(0.20870)	(0.53975)	(0.00756)
1/d			0.23342**	0.77074**	0.00014
			(0.00050)	(0.09675)	(0.15774)
λ					0.00014
					(0.15774)
μ					0.00010
					(0.11261)
δ^2					0.00021
					(0.00030)
L(θ)		455.898	470.175	474.841	-32223.612

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.24
AR(1)-GARCH(1,1) Estimates of NASDAQ Stock 24

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.46198	0.37393	0.48618	0.46000
		(0.43782)	(0.44791)	(0.39919)	(2.92531)
$\varnothing_1$		0.20916**	0.20739**	0.18420**	0.20900**
		(0.05857)	(0.06002)	(0.05664)	(0.08236)
α_0	x10^2	0.50463**	0.50527**	0.53728**	0.50000
		(0.11723)	(0.12799)	(0.19079)	(146.44164)
α_1		0.20408**	0.20890**	0.20477**	0.20400
		(0.06544)	(0.07484)	(0.10581)	(0.14567)
β_1		0.00000	0.00000	0.00000	0.00001
		(0.17283)	(0.18624)	(0.26375)	(0.30495)
1/d			0.57905**	0.72916**	0.00017
			(0.01009)	(0.07955)	(0.13380)
λ					0.00017
					(0.13380)
μ					0.00013
					(0.00329)
δ^2					0.00021
					(0.16200)
L(θ)		402.562	404.710	404.055	-31534.063
$\alpha_1+\beta_1$		0.20408	0.20890	0.20477	
HL		1.43614	1.44265	1.43707	
σ_e^2		0.00634	0.00639	0.00676	
σ_R^2		0.00663	0.00668	0.00700	
AIC		397.56	398.71	398.06	
SIC		-775.81	-774.24	-772.93	
LR			4.30*	3.00	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.25
AR(1)-GARCH(1,1) Estimates of NASDAQ Portfolio P1

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.08286 (0.20950)	-0.02815 (0.18100)	-0.05143 (0.19085)	0.00260 (0.75983)
$\varnothing_1$		0.35758** (0.06260)	0.31173** (0.05568)	0.28559** (0.05799)	0.37384 (1.83870)
α_0	x10^4	0.89965** (0.32747)	5.90040** (1.65410)	6.40190** (1.33524)	0.00180 (0.07440)
α_1		0.10890** (0.03362)	0.15818** (0.05410)	0.15704 (0.03749)	0.29373 (0.69180)
β^1		0.84110** (0.03905)	0.31127** (0.14959)	0.29373** (0.10771)	0.15704 (1.34860)
1/d			0.04568** (0.00085)	0.50730** (0.02086)	
λ					0.00015 (0.18365)
μ					0.00008 (0.02395)
δ^2					0.000299 (0.30901)
L(θ)		651.753	655.796	636.6103	-31904.62
$\alpha_1+\beta_1$		0.9500	0.46945	0.45077	
HL		14.5125	1.91660	1.87000	
σ_e^2		0.001799	0.00111	0.001166	
σ_R^2		0.002063	0.00123	0.00127	
AIC		646.75	649.76	630.61	
SIC		-1274.19	-1276.41	-1238.04	
LR			8.09**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.26
AR(1)-GARCH(1,1) Estimates of NASDAQ Portfolio P2

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$\times 10^2$	0.24970	0.11083	0.17585	0.003344
		(0.19240)	(0.16152)	(0.15612)	(0.34700)
$\varnothing_1$		0.21186**	0.17985**	0.20245**	0.23278
		(0.06793)	(0.05625)	(0.05506)	(7.99600)
α_0	$\times 10^4$	4.30810**	2.11648*	2.73823*	0.00010
		(0.91773)	(1.07204)	(1.28505)	(0.43090)
α_1		0.25095**	0.17530*	0.19300*	0.33373
		(0.07677)	(0.07798)	(0.09539)	(0.40060)
β_1		0.44326**	0.65920**	0.60110**	0.15704
		(0.09401)	(0.12958)	(0.15071)	(0.71303)
1/d			0.15891**	0.78950**	
			(0.03581)	(0.03770)	
λ					0.000143
					(0.07072)
μ					0.00008
					(0.00880)
δ^2					0.00030
					(0.12280)
$L(\theta)$		682.463	700.763	696.734	-31902.85
$\alpha_1+\beta_1$		0.69421	0.8345	0.7941	
HL		2.8991	4.8313	4.0065	
σ_e^2		0.00141	0.00128	0.00133	
σ_R^2		0.00148	0.00132	0.00139	
AIC		677.46	694.76	690.73	
SIC		-1335.61	-1366.34	-1358.29	
LR			36.60**	28.54**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.27
AR(1)-GARCH(1,1) Estimates of NASDAQ Portfolio P3

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.38819* (0.20323)	0.29996 (0.18730)	0.39021* (0.20760)	0.004494 (0.20799)
$\varnothing_1$	0.25933** (0.06155)	0.24205** (0.05215)	0.23964** (0.06292)	0.25445 (0.34500)
α_0 x10^4	5.82712** (2.26660)	4.54672 (3.19355)	7.62356** (3.23643)	0.00170 (0.26060)
α_1	0.14094** (0.03883)	0.08521 (0.06379)	0.13699** (0.05288)	0.29373 (0.43661)
β_1	0.45567** (0.15570)	0.59079* (0.25419)	0.32946 (0.22744)	0.15704 (0.13118)
1/d		0.17277** (0.00234)	0.50624** (0.04531)	
λ				0.00002 (0.25363)
μ				0.00008 (0.03634)
δ^2				0.00019 (0.43906)
L(θ)	658.246	662.767	658.472	-37591.33
$\alpha_1+\beta_1$	0.59661		0.46645	
HL	2.34207		1.9089	
σ_e^2	0.00145		0.00143	
σ_R^2	0.00155		0.00152	
AIC	653.25		652.47	
SIC	-1287.17		-1281.76	
LR			0.452	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.A.28
AR(1)-GARCH(1,1) Estimates of NASDAQ Portfolio ALL

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.20079	8.37287	0.10022	-0.05141
		(0.15694)	(0.1345)	(0.13297)	(109.9758)
$\varnothing_1$		0.34758**	0.32719**	0.33913**	0.28593
		(0.06456)	(0.0512)	(0.05125)	(1531)
α_0	x10^4	2.79644**	1.32045*	1.82677*	6.40644
		(0.7776)	(0.73065)	(0.89366)	(3353.8)
α_1		0.24961**	0.15205*	0.16729**	0.29373
		(0.037928)	(0.06698)	(0.06498)	(0.68787)
β_1		0.48364**	0.70983**	0.63740**	0.15704
		(0.08817)	(0.11311)	(0.11871)	(1.3209)
1/d			0.19001**	0.78251**	
			(0.04539)	(0.03942)	
λ					0.00014
					(1.2492)
μ					0.00008
					(0.17102)
δ^2					0.0003
					(2.1009)
L(θ)		736.736	755.260	751.238	-31909.865
$\alpha_1+\beta_1$		0.73325	0.86188	0.80469	
HL		3.234	5.6634	4.1898	
σ_e^2		0.00105	0.00096	0.000935	
σ_R^2		0.00119	0.00107	0.00106	
AIC		731.74	749.26	745.24	
SIC		-1444.15	-1475.34	-1467.29	
LR			37.05**	29.00**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.1
AR(1)-GARCH(1,1) Estimates of NYSE Stock 1

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.21985	-0.39768	-0.00008	0.21985
	(0.45592)	(0.35063)	(0.30271)	(10.27714)
$\varnothing_1$	0.12837*	0.09416*	0.00003	0.12837
	(0.06844)	(0.06082)	(0.05218)	(39.56854)
α_0 x10^2	0.49479**	0.40046**	0.40809**	0.49479
	(0.08574)	(0.11661)	(0.12232)	(127.54556)
α_1	0.29334**	0.43022**	0.39985**	0.29334*
	(0.08662)	(0.17199)	(0.16970)	(0.17036)
β_1	0.00000	0.07382	0.07171	0.00000
	(0.12488)	(0.14315)	(0.18459)	(0.32034)
1/d	0.00000	0.25919**	1.00000	0.00011
		(0.01071)	(0.09438)	(0.08645)
λ				0.00011
				(0.08645)
μ				0.00005
				(0.00351)
δ^2				0.00020
				(0.15597)
L(θ) x10^{-3}	0.39612	0.42642	0.43394	-32.95363
α_1+β_1	0.29334	0.50404	0.47156	
HL	1.56518	2.01175	1.92209	
σ_e^2 x10^2	0.70018	0.80745	0.77225	
σ_R^2 x10^1	0.10911	0.11649	0.07763	
AIC	391.12	420.42	427.94	
SIC	-762.92	-817.66	-832.70	
LR		60.60**	75.64**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.2
GARCH(1,1) Estimates of NYSE Stock 2

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^3$	-0.27065	0.80300	-0.00134	-0.20000
		(3.73936)	(3.59820)	(2.59879)	(45.47015)
α_0	$x10^3$	0.27368*	1.09800	0.74443	0.30000
		(0.14247)	(0.67746)	(0.72280)	(1.11193)
α_1	$x10^1$	0.52357**	2.07700*	0.72669	0.52400
		(0.17828)	(1.15020)	(0.62326)	(0.35009)
β_1		0.89272**	0.67750**	0.76044**	0.89270**
		(0.04183)	(0.14128)	(0.19814)	(0.09020)
1/d			0.25000**	1.00000**	0.00012
			(0.07171)	(0.08638)	(0.00640)
λ	$x10^2$				0.01208
					(0.64011)
μ	$x10^2$				0.00600
					(0.51181)
δ^2	$x10^2$				0.02000
					(0.10819)
$L(\theta)$	$x10^{-3}$	0.45517	0.42722	0.48475	-32.74616
$\alpha_1+\beta_1$		0.94508			
HL		13.27038			
σ_e^2	$x10^2$	0.49828			
σ_R^2		0.49828			
AIC		451.17			
SIC		-886.87			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.3
AR(1)-GARCH(1,1) Estimates of NYSE Stock 3

Statistics		(N)	(T)[1]	(PE)[1]	(MJ)[1]
$\varnothing_0$	x10^2	0.00848	-0.28846	-0.12202	-0.10850
		(0.39914)	(0.35786)	(0.36125)	(2.00454)
$\varnothing_1$	x10^1	0.52617			
		(0.63831)			
α_0	x10^3	1.67694**	0.84171	0.97241	1.09800
		(0.47041)	(0.86568)	(0.75151)	(1.45139)
α_1	x10^1	1.25389**	0.60855	0.63835	2.07700
		(0.43650)	(0.52939)	(0.50872)	(0.96697)
β_1		0.56093**	0.78254**	0.73549**	0.67750
		(0.10656)	(0.19882)	(0.18988)	(0.11961)
1/d			0.18234**	0.67207**	0.00001
			(0.00022)	(0.05227)	(0.00221)
λ					0.00001
					(0.00221)
μ					0.00001
					(0.00221)
δ^2					0.00010
					(0.00045)
L(θ)		426.65641	441.11866	439.56587	-33220.638
$\alpha_1+\beta_1$		0.68631			
HL		2.84142			
σ_e^2	x10^2	0.53459			
σ_R^2	x10^2	0.69372			
AIC		421.66			
SIC		-823.99			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.
[1] The AR term was not used. The sample size for this model is 353.

Table B.5.B.4
GARCH(1,1) Estimates of NYSE Stock 4

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.01810	-0.67334	-0.03960	0.08030
		(0.51063)	(0.34807)	(0.32326)	(2.04479)
α_0	x10^2	0.07260	0.42286	0.26928*	0.10980
		(0.04487)	(0.31932)	(0.13269)	(0.41915)
α_1	x10^1	1.11214**	0.67364	1.04466	2.07700*
		(0.27060)	(0.70680)	(0.70813)	(0.91514)
β_1		0.79893**	0.21239	0.30590	0.67750**
		(0.07424)	(0.54508)	(0.30386)	(0.11419)
1/d			0.24631**	0.85047**	0.00010
			(0.02705)	(0.00254)	(0.00263)
λ	x10^2				0.01010
					(0.26295)
μ	x10^2				0.00100
					(0.22105)
δ^2	x10^2				0.01000
					(0.14260)
L(θ)	x10^{-3}	0.38340	0.43678	0.43258	-33.27337

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.5
GARCH(1,1) Estimates of NYSE Stock 5

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.43040	-0.43430	-0.47141	-0.43000
		(0.41107)	(0.40962)	(0.37445)	(1.73670)
α_0	x10^2	0.40330**	0.43999**	0.37437**	0.40000
		(0.10252)	(0.18766)	(0.15150)	(9.64912)
α_1		0.20925**	0.24270*	0.22371*	0.20900**
		(0.06969)	(0.11441)	(0.10696)	(0.07753)
β_1		0.18593	0.17227	0.21847	0.18600
		(0.16764)	(0.27006)	(0.25008)	(0.17078)
1/d	x10^1		1.81000**	7.75441**	0.00051
			(0.71270)	(0.58404)	(0.13114)
λ	x10^1				0.00051
					(0.13114)
μ	x10^2				0.00200
					(0.19867)
δ^2	x10^1				0.00010
					(0.13067)
L(θ)	x10^{-3}	0.38992	0.39743	0.39900	-35.43589
$\alpha_1+\beta_1$		0.39518	0.41498	0.44218	
HL		1.74659	1.78808	1.84941	
σ_e^2	x10^2	0.66680	0.75209	0.67113	
σ_R^2		0.66680	0.75209	0.67113	
AIC		385.92	392.43	394.00	
SIC		-756.37	-765.53	-768.67	
LR			15.02**	18.16**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.6
AR(1)-GARCH(1,1) Estimates of NYSE Stock 6

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.08261	-0.44445	-0.50544	0.13650
		(0.50049)	(0.46532)	(0.45345)	(20.48794)
$\varnothing_1$		0.23043**	0.19087**	0.17959**	0.23824
		(0.05794)	(0.05627)	(0.05554)	(110.73048)
α_0	x10^3	0.86067**	0.79744	0.85401*	4.86800
		(0.33197)	(0.49230)	(0.50097)	(329.67113)
α_1		0.12304**	0.13408**	0.13750**	0.09070
		(0.02959)	(0.05752)	(0.05220)	(0.12697)
β_1		0.78695**	0.79687**	0.78073**	0.29070
		(0.05748)	(0.08234)	(0.08574)	(0.56114)
1/d			0.19219**	0.76333**	0.00010
			(0.00568)	(0.01474)	(0.17247)
λ					0.00010
					(0.17247)
μ	x10^1				0.00450
					(0.65740)
δ^2					0.00020
					(0.31924)
L(θ)	x10^{-3}	0.32549	0.33836	0.33652	-33.30053
$\alpha_1+\beta_1$		0.90999		0.91823	
HL		8.34870		9.12526	
σ_e^2	x10^1	0.09562		0.10444	
σ_R^2	x10^1	0.18389		0.18125	
AIC		320.49		330.52	
SIC		-621.66		-637.86	
LR				22.06**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.7
AR(1)-GARCH(1,1) Estimates of NYSE Stock 7

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.28100	-0.11330	-0.24800	0.28000
		(0.45374)	(0.39747)	(0.38075)	(12.89129)
$\varnothing_1$		0.14830**	0.11808*	0.09570*	0.14830*
		(0.05701)	(0.05567)	(0.05446)	(0.06525)
α_0	x10^2	0.58006	0.63500	0.52106	0.00580
		(0.99745)	(0.41211)	(0.38549)	(236.13000)
α_1	x10^1	0.32302	1.29200	0.97804	0.32300
		(0.54968)	(1.28386)	(0.89268)	(1.02462)
β_1		0.00000	0.00000	0.00000	0.00010
		(1.70848)	(0.59607)	(0.69840)	(2.11803)
1/d				0.76000**	0.00030
				(0.03684)	(0.78195)
λ					0.00030
					(0.78195)
μ	x10^1				0.00400
					(0.14145)
δ^2					0.00010
					(0.26038)
$L(\theta)$	x10^{-3}	0.40298	0.42300	0.42017	-29.80350

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.8
AR(1)-GARCH(1,1) Estimates of NYSE Stock 8

Statistics		(N)	(T)	(PE)	(MJ)
$\emptyset_0$	x10^2	1.30190	-0.55837	-0.28885	0.78000
		(0.79701)	(0.58686)	(0.49598)	(28.04198)
$\emptyset_1$		0.18428**	0.13764**	0.08377*	0.15900*
		(0.06205)	(0.04572)	(0.04016)	(0.07092)
α_0	x10^3	0.15044	0.61793	0.59181	6.80000
		(0.12396)	(0.63010)	(0.65398)	(36.05964)
α_1	x10^1	0.33823**	0.33955	0.27622	0.12500
		(0.09857)	(0.23648)	(0.22616)	(0.50609)
β_1		0.95907**	0.92814**	0.93190**	0.59160
		(0.01123)	(0.05061)	(0.05538)	(1.41109)
1/d			0.26264**	0.97557**	0.00015
			(0.00627)	(0.01059)	(0.01669)
λ	x10^1				0.00151
					(0.16692)
μ	x10^1				0.00300
					(0.31188)
δ^2	x10^2				0.02000
					(0.75677)
L(θ)		0.20989	0.25088	0.25122	-32.16885

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.9
GARCH(1,1) Estimates of NYSE Stock 9

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	-0.80922	-1.10233	-0.59313	-0.80000
		(0.58954)	(0.47036)	(0.49465)	(1.86074)
α_0	x10^2	0.61522**	0.56131**	0.29767**	0.60000
		(0.13250)	(0.19762)	(0.07397)	(23.33710)
α_1		0.27645**	0.34948**	0.51328**	0.27600**
		(0.08296)	(0.14417)	(0.10519)	(0.09126)
β_1		0.23605*	0.24923	0.38157**	0.23600*
		(0.13906)	(0.16928)	(0.08523)	(0.13896)
1/d	x10^1		2.50942**	5.00000**	0.00010
			(0.08457)	(0.25391)	(0.33732)
λ	x10^1				0.00010
					(0.33732)
μ	x10^2				0.00100
					(0.19514)
δ^2	x10^1				0.00020
					(0.33653)
L(θ)	x10^{-3}	0.28955	0.30274	0.28221	-40.80606
$\alpha_1+\beta_1$		0.41551	0.59871	0.89485	
HL		2.03692	2.35121	7.23899	
σ_e^2	x10^1	0.12620	0.13987	0.28309	
σ_R^2		0.12620	0.13987	0.28309	
AIC		285.55	297.74	277.21	
SIC		-555.63	-576.15	-535.09	
LR			26.38**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.10
GARCH(1,1) Estimates of NYSE Stock 10

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.38738**	0.44450**	0.55162**	0.39000
		(0.11071)	(0.08982)	(0.08491)	(5.18380)
α_0	x10^3	0.22102**	0.25136	0.22362	0.20000
		(0.06242)	(0.19674)	(0.14262)	(16.17558)
α_1		0.18711**	0.09965	0.11241*	0.18710
		(0.04293)	(0.07600)	(0.06296)	(0.45642)
β_1		0.29099*	0.33237	0.32487	0.29100
		(0.16287)	(0.46258)	(0.37640)	(1.77836)
1/d	x10^1		2.69706**	9.01089**	0.00011
			(0.42165)	(0.37542)	(0.05329)
λ	x10^2				0.00112
					(0.53293)
μ	x10^2				0.01100
					(0.57950)
δ^2	x10^2				0.03200
					(0.25542)
L(θ)	x10^{-3}	0.88070	0.90263	0.90088	-40.06988
$\alpha_1+\beta_1$		0.47810			
HL		1.93930			
σ_e^2	x10^3	0.42349			
σ_R^2		0.42349			
AIC		876.70			
SIC		-1737.93			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.11
GARCH(1,1) Estimates of NYSE Stock 11

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.32439*	0.19030*	0.14669	0.32000
		(0.14276)	(0.09197)	(0.13179)	(12.08801)
α_0	x10^3	0.21451*	0.13000	0.15286	0.20000
		(0.11407)	(0.09499)	(0.10166)	(10.49364)
α_1		0.11452*	0.15170	0.13144*	0.11450
		(0.05790)	(0.09234)	(0.07534)	(0.80232)
β_1		0.54585**	0.64200**	0.63350**	0.54590
		(0.21100)	(0.19037)	(0.20161)	(3.97452)
1/d	x10^1		3.10000**	7.20093**	0.00110
			(0.75013)	(0.13036)	(0.03697)
λ	x10^2				0.01103
					(0.36971)
μ	x10^1				0.00410
					(0.13640)
δ^2	x10^2				0.07200
					(0.25870)
L(θ)	x10^{-3}	0.80309	0.79512	0.80844	-32.93402
$\alpha_1+\beta_1$		0.66038			
HL		2.67045			
σ_e^2	x10^3	0.63160			
σ_R^2		0.63160			
AIC		799.09			
SIC		-1582.71			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.12
AR(1)-GARCH(1,1) Estimates of NYSE Stock 12

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.07823 (0.31445)	-0.16968 (0.25990)	-0.39586 (0.23960)	0.08000 (2.96931)
$\varnothing_1$		0.19814** (0.06456)	0.16254** (0.05755)	0.13817** (0.05457)	0.19810* (0.09529)
α_0	x10^2	0.19946** (0.05641)	0.15634* (0.07173)	0.17988** (0.07078)	0.20000 (4.92141)
α_1		0.18794** (0.06417)	0.27018* (0.13009)	0.26817* (0.12503)	0.18790 (0.14577)
β_1		0.20667 (0.18890)	0.29911 (0.23281)	0.20883 (0.24801)	0.20670 (0.38905)
1/d	x10^1		2.32226** (0.64450)	8.84697** (0.75687)	0.00250 (0.12734)
λ	x10^1				0.00250 (0.12734)
μ	x10^2				0.01100 (0.33339)
δ^2	x10^2				0.01700 (0.68753)
L(θ)	x10^{-3}	0.51479	0.53258	0.53215	-30.27869
$\alpha_1+\beta_1$		0.39461	0.56930	0.47701	
HL		1.74543	2.23039	1.93640	
σ_e^2	x10^2	0.32948	0.36300	0.34395	
σ_R^2	x10^2	0.59379	0.60821	0.54744	
AIC		509.79	526.58	526.15	
SIC		-1000.26	-1029.98	-1029.12	
LR			35.58**	34.72**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.13
AR(1)-GARCH(1,1) Estimates of NYSE Stock 13

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	-0.11234 (0.47820)	-0.66262 (0.35957)	-0.48405 (0.41803)	-0.11000 (1.68571)
$\varnothing_1$	$x10^1$	1.56032** (0.64871)	0.91515* (0.47789)	1.11314* (0.56367)	1.56000* (0.78125)
α_0	$x10^3$	0.73975* (0.33662)	0.38842 (0.30258)	0.75436 (0.48719)	0.70000 (4.60523)
α_1	$x10^1$	1.59267** (0.45921)	0.91829* (0.49417)	1.44694* (0.71375)	1.59300** (0.64766)
β_1		0.76118** (0.06852)	0.85579** (0.07176)	0.76870** (0.10249)	0.76120** (0.09248)
1/d	$x10^1$		2.33415** (0.00038)	7.42371** (0.66128)	0.01944 (0.03973)
λ	$x10^2$				0.01600 (0.21310)
μ	$x10^2$				0.01300 (0.18817)
δ^2	$x10^2$				0.01600 (0.21310)
$L(\theta)$	$x10^{-3}$	0.36081	0.37186	0.36986	-31.22107
$\alpha_1+\beta_1$		0.92045			
HL		9.36201			
σ_e^2	$x10^2$	0.92992			
σ_R^2	$x10^1$	0.15371			
AIC		355.81			
SIC		-692.30			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.14
AR(1)-GARCH(1,1) Estimates of NYSE Stock 14

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.42165 (0.40274)	0.02744 (0.32639)	0.04605 (0.33251)	0.42000 (60.04073)
$\varnothing_1$		0.18597** (0.05812)	0.18763** (0.04889)	0.18534** (0.04631)	0.18600 (0.38859)
α_0	x10^2	0.03427 (0.04013)	0.48153 (0.64072)	0.01651 (0.03534)	0.30000 (0.61978)
α_1	x10^1	0.24793 (0.17286)	0.43341 (0.73831)	0.13274 (0.14891)	0.24800 (1.91781)
β_1		0.90402** (0.09677)	0.00809 (1.22398)	0.94771** (0.09119)	0.90400** (0.14655)
1/d			0.25948** (0.01165)	0.74255** (0.00019)	0.00035 (0.11138)
λ					0.00035 (0.11138)
μ	x10^1				0.00210 (0.66731)
δ^2	x10^2				0.03200 (0.23370)
L(θ)	x10^{-3}	0.44356	0.46200	0.45976	-29.47017

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.15
AR(1)-GARCH(1,1) Estimates of NYSE Stock 15

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.14903	-0.05214	-0.12167	0.42000
		(0.32286)	(0.28159)	(0.27555)	(60.64023)
$\varnothing_1$		0.23967**	0.16392**	0.18379**	0.18600
		(0.07209)	(0.05822)	(0.05817)	(0.49382)
α_0	x10^2	0.17210**	0.16881	0.16432*	0.30000
		(0.06018)	(0.10871)	(0.09433)	(0.63333)
α_1		0.19131**	0.15087	0.16876	0.02480
		(0.07877)	(0.09949)	(0.10379)	(0.24853)
β_1		0.32520	0.37601	0.35920	0.90400**
		(0.20820)	(0.34774)	(0.32024)	(0.14086)
1/d			0.19053**	0.76371**	0.00035
			(0.04187)	(0.06586)	(0.11230)
λ					0.00035
					(0.11230)
μ	x10^1				0.00210
					(0.67277)
δ^2	x10^2				0.03200
					(0.23902)
L(θ)	x10^{-3}	0.50363	0.51499	0.51335	-29.45446
$\alpha_1+\beta_1$		0.51651			
HL		2.04917			
σ_e^2	x10^2	0.35595			
σ_R^2	x10^2	0.69735			
AIC		498.63			
SIC		-977.94			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.16
GARCH(1,1) Estimates of NYSE Stock 16

Statistics		(N)	(T)	(PE)	(MJ)
$\emptyset_0$	x10^2	0.27242 (0.17791)	0.11847 (0.13578)	0.19000 (0.14882)	0.27200 (6.51757)
α_0	x10^3	0.06766** (0.01277)	0.18707* (0.11286)	0.20000** (0.02919)	0.06000 (2.10971)
α_1		0.11933** (0.01597)	0.08480 (0.05291)	0.15630** (0.03590)	0.11930 (0.22448)
β_1		0.84019** (0.01734)	0.75061** (0.11548)	0.60230** (0.05590)	0.84020** (0.27085)
1/d	x10^1		2.83616** (0.35121)	5.20000** (0.19276)	0.01148 (0.19027)
λ	x10^1				0.01148 (0.19027)
μ	x10^2				0.04500 (0.74089)
δ^2	x10^2				0.07900 (0.14749)
L(θ)	x10^{-3}	0.69768	0.74218	0.67799	-25.53436
$\alpha_1+\beta_1$		0.95952	0.83541	0.75860	
HL		17.77476	4.85446	3.50885	
σ_e^2	x10^2	0.16714	0.11366	0.08285	
σ_R^2		0.16714	0.11366	0.08285	
AIC		693.68	737.18	672.99	
SIC		-1371.89	-1455.03	-1326.65	
LR			89.00**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.17
GARCH(1,1) Estimates of NYSE Stock 17

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.37485 (0.29049)	0.08979 (0.23682)	0.13902 (0.25827)	0.37000 (2.38393)
α_0 x10^3	0.44117** (0.11685)	1.24756** (0.50731)	1.14255** (0.32997)	0.40000 (8.24718)
α_1	0.25759** (0.05566)	0.41472** (0.16219)	0.37469** (0.10736)	0.25760* (0.15249)
β_1	0.62915** (0.05022)	0.28913 (0.18416)	0.28428* (0.14036)	0.62920** (0.20465)
1/d		0.20256** (0.00610)	0.89171** (0.00240)	0.00053 (0.00498)
				0.00053 (0.00498)
μ x10^1				0.00370 (0.02698)
δ^2				0.00043 (0.00248)
L(θ) x10^{-3}	0.53331	0.54601	0.54297	-28.01422
$\alpha_1+\beta_1$	0.88674	0.70385	0.65898	
HL	6.76640	2.97372	2.66195	
σ_e^2 x10^1	0.03895	0.04213	0.03350	
σ_R^2 x10^1	0.03895	0.04213	0.03350	
AIC	529.31	541.01	537.97	
SIC	-1043.15	-1062.69	-1056.61	
LR		25.40**	19.32**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.18
AR(1)-GARCH(1,1) Estimates of NYSE Stock 18

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.30285 (0.25592)	0.18325 (0.23002)	0.04457 (0.22935)	0.30000 (1.74422)
$\varnothing_1$	0.13327** (0.05714)	0.11916* (0.05280)	0.10619* (0.05415)	0.13300 (0.08952)
α_0 x10^3	0.58762** (0.19119)	0.44096* (0.21929)	0.52573* (0.24817)	0.60000 (12.43244)
α_1	0.30570** (0.04810)	0.18668** (0.07249)	0.24090** (0.06936)	0.30570** (0.08595)
β_1	0.54176** (0.08205)	0.68517** (0.10898)	0.59819** (0.11519)	0.54180** (0.17314)
1/d		0.22870** (0.00958)	0.80141** (0.03035)	0.00015 (0.00355)
λ				0.00015 (0.00355)
μ x10^1				0.00110 (0.02062)
δ^2				0.00022 (0.00302)
L(θ) x10^{-3}	0.53661	0.55030	0.54906	-31.88555
$\alpha_1+\beta_1$	0.84756	0.87185	0.83909	
HL	5.18782	6.05424	4.95097	
σ_e^2 x10^1	0.03852	0.03441	0.03267	
σ_R^2 x10^1	0.03922	0.03491	0.03305	
AIC	531.61	544.30	543.06	
SIC	-1043.90	-1065.42	-1062.94	
LR		27.38**	24.90**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.19
GARCH(1,1) Estimates of NYSE Stock 19

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.06553	-0.49412	-0.49008	0.07000
	(0.28545)	(0.23658)	(0.24054)	(2.92344)
α_0 x10^3	0.22713*	0.99980	0.68586*	0.23000
	(0.11441)	(0.65442)	(0.38877)	(1.90918)
α_1	0.13870**	0.24990*	0.18048*	0.13870
	(0.03411)	(0.14595)	(0.08482)	(0.08782)
β_1	0.81428**	0.59169**	0.65196**	0.81430**
	(0.04403)	(0.15275)	(0.13550)	(0.12939)
1/d		0.33180**	0.91392**	0.00054
		(0.00009)	(0.06620)	(0.00707)
λ				0.00543
				(0.00707)
μ x10^1				0.00270
				(0.03688)
δ^2				0.00033
				(0.00112)
L(θ) x10^{-3}	0.49399	0.50951	0.51064	-27.94463
$\alpha_1+\beta_1$	0.95298		0.83244	
HL	15.39115		4.77955	
σ_ϵ^2 x10^1	0.04830		0.04093	
σ_R^2 x10^1	0.04830		0.04093	
AIC	489.99		505.64	
SIC	-964.51		-991.95	
LR			33.30**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.20
GARCH(1,1) Estimates of NYSE Stock 20

Statistics		(N)	(T)	(PE)	(MJ)
$\emptyset_0$	x10^2	0.36999*	0.31276*	0.31741*	0.37000
		(0.17084)	(0.16314)	(0.15450)	(3.39650)
α_0	x10^3	0.62600**	0.51382**	0.54737*	0.60000
		(0.22682)	(0.20957)	(0.29714)	(1.94309)
α_1		0.19449**	0.21960**	0.19182**	0.19450
		(0.04944)	(0.07572)	(0.07834)	(0.14656)
β_1		0.25595	0.30831	0.32496	0.25600
		(0.21962)	(0.22466)	(0.29904)	(0.83720)
1/d			0.08563**	0.74268**	0.00054
			(0.00077)	(0.06257)	(0.01396)
λ					0.00054
					(0.01396)
μ	x10^1				0.00170
					(0.03831)
δ^2					0.00024
					(0.00291)
L(θ)	x10^{-3}	0.70248	0.70964	0.71095	-27.77688
$\alpha_1+\beta_1$		0.45045	0.52791	0.51678	
HL		1.86913	2.08502	2.05000	
σ_e^2	x10^1	0.01139	0.01088	0.01133	
σ_R^2	x10^1	0.01139	0.01088	0.01133	
AIC		698.48	704.64	705.95	
SIC		-1381.49	-1389.95	-1392.57	
LR			14.32**	16.94**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.21
GARCH(1,1) Estimates of NYSE Stock 21

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.95988**	1.08984**	1.04881**	0.96000
	(0.28284)	(0.29750)	(0.26411)	(8.10322)
α_0 x10^3	0.05751	1.35472	0.06356	0.06000
	(0.06088)	(15.13802)	(0.09254)	(0.32069)
α_1	0.03195	0.00000	0.03059	0.03195
	(0.01962)	(0.05306)	(0.02726)	(0.06692)
β_1	0.94682**	0.60386	0.94648**	0.94680**
	(0.03578)	(4.38779)	(0.05163)	(0.10961)
1/d		0.15963**	0.70379**	0.00052
		(0.05833)	(0.00115)	(0.01629)
λ				0.00052
				(0.01629)
μ x10^1				0.00290
				(0.08993)
δ^2				0.00037
				(0.00036)
L(θ) x10^{-3}	0.52896	0.53077	0.53286	-28.03653

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.22
GARCH(1,1) Estimates of NYSE Stock 22

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	x10^2	0.61402**	0.38320*	0.47829**	0.61000
		(0.23347)	(0.20014)	(0.20083)	(1.76021)
α_0	x10^3	0.24394**	0.30000**	0.23511	0.20000
		(0.10355)	(0.22434)	(0.17650)	(0.49847)
α_1		0.12627**	0.15830*	0.12140*	0.12630
		(0.04175)	(0.09078)	(0.06884)	(0.09087)
β_1		0.76674**	0.75050**	0.77843**	0.76670**
		(0.06481)	(0.11660)	(0.11139)	(0.15082)
1/d			0.26350**	0.79298**	0.00058
			(0.07364)	(0.02203)	(0.00602)
λ					0.00058
					(0.00602)
μ	x10^1				0.00190
					(0.00197)
δ^2					0.00017
					(0.00021)
L(θ)	x10^{-3}	0.57420	0.58122	0.58126	-27.66269
$\alpha_1+\beta_1$		0.89301	0.90880		
HL		7.12571	8.24820		
σ_e^2	x10^1	0.02280	0.03290		
σ_R^2	x10^1	0.02280	0.03290		
AIC		570.20	576.22		
SIC		-1124.93	-1133.11		
LR			14.04**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 353.

Table B.5.B.23
AR(1)-GARCH(1,1) Estimates of NYSE Stock 23

Statistics		(N)	(T)	(PE)	(MJ)[1]
$\varnothing_0$	x10^2	0.59058**	0.44240*	0.49753**	0.59020
		(0.21140)	(0.20513)	(0.20962)	(1.53530)
$\varnothing_1$		0.06048	0.03332	0.03990	
		(0.06321)	(0.05470)	(0.05306)	
α_0	x10^3	0.66850**	0.28784	0.04789	60.50000
		(0.19471)	(0.18284)	(0.03606)	(1150.70279)
α_1		0.38095**	0.12235*	0.06689**	0.00070
		(0.06266)	(0.06277)	(0.02805)	(1.34156)
β_1		0.40879**	0.75396**	0.91443**	0.38090
		(0.10095)	(0.11104)	(0.03101)	(4.13934)
1/d			0.22036**	0.75128**	0.00042
			(0.00905)	(0.01002)	(9.13192)
λ					0.00042
					(9.13192)
μ	x10^1				0.00790
					(170.05851)
δ^2					0.00087
					(0.13403)
L(θ)	x10^{-3}	0.57735	0.59470	0.59110	-29.04818
$\alpha_1+\beta_1$		0.78774			
HL		3.93641			
σ_e^2	x10^1	0.03180			
σ_R^2	x10^1	0.03190			
AIC		572.35			
SIC		-1125.38			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

[1] The AR term was not used. The sample size for this model is 353.

Table B.5.B.24
AR(1)-GARCH(1,1) Estimates of NYSE Stock 24

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.38374*	0.25984	0.28456	0.38300
	(0.19055)	(0.19666)	(0.19070)	(2.43927)
$\varnothing_1$	0.08070	0.10276*	0.09783*	0.08070
	(0.05140)	(0.05369)	(0.05318)	(0.11513)
α_0 x10^3	0.12227*	0.18861*	0.15064	0.10000
	(0.05821)	(0.10605)	(0.09268)	(1.42409)
α_1	0.13944**	0.12499**	0.12567**	0.13940
	(0.03509)	(0.03971)	(0.04218)	(0.09612)
β_1	0.78423**	0.74530**	0.77470**	0.78420**
	(0.04885)	(0.08835)	(0.07747)	(0.17899)
1/d		0.07771**	0.67078**	0.00015
		(0.00099)	(0.00963)	(0.00382)
λ				0.00015
				(0.00382)
μ x10^1				0.00110
				(0.02779)
δ^2				0.00022
				(0.00072)
L(θ) x10^{-3}	0.65155	0.65510	0.65625	-31.76867
$\alpha_1+\beta_1$	0.92366	0.87029		
HL	9.72876	5.98903		
σ_e^2 x10^1	0.01600	0.01450		
σ_R^2 x10^1	0.01610	0.01470		
AIC	646.55	649.10		
SIC	-1273.78	-1275.02		
LR		7.10**		

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.25
AR(1)-GARCH(1,1) Estimates of NYSE Portfolio P1

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.10549 (0.23820)	-7.58450 (0.22030)	-0.05024 (0.21447)	0.00079 (0.22125)
$\varnothing_1$	0.31305** (0.05666)	0.29110** (0.05450)	0.30315** (0.05450)	0.32277 (0.18174)
α_0 x10^4	6.10367** (1.92906)	4.43580* (2.43930)	5.50680* (2.64380)	0.00204 (0.12241)
α_1	0.22270** (0.05325)	0.15361** (0.06520)	0.19059** (0.07314)	0.29373 (0.4637)
β_1	0.44518** (0.12944)	0.58330** (0.18429)	0.49974** (0.18755)	0.15704 (0.115204)
1/d		0.10494** (0.00536)	0.677491** (0.04418)	
λ				0.00015 (0.22030)
μ				0.00007 (0.01805)
δ^2				0.00020 (0.26634)
L(θ)	624.767	630.869	629.638	-31888.29
$\alpha_1+\beta_1$	0.66788	0.73691	0.69033	
HL	2.7172	3.2704	2.87	
σ_e^2	0.00184	0.00169	0.00178	
σ_R^2	0.00204	0.00184	0.00196	
AIC	619.76	624.87	623.64	
SIC	-1220.20	-1226.56	-1224.09	
LR		12.20**	9.74**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.26
AR(1)-LRCH(1,1) Estimates of NYSE Portfolio P2

Statistics		(N)	(T)	(PE)	(MJ)
$\varnothing_0$	$x10^2$	0.11573	0.06526	0.02035	0.00274
		(0.19190)	(0.13542)	(0.16580)	(0.48550)
$\varnothing_1$		0.22987**	0.23019**	0.22543**	0.23420
		(0.06515)	(0.04904)	(0.05805)	(0.13640)
α_0	$x10^4$	9.24670**	6.46140*	8.37819*	0.96352
		(3.53740)	(2.89690)	(3.72586)	(0.56824)
α_1		0.18590*	0.21611*	0.19393*	0.33373
		(0.09936)	(0.12497)	(0.11260)	(0.58204)
β_1		0.00000	0.17365	0.00000	0.15704
		(0.35280)	(0.29166)	(0.37290)	(1.03550)
1/d			0.24110**	0.65390**	
			(0.05920)	(0.04326)	
λ					0.00015
					(0.11142)
μ					0.00008
					(0.01478)
δ^2					0.00029
					(0.18770)
$L(\theta)$		711.569	721.663	720.3996	-31835.61
$\alpha_1+\beta_1$		0.1859	0.38976	0.19393	
HL		1.412	1.736	1.423	
σ_e^2		0.001136	0.001059	0.001039	
σ_R^2		0.001199	0.001118	0.001095	
AIC		706.57	715.66	714.40	
SIC		-1393.82	-1408.14	-1405.62	
LR			20.19**	17.66**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.27
AR(1)-GARCH(1,1) Estimates of NYSE Portfolio P3

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.41525**	0.36242**	0.35160**	0.48488
	(0.15210)	(0.12339)	(0.11670)	(0.88359)
$\varnothing_1$	0.15667*	0.11420*	0.11466*	0.13477
	(0.06984)	(0.05187)	(0.04959)	(0.15956)
α_0	0.96892*	1.34034	1.19000	0.96142
	(0.43923)	(0.90385)	(0.82298)	(0.53330)
α_1	0.15257**	0.10523	0.11286*	0.29300
	(0.03672)	(0.06612)	(0.06592)	(0.53185)
β_1	0.74475**	0.72531**	0.73404**	0.15700
	(0.06308)	(0.14439)	(0.13523)	(0.10806)
1/d		0.22870	0.87155**	
		(0.47475)	(0.06494)	
λ				0.00002
				(0.07333)
μ				0.00009
				(0.01827)
δ^2				0.00039
				(0.22415)
L(θ)	762.937	787.420	784.416	-37592.9
$\alpha_1+\beta_1$	0.89732			
HL	7.39790			
σ_e^2	0.00094			
σ_R^2	0.00097			
AIC	757.94			
SIC	-1496.56			

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

Table B.5.B.28
AR(1)-GARCH(1,1) Estimates of NYSE Portfolio ALL

Statistics	(N)	(T)	(PE)	(MJ)
$\varnothing_0$ x10^2	0.16697	0.13633	0.09412	0.05143
	(0.14242)	(0.10260)	(0.11661)	(0.10010)
$\varnothing_1$	0.35942**	0.34088**	0.32888**	0.28559
	(0.06232)	(0.04569)	(0.05256)	(1.44170)
α_0	3.06974**	2.51481*	2.54931*	1.40197
	(0.58974)	(1.44808)	(1.13102)	(0.9452)
α_1	0.30787**	0.16730*	0.21557**	0.59373
	(0.06163)	(0.09970)	(0.08338)	(0.74509)
β_1	0.30212**	0.50046*	0.42772*	0.15704
	(0.10502)	(0.23810)	(0.20101)	(0.87780)
1/d		0.29400**	0.79340**	
		(0.06850)	(0.07754)	
λ				0.00014
				(0.12680)
μ				0.00008
				(0.01710)
δ^2				0.00029
				(0.21510)
L(θ)	786.767	800.043	800.206	-31883.88
$\alpha_1+\beta_1$	0.60999	0.66776	0.64329	
HL	2.4023	2.716	2.5712	
σ_e^2	0.00079	0.00076	0.00072	
σ_R^2	0.00090	0.00086	0.00080	
AIC	781.77	794.04	794.21	
SIC	-1544.22	-1564.90	-1565.23	
LR		26.55**	26.88**	

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively. Standard errors are contained within parentheses. The sample size is 352.

APPENDIX C

EMPIRICAL CHARACTERISTICS OF STANDARDIZED RESIDUALS

Table C.5.A.1
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 1

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.04594	0.10886	0.10727	-0.04587
Variance	0.70101	1.11943	1.12930	0.69942
Skewness	2.02649**	2.54330**	2.25810**	2.02720**
Kurtosis	12.96510**	18.43490**	15.27530**	12.97070**
χ^2	105.81300**	75.41500**	39.47700**	
Dependence Residuals				
Autocorrelation:				
lag 1	-0.00596	0.02689	0.01093	-0.00600
lag 2	-0.07574	-0.06259	-0.0686	-0.07580
lag 3	-0.01052	-0.01190	-0.01352	-0.01052
lag 4	-0.03363	-0.01098	-0.03154	-0.03362
lag 5	0.00813	0.01919	0.02664	0.00820
lag 6	-0.08760	-0.08496	-0.0896	-0.08761
Ljung-Box:				
Q(6)	5.29	4.48	5.29	5.29
Q(12)	13.33	10.97	13.71	13.33
Q(24)	21.58	21.50	22.56	21.58
Squared Residuals				
Autocorrelation:				
lag 1	-0.02677	-0.00698	-0.01297	-0.02674
lag 2	-0.01265	-0.01687	-0.00697	-0.01263
lag 3	-0.02989	-0.02569	-0.02380	-0.02988
lag 4	0.04448	-0.01173	0.02259	0.04440
lag 5	-0.00660	-0.00889	0.00437	-0.00660
lag 6	-0.01451	-0.01617	-0.01475	-0.01450
Ljung-Box:				
Q(6)	1.43	0.53	0.55	1.43
Q(12)	3.22	0.97	1.51	3.22
Q(24)	10.00	9.45	9.91	10.00

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.2
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 2

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.00473	0.05587	0.50488	-0.00410
Variance	1.01329	1.03955	1.15130	0.96380
Skewness	1.19450**	1.23840**	1.23900**	1.19390**
Kurtosis	5.26090**	6.12680**	5.81810**	5.20900**
χ^2	36.21000	70.44300**	25.84100**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01456	0.05664	0.04713	0.01415
lag 2	-0.06397	-0.04770	-0.05341	-0.06451
lag 3	-0.03327	-0.02615	-0.02720	-0.03362
lag 4	0.08699	0.07334	0.07931	0.08762
lag 5	-0.07317	-0.07242	-0.07646	-0.07391
lag 6	-0.02292	-0.03475	-0.03069	-0.02264
Ljung-Box:				
Q(6)	6.75	6.44	6.76	6.85
Q(12)	15.38	14.63	15.22	15.50
Q(24)	22.77	21.99	22.87	22.91
Squared Residuals				
Autocorrelation:				
lag 1	0.05974	0.00896	0.02328	0.06487
lag 2	-0.03517	-0.04368	-0.04132	-0.03418
lag 3	-0.03478	-0.04368	-0.03981	-0.03404
lag 4	-0.02666	-0.04270	-0.02930	-0.02584
lag 5	-0.01649	-0.03424	-0.01699	-0.01608
lag 6	0.03404	-0.01788	0.03307	0.03417
Ljung-Box:				
Q(6)	2.91	2.27	2.17	3.08
Q(12)	10.83	10.13	10.76	11.06
Q(24)	16.79	16.14	16.98	17.01

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.3
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 3

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02002	0.04293	0.02026	0.02020
Variance	0.99110	0.92413	1.01760	0.99020
Skewness	0.60890**	0.67075**	0.65291**	0.60920**
Kurtosis	2.32230**	2.72270**	2.72370**	2.32250**
χ^2	50.55700**	57.51700**	23.56800**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.05667	0.09889	0.11087	0.05664
lag 2	-0.14419	-0.13346	-0.12820	-0.14420
lag 3	-0.05427	-0.04638	-0.04939	-0.05423
lag 4	0.03635	0.03585	0.03457	0.03636
lag 5	0.06375	0.05509	0.05543	0.06375
lag 6	-0.04469	-0.03826	-0.03917	-0.04469
Ljung-Box:				
Q(6)	12.25	12.66	13.17*	12.25
Q(12)	15.80	16.62	17.17	15.80
Q(24)	27.82	29.18	29.79	27.82
Squared Residuals				
Autocorrelation:				
lag 1	-0.02927	-0.00179	-0.00671	-0.02921
lag 2	-0.01340	-0.00426	-0.01093	-0.01335
lag 3	0.03487	0.05126	0.04821	0.03491
lag 4	-0.06480	-0.05184	-0.05365	-0.06478
lag 5	-0.07493	-0.06871	-0.07556	-0.07486
lag 6	0.02149	0.01005	0.00793	0.02150
Ljung-Box:				
Q(6)	4.49	3.64	3.99	4.48
Q(12)	9.83	8.16	8.46	9.83
Q(24)	14.16	12.99	13.31	14.16

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.4
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 4

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01673	0.09095	0.08324	-0.01584
Variance	1.02155	1.01117	1.01728	1.01210
Skewness	0.78371**	0.81184**	0.80679**	0.78510**
Kurtosis	1.98911**	2.23790**	2.13014**	2.00000**
χ^2	33.79500	47.57400**	34.93200**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01797	0.00810	0.04266	0.01848
lag 2	-0.01487	-0.02388	-0.01420	-0.01516
lag 3	0.00821	0.00022	0.00306	0.00780
lag 4	-0.01791	-0.01704	-0.01700	-0.01759
lag 5	0.03867	0.03655	0.03479	0.03874
lag 6	-0.07550	-0.07651	-0.07260	-0.07500
Ljung-Box:				
Q(6)	2.92	2.92	3.16	2.9
Q(12)	11.73	11.56	11.73	11.76
Q(24)	18.31	18.03	18.26	18.34
Squared Residuals				
Autocorrelation:				
lag 1	0.03287	0.03274	0.02850	0.03300
lag 2	0.06811	0.05872	0.06330	0.06820
lag 3	-0.01990	-0.03065	-0.02620	-0.02030
lag 4	-0.04294	-0.04465	-0.04279	-0.04291
lag 5	0.00754	0.01273	0.01127	0.00810
lag 6	-0.04326	-0.03993	-0.03950	-0.04273
Ljung-Box:				
Q(6)	3.53	3.29	3.22	3.53
Q(12)	6.28	5.56	5.65	6.28
Q(24)	13.35	12.42	12.93	13.38

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.5
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 5

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02777	0.07102	0.04887	0.02835
Variance	1.00153	0.92438	1.01920	0.99140
Skewness	0.71815**	0.86036**	0.81030**	0.72540**
Kurtosis	2.31718**	2.89098**	2.67530**	2.33570**
χ^2	44.16500**	79.39200**	31.94900**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00908	0.05610	0.04180	0.00942
lag 2	-0.03585	-0.04153	-0.03844	-0.03652
lag 3	0.00197	-0.00603	-0.00294	0.00221
lag 4	-0.07833	-0.07166	-0.07313	-0.07810
lag 5	-0.02523	-0.02885	-0.02708	-0.02534
lag 6	0.02669	0.02413	0.02526	0.02663
Ljung-Box:				
Q(6)	3.17	4.09	3.56	3.18
Q(12)	5.74	6.50	6.00	5.73
Q(24)	17.13	20.51	19.04	17.14
Squared Residuals				
Autocorrelation:				
lag 1	0.03636	0.05109	0.04326	0.03810
lag 2	0.01188	-0.00710	-0.00350	0.01220
lag 3	-0.00108	0.00049	-0.00152	-0.00051
lag 4	-0.01155	-0.00727	-0.01023	-0.01051
lag 5	-0.02312	-0.02741	-0.02681	-0.02301
lag 6	-0.07235	-0.05393	-0.06094	-0.07165
Ljung-Box:				
Q(6)	2.64	2.28	2.30	2.65
Q(12)	6.57	5.12	5.52	6.51
Q(24)	11.08	9.76	9.96	10.98

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.6
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NASDAQ Stock 6

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.02239	0.10096	0.12250	-0.02333
Variance	1.00230	0.96726	1.06810	1.00640
Skewness	0.67780**	0.88742**	0.79290**	0.68080**
Kurtosis	4.09181**	4.93678**	4.59210**	4.08442**
χ^2	84.64800**	132.94300**	112.48800**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.14041	0.13643	0.13412	0.13950
lag 2	-0.05932	-0.07739	-0.06970	-0.05946
lag 3	-0.01706	-0.01498	-0.01489	-0.01521
lag 4	0.00279	0.00703	0.00560	0.00347
lag 5	-0.05088	-0.05391	-0.05330	-0.04932
lag 6	-0.05515	-0.04706	-0.04995	-0.05527
Ljung-Box:				
Q(6)	10.41	10.52	10.15	10.22
Q(12)	16.22	15.73	15.57	16.13
Q(24)	26.14	25.72	25.41	26.01
Squared Residuals				
Autocorrelation:				
lag 1	-0.03317	-0.01347	-0.02364	-0.03343
lag 2	0.18207	0.20710	0.19371	0.18160
lag 3	-0.06870	-0.05985	-0.06392	-0.06838
lag 4	-0.02318	-0.02008	-0.02361	-0.02350
lag 5	-0.05230	-0.05779	-0.06138	-0.05220
lag 6	-0.03036	-0.02644	-0.02653	-0.03074
Ljung-Box:				
Q(6)	15.43*	18.26**	16.87**	15.32*
Q(12)	19.35	21.42	20.06	19.28
Q(24)	31.07	33.83	32.87	31.03

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.7
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 7

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.00845	0.05517	-0.03993	-0.00780
Variance	1.00560	0.97232	1.00500	1.00100
Skewness	0.54740**	0.62897**	0.56270**	0.54740**
Kurtosis	4.23140**	4.48095**	4.20620	4.23210**
χ^2	149.84700**	153.54000**	168.59700**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00341	-0.01425	0.00780	0.00329
lag 2	-0.06419	-0.06762	-0.06090	-0.06423
lag 3	0.12753	0.12290	0.12278	0.12751
lag 4	0.11098	0.10653	0.11040	0.11102
lag 5	-0.02485	-0.02782	-0.02610	-0.02490
lag 6	0.04180	0.04055	0.04260	0.04172
Ljung-Box:				
Q(6)	12.54	12.03	12.43	12.54
Q(12)	18.38	17.88	18.18	18.37
Q(24)	34.12	33.22	33.87	34.10
Squared Residuals				
Autocorrelation:				
lag 1	0.05176	0.04960	0.05633	0.05234
lag 2	-0.02482	-0.02268	-0.02486	-0.02461
lag 3	-0.03486	-0.03544	-0.03645	-0.03475
lag 4	0.01821	0.01006	0.01370	0.01843
lag 5	0.01946	0.00913	0.01913	0.01975
lag 6	-0.02733	-0.02866	-0.02814	-0.02725
Ljung-Box:				
Q(6)	2.13	1.87	2.30	2.15
Q(12)	13.22	12.52	13.63	13.30
Q(24)	20.14	19.04	20.41	20.24

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.8
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 8

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.03481	0.05792	0.04559	0.03419
Variance	1.00300	0.97391	1.01950	1.01094
Skewness	0.49024**	0.48327**	0.48831**	0.49012**
Kurtosis	3.01098**	3.08532**	2.95630**	3.00870**
χ^2	37.63100	60.07400**	20.30100**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04361	0.03520	0.09536	0.04358
lag 2	0.02024	0.01394	0.03302	0.02032
lag 3	-0.01176	-0.01062	-0.01163	-0.01182
lag 4	-0.06388	-0.06694	-0.06043	-0.06381
lag 5	0.00427	0.00671	0.00174	0.00423
lag 6	-0.02904	-0.02314	-0.02710	-0.02919
Ljung-Box:				
Q(6)	2.64	2.36	5.24	2.64
Q(12)	9.91	9.60	12.16	9.91
Q(24)	19.64	19.83	21.64	19.63
Squared Residuals				
Autocorrelation:				
lag 1	-0.01949	-0.00178	-0.00920	-0.01999
lag 2	-0.00710	-0.00731	-0.00312	-0.00718
lag 3	0.00613	-0.00199	0.02780	0.00602
lag 4	-0.03925	-0.04096	-0.03661	-0.03926
lag 5	0.01283	0.00696	0.01611	0.01293
lag 6	-0.02841	-0.02275	-0.02397	-0.02857
Ljung-Box:				
Q(6)	1.07	0.83	1.09	1.08
Q(12)	6.21	5.87	6.13	6.22
Q(24)	21.90	22.12	21.91	21.88

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.9
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 9

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01257	0.04019	0.04006	0.01271
Variance	1.00216	0.94624	0.99200	1.00934
Skewness	0.44980**	0.50240**	0.48180**	0.45000**
Kurtosis	1.19962**	1.39450**	1.31100**	1.20030**
χ^2	42.17600*	74.42000**	23.28400	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01047	0.01070	0.00541	0.01047
lag 2	0.01945	0.01582	0.01630	0.01933
lag 3	-0.08879	-0.07928	-0.08294	-0.08871
lag 4	0.00867	0.00700	0.00772	0.00870
lag 5	0.05220	0.05670	0.05531	0.05226
lag 6	0.04989	0.05074	0.05082	0.04995
Ljung-Box:				
Q(6)	4.89	4.47	4.61	4.89
Q(12)	12.55	11.94	12.06	12.54
Q(24)	25.68	24.68	24.89	25.66
Squared Residuals				
Autocorrelation:				
lag 1	0.02143	-0.01617	-0.00340	0.02114
lag 2	0.00843	-0.01123	-0.00424	0.00823
lag 3	-0.01670	-0.03983	-0.03414	-0.01691
lag 4	-0.02012	-0.02986	-0.02650	-0.02025
lag 5	-0.04643	-0.05010	-0.04790	-0.04652
lag 6	0.06508	0.06076	0.06160	0.06495
Ljung-Box:				
Q(6)	2.73	3.25	2.87	2.73
Q(12)	12.78	11.36	11.54	12.73
Q(24)	25.58	26.39	26.16	25.55

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.10
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 10

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01305	0.07979	0.08542	0.01300
Variance	0.99990	0.98666	1.02830	1.00153
Skewness	0.78262**	0.81178**	0.79945**	0.78260**
Kurtosis	2.73520**	3.23520**	3.05040**	2.73570
χ^2	37.77300*	70.58500**	25.41500	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01864	0.04025	0.05524	0.01866
lag 2	-0.01843	-0.00809	-0.00573	-0.01840
lag 3	-0.01569	-0.02526	-0.02164	-0.01571
lag 4	-0.00749	-0.00960	-0.00970	-0.00748
lag 5	-0.05420	-0.05419	-0.05457	-0.05420
lag 6	0.00342	-0.00362	-0.00110	0.00340
Ljung-Box:				
Q(6)	1.41	1.92	2.37	1.41
Q(12)	6.73	7.49	7.43	6.73
Q(24)	17.56	17.30	17.33	17.56
Squared Residuals				
Autocorrelation:				
lag 1	0.00240	-0.01752	-0.01070	0.00230
lag 2	-0.01244	-0.03611	-0.02887	-0.01248
lag 3	-0.00374	-0.02848	-0.01814	-0.00380
lag 4	-0.04330	-0.04765	-0.04385	-0.04328
lag 5	0.02132	0.00678	0.01031	0.02133
lag 6	0.02601	-0.00440	-0.00082	0.02595
Ljung-Box:				
Q(6)	1.14	1.70	1.18	1.14
Q(12)	5.57	6.21	6.02	5.57
Q(24)	22.71	26.00	24.28	22.71

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.11
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 11

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01713	0.06062	0.05102	0.01658
Variance	1.00382	0.91380	1.09866	1.03830
Skewness	0.75967**	0.77900**	0.78132**	0.76088**
Kurtosis	2.99930**	3.47810**	3.36830**	3.01361**
χ^2	46.15300**	73.56800**	25.13100	
Dependence Residuals				
Autocorrelation:				
lag 1	0.05427	0.09556	0.08890	0.05467
lag 2	-0.16057	-0.13625	-0.14016	-0.16004
lag 3	0.00750	-0.00738	-0.00357	0.00735
lag 4	-0.09018	-0.09138	-0.09087	-0.09001
lag 5	-0.11385	-0.11977	-0.11789	-0.11400
lag 6	0.07300	0.08120	0.07861	0.07326
Ljung-Box:				
Q(6)	19.73**	20.39**	19.98**	19.70**
Q(12)	29.32**	29.41**	29.17**	29.26**
Q(24)	59.54**	60.01**	59.53**	59.39**
Squared Residuals				
Autocorrelation:				
lag 1	-0.01193	-0.04141	-0.03376	-0.01349
lag 2	0.06019	0.02531	0.02737	0.05878
lag 3	-0.04779	-0.05171	-0.05164	-0.04793
lag 4	-0.02510	-0.01574	-0.01915	-0.02511
lag 5	0.02474	0.03528	0.03196	0.02514
lag 6	-0.06130	-0.05219	-0.05464	-0.06104
Ljung-Box:				
Q(6)	3.95	3.31	3.20	3.91
Q(12)	6.29	5.74	5.65	6.27
Q(24)	12.13	11.29	11.03	12.07

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.12
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 12

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01663	0.04230	0.01621	-0.01664
Variance	0.99825	1.10440	1.23010	1.00510
Skewness	0.79303**	1.11789**	0.68170**	0.79710**
Kurtosis	7.91398**	9.54300**	9.56510**	7.92660**
χ^2	62.77300**	72.14800**	25.13100	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01574	0.00613	0.01420	0.01579
lag 2	-0.01528	-0.01557	-0.02942	-0.01514
lag 3	0.00810	-0.00040	-0.00695	0.00810
lag 4	-0.07167	-0.05215	-0.05410	-0.07158
lag 5	0.07075	0.06790	0.06155	0.07067
lag 6	-0.06780	-0.06820	-0.06780	-0.06770
Ljung-Box:				
Q(6)	5.49	4.41	4.46	5.47
Q(12)	13.90	12.32	13.52	13.87
Q(24)	31.42	30.75	30.01	31.40
Squared Residuals				
Autocorrelation:				
lag 1	-0.01159	-0.01875	0.01869	-0.01189
lag 2	-0.01401	-0.02420	-0.01275	-0.01412
lag 3	0.00131	-0.02485	-0.02314	0.00107
lag 4	-0.01453	-0.01499	-0.02052	-0.01455
lag 5	0.01702	0.00143	-0.02040	0.01701
lag 6	-0.00611	-0.01190	-0.02274	-0.00618
Ljung-Box:				
Q(6)	0.31	0.69	0.86	0.32
Q(12)	1.55	1.81	2.29	1.54
Q(24)	38.66*	52.52**	38.17	38.82*

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.13
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 13

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01504	0.06039	0.04845	0.06039
Variance	1.00179	0.91265	1.13322	0.91265
Skewness	0.76119**	0.77976**	0.78660**	0.77976**
Kurtosis	2.99691**	3.48060**	3.45720**	3.48060**
χ^2	48.71000**	73.56800**	20.86900	
Dependence Residuals				
Autocorrelation:				
lag 1	0.05414	0.09573	0.09631	0.09573
lag 2	-0.16015	-0.13695	-0.13570	-0.13595
lag 3	0.00800	-0.00725	-0.00587	-0.00725
lag 4	-0.08986	-0.09131	-0.09093	-0.09130
lag 5	-0.11373	-0.11977	-0.11870	-0.11980
lag 6	0.07274	0.08118	0.07955	0.08118
Ljung-Box:				
Q(6)	19.64*	20.36**	20.16**	20.36**
Q(12)	29.23**	29.39**	29.26**	29.39**
Q(24)	59.37**	59.95**	59.74**	59.95**
Squared Residuals				
Autocorrelation:				
lag 1	-0.01012	-0.04116	-0.03770	-0.04116
lag 2	0.05854	0.02437	0.02262	0.02437
lag 3	-0.04824	-0.05184	-0.05230	-0.05184
lag 4	-0.02598	-0.01592	-0.01815	-0.01592
lag 5	0.02417	0.03520	0.03417	0.03520
lag 6	-0.06151	-0.05213	-0.05352	-0.05213
Ljung-Box:				
Q(6)	3.90	3.29	3.23	3.29
Q(12)	6.24	5.72	5.71	5.72
Q(24)	12.01	11.24	11.02	11.24

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.14
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NASDAQ Stock 14

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.00509	0.13475**	0.12305**	-0.00500
Variance	1.00650	0.93500	1.05410	1.00430
Skewness	1.23781**	1.26387**	1.25910**	1.23788**
Kurtosis	3.63523**	3.93340**	3.80110**	3.63400**
χ^2	106.23400**	114.76100**	52.26100**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.11953	0.10522	0.11000	0.11951
lag 2	-0.03126	-0.03951	-0.03836	-0.03128
lag 3	0.04642	0.04303	0.04281	0.04644
lag 4	-0.03532	-0.04174	-0.04161	-0.03532
lag 5	-0.07028	-0.07695	-0.07508	-0.07027
lag 6	-0.01906	-0.02255	-0.02202	-0.01905
Ljung-Box:				
Q(6)	8.56	8.10	8.32	8.56
Q(12)	19.05	18.94	18.97	19.05
Q(24)	33.05	33.51	33.33	33.06
Squared Residuals				
Autocorrelation:				
lag 1	-0.02469	-0.03326	-0.02450	-0.02464
lag 2	-0.04001	-0.04569	-0.04126	-0.03995
lag 3	0.05659	0.05850	0.06220	0.05676
lag 4	-0.00257	-0.00533	-0.00400	-0.00252
lag 5	-0.02495	-0.03338	-0.03027	-0.02486
lag 6	-0.02539	-0.01690	-0.01904	-0.02531
Ljung-Box:				
Q(6)	2.39	2.88	2.67	2.40
Q(12)	12.29	13.08	12.24	12.31
Q(24)	17.69	18.79	17.71	17.71

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.15
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 15

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01182	-0.00627	0.04663	-0.01191
Variance	1.00768	0.93748	1.01860	1.01637
Skewness	0.35087**	0.28974*	0.31630**	0.35114**
Kurtosis	0.56302	0.77500**	0.61960**	0.56380**
χ^2	37.34700	55.52800**	41.75000*	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00165	0.04391	0.04760	0.00168
lag 2	-0.06150	-0.04961	-0.05174	-0.06141
lag 3	0.03053	0.02411	0.02870	0.03050
lag 4	0.01505	0.01661	0.01833	0.01512
lag 5	0.06873	0.06790	0.06770	0.06871
lag 6	-0.01888	-0.00481	-0.01342	0.01884
Ljung-Box:				
Q(6)	3.59	3.53	3.88	3.58
Q(12)	9.87	9.78	10.29	9.86
Q(24)	18.84	18.93	19.21	18.84
Squared Residuals				
Autocorrelation:				
lag 1	-0.00030	0.02352	-0.00039	-0.00105
lag 2	0.01604	-0.01367	0.01110	0.01540
lag 3	-0.04971	-0.07427	-0.05860	-0.04996
lag 4	0.09221	0.04186	0.08284	0.09225
lag 5	-0.00796	-0.04320	-0.01981	-0.00813
lag 6	0.00627	-0.02507	0.00585	0.00615
Ljung-Box:				
Q(6)	4.06	3.76	3.88	4.06
Q(12)	10.39	11.50	9.86	10.41
Q(24)	24.10	26.29	22.70	24.11

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.16
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NASDAQ Stock 16

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.00499	0.03936	0.07214	-0.00505
Variance	1.00241	1.06844	1.00580	1.00567
Skewness	0.45617**	0.49460**	0.47083**	0.45609**
Kurtosis	1.58229**	1.84070**	1.64240**	1.58280**
χ^2	49.27800**	39.19300**	37.91500**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.07727	0.08056	0.07654	0.07726
lag 2	0.01775	0.01064	0.01259	0.01777
lag 3	-0.00130	-0.0075	-0.00260	-0.00129
lag 4	0.04524	0.04245	0.04340	0.04522
lag 5	0.03925	0.04209	0.04032	0.03925
lag 6	-0.01752	-0.02172	-0.01900	-0.01752
Ljung-Box:				
Q(6)	3.64	3.81	3.54	3.64
Q(12)	4.72	4.82	4.60	4.72
Q(24)	12.19	11.98	12.07	12.19
Squared Residuals				
Autocorrelation:				
lag 1	-0.01912	0.00687	0.00763	-0.00380
lag 2	-0.01992	-0.03660	-0.02162	-0.00800
lag 3	0.01128	0.00200	0.02962	0.05150
lag 4	-0.04582	-0.03440	-0.02186	-0.03200
lag 5	0.01273	-0.01579	-0.00628	-0.01184
lag 6	0.05198	0.03348	0.04124	0.03889
Ljung-Box:				
Q(6)	2.11	1.42	1.30	1.94
Q(12)	6.89	3.90	3.90	4.73
Q(24)	17.84	14.92	14.75	15.82

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.17
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 17

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00927	0.04919	0.07578	0.009715
Variance	1.00257	0.91465	1.01473	0.99590
Skewness	0.35614**	0.36905**	0.36770**	0.35610**
Kurtosis	1.79045**	2.22055**	2.08960**	1.78880**
χ^2	46.29500**	77.11900**	33.65300	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01114	0.01154	0.02115	0.01105
lag 2	-0.06257	-0.06934	-0.06554	-0.06254
lag 3	-0.00758	-0.00540	-0.00563	-0.00758
lag 4	-0.01884	-0.02251	-0.02157	0.01883
lag 5	0.03085	0.02878	0.02863	0.03087
lag 6	-0.02284	-0.02202	-0.02279	0.02285
Ljung-Box:				
Q(6)	2.12	2.42	2.35	2.11
Q(12)	20.29	20.47	20.50	20.29
Q(24)	27.95	27.69	27.75	27.95
Squared Residuals				
Autocorrelation:				
lag 1	-0.01370	-0.05574	-0.04604	-0.01335
lag 2	0.01582	-0.00604	-0.00191	0.01585
lag 3	-0.05283	-0.04335	-0.04510	-0.05284
lag 4	0.08125	0.09562	0.08980	0.08109
lag 5	-0.07921	-0.07065	-0.07093	-0.07924
lag 6	-0.01448	-0.00665	-0.00720	-0.01448
Ljung-Box:				
Q(6)	5.84	6.87	6.19	5.83
Q(12)	14.52	16.11	15.88	14.51
Q(24)	32.72	37.03*	37.07	37.72

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.18
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 18

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00583	0.05758	0.04621	0.00550
Variance	1.00146	0.98520	1.01860	1.08181
Skewness	0.52293**	0.49686**	0.51500**	0.50980**
Kurtosis	2.03136**	2.42250**	2.26370**	1.96150**
χ^2	35.92600	50.13100**	19.73300	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04874	0.07208	0.06980	0.05065
lag 2	-0.08913	-0.09202	-0.08962	-0.08929
lag 3	-0.01654	-0.03097	-0.02533	-0.01591
lag 4	0.02782	0.03115	0.03084	0.02559
lag 5	0.02548	0.02685	0.02674	0.02576
lag 6	0.03393	0.03802	0.03788	0.03038
Ljung-Box:				
Q(6)	4.69	6.33	5.93	4.64
Q(12)	14.24	15.37	15.06	14.23
Q(24)	21.27	22.43	22.04	21.31
Squared Residuals				
Autocorrelation:				
lag 1	0.02768	0.05999	0.04879	0.02096
lag 2	-0.00320	0.00975	0.00376	-0.00573
lag 3	-0.06557	-0.03989	-0.04810	-0.06927
lag 4	-0.03756	-0.01648	-0.02301	-0.04165
lag 5	-0.00736	-0.00077	-0.00376	-0.00745
lag 6	0.03353	0.02672	0.02731	0.03068
Ljung-Box:				
Q(6)	2.74	2.23	2.14	2.86
Q(12)	6.19	5.20	5.08	6.25
Q(24)	15.92	12.74	13.21	16.38

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.19
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 19

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00325	0.02807	0.04881	0.05881
Variance	0.99855	0.93495	1.02393	1.52710
Skewness	0.04675	0.05761	0.05049	0.05084
Kurtosis	1.75841**	1.75147**	1.74150**	1.73600**
χ^2	48.42600**	61.35200**	30.10200**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00717	0.01010	0.00495	0.00054
lag 2	-0.01195	-0.01342	-0.01341	-0.01410
lag 3	-0.01049	-0.00838	-0.00865	-0.00744
lag 4	-0.06883	-0.07036	-0.06981	-0.07086
lag 5	-0.04331	-0.04291	-0.04271	-0.04234
lag 6	0.07787	0.07800	0.07865	0.07997
Ljung-Box:				
Q(6)	4.66	4.75	4.73	4.84
Q(12)	17.48	17.70	17.76	18.08
Q(24)	24.62	24.85	24.97	25.31
Squared Residuals				
Autocorrelation:				
lag 1	0.00271	-0.00876	-0.00355	-0.01095
lag 2	-0.02156	-0.03259	-0.02917	-0.02664
lag 3	-0.01402	-0.01678	-0.01375	-0.01367
lag 4	-0.03525	-0.03840	-0.04000	-0.03918
lag 5	-0.04175	-0.04564	-0.04678	-0.04757
lag 6	-0.04661	-0.04708	-0.04669	-0.04654
Ljung-Box:				
Q(6)	2.09	2.58	2.52	2.50
Q(12)	6.08	6.79	6.72	6.72
Q(24)	15.94	16.67	16.83	16.90

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.20
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NASDAQ Stock 20

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01362	-0.00170	0.00104	-0.01366
Variance	1.00494	1.00438	1.00501	1.00590
Skewness	0.09776	0.09557	0.09486	0.09780
Kurtosis	0.50658*	0.51980*	0.51512*	0.50640*
χ^2	26.9770	28.68100	34.08000	
Dependence Residuals				
Autocorrelation:				
lag 1	0.11842	0.11848	0.11829	0.11842
lag 2	-0.06792	-0.06863	-0.06820	-0.06792
lag 3	0.03491	0.03440	0.03480	0.03492
lag 4	0.03063	0.03088	0.03074	0.03063
lag 5	0.00324	0.00407	0.00343	0.00323
lag 6	0.05518	0.05543	0.05507	0.05518
Ljung-Box:				
Q(6)	8.52	8.56	8.52	8.52
Q(12)	12.10	12.21	12.12	12.10
Q(24)	26.54	26.60	26.57	26.54
Squared Residuals				
Autocorrelation:				
lag 1	-0.00581	-0.00061	-0.01489	-0.00590
lag 2	0.02338	0.03084	0.02442	0.02331
lag 3	0.01402	0.01650	0.01426	0.01399
lag 4	-0.00048	0.00030	-0.00086	-0.00048
lag 5	-0.02886	-0.02840	-0.02825	-0.02890
lag 6	-0.01501	-0.01560	-0.01576	-0.01501
Ljung-Box:				
Q(6)	0.66	0.81	0.68	0.66
Q(12)	2.56	2.64	2.52	2.56
Q(24)	12.51	12.32	12.32	12.51

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.21
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 21

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01428	0.00379	0.01591	-0.01379
Variance	1.03641	0.88700	1.00583	1.10760
Skewness	0.05740	0.01929	0.05624	0.06819
Kurtosis	1.11863**	1.07635**	0.98606**	1.11430**
χ^2	36.63600	56.10000**	27.11900	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01928	0.04882	0.05612	0.01903
lag 2	-0.18760**	-0.18621**	-0.18224	-0.18650
lag 3	-0.02570	-0.02962	-0.03143	-0.02592
lag 4	-0.03605	-0.02909	-0.02881	-0.03655
lag 5	0.00697	0.00825	0.00727	0.00671
lag 6	0.03860	0.03562	0.03269	0.03788
Ljung-Box:				
Q(6)	13.92*	14.29*	14.00*	13.77*
Q(12)	16.72	17.74	17.32	16.50
Q(24)	27.12	28.39	27.02	26.68
Squared Residuals				
Autocorrelation:				
lag 1	-0.01107	0.00686	-0.00670	-0.01476
lag 2	-0.04071	-0.02988	-0.04210	-0.04398
lag 3	-0.04292	-0.02591	-0.02790	-0.04468
lag 4	0.04452	0.06550	0.04280	0.03871
lag 5	0.10586	0.11100	0.09820	0.10304
lag 6	-0.02896	-0.01677	-0.02670	-0.03169
Ljung-Box:				
Q(6)	6.33	6.64	5.30	6.19
Q(12)	13.46	13.48	12.68	13.42
Q(24)	25.84	25.43	21.82	25.27

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.22
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NASDAQ Stock 22

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01473	-0.00194	0.01092	-0.01443
Variance	0.99886	0.97635	1.02480	0.99190
Skewness	-0.22430*	-0.22180*	-0.22390*	-0.22460*
Kurtosis	1.91859**	1.93000**	1.93530**	1.90520*
χ^2	44.02300*	69.44900**	38.76700*	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04360	0.04463	0.04363	0.04347
lag 2	-0.09905	-0.09977	-0.09990	-0.09926
lag 3	-0.00570	-0.00659	-0.00590	-0.00543
lag 4	-0.05496	-0.05460	-0.05495	-0.05489
lag 5	-0.03269	-0.03242	-0.03240	-0.03282
lag 6	0.07263	0.07237	0.07340	0.07290
Ljung-Box:				
Q(6)	7.57	7.62	7.66	7.57
Q(12)	13.50	13.56	13.59	13.50
Q(24)	34.60	34.67	34.76	34.55
Squared Residuals				
Autocorrelation:				
lag 1	-0.01283	-0.01841	-0.01493	-0.01297
lag 2	0.02872	0.02447	0.02823	0.02915
lag 3	-0.01171	0.01407	-0.01380	-0.01114
lag 4	-0.01628	-0.01588	-0.01542	-0.01637
lag 5	-0.01684	-0.01405	-0.01370	-0.01637
lag 6	-0.00127	0.00068	0.00110	-0.00158
Ljung-Box:				
Q(6)	0.60	0.57	0.58	0.60
Q(12)	4.29	4.47	4.43	4.32
Q(24)	10.24	10.42	10.31	10.26

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.23
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 23

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.12432	-0.00280	0.05280	0.08875
Variance	1.03146	0.87330	0.96830	0.52850
Skewness	0.05058	0.29490**	0.26280**	0.24220**
Kurtosis	0.84245**	0.68250**	0.59640**	1.42590**
χ^2	46.43800**	45.72700**	35.64200	
Dependence Residuals				
Autocorrelation:				
lag 1	0.24376**	0.02319	0.02233	0.20214
lag 2	0.00045	-0.04690	-0.04908	-0.02852
lag 3	-0.03371	-0.02280	-0.03154	-0.01883
lag 4	-0.00364	-0.00511	0.00352	0.02696
lag 5	0.01886	0.01804	0.01922	0.00520
lag 6	0.01815	0.02251	0.02227	-0.00045
Ljung-Box:				
Q(6)	21.75**	1.47	1.71	15.19*
Q(12)	34.45**	11.04	10.55	24.08*
Q(24)	60.92**	33.03	31.34	51.57**
Squared Residuals				
Autocorrelation:				
lag 1	0.23357**	0.07974	0.02426	0.23440
lag 2	0.00275	-0.06801	-0.03491	0.05843
lag 3	-0.05053	-0.05798	-0.00861	0.02400
lag 4	-0.06471	-0.05543	-0.03349	0.01695
lag 5	-0.05862	-0.02375	0.00020	0.02113
lag 6	0.00746	0.00027	0.04419	0.17270
Ljung-Box:				
Q(6)	23.03**	6.41	1.77	31.93**
Q(12)	24.81*	7.88	3.27	43.94**
Q(24)	37.09*	19.24	17.98	77.47**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.24
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Stock 24

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01021	0.02158	0.00886	0.01050
Variance	0.98014	0.97553	0.92940	0.98790
Skewness	0.57839**	0.57780**	0.58150**	0.57820**
Kurtosis	0.78340**	0.78620**	0.78590**	0.78390**
χ^2	41.46600*	102.83000**	30.95500	
Dependence Residuals				
Autocorrelation:				
lag 1	0.03790	0.03869	0.05660	0.03796
lag 2	-0.16017**	-0.16009**	-0.15397	-0.16015
lag 3	0.01510	0.01504	0.01237	0.01502
lag 4	-0.05035	-0.05025	-0.05000	-0.05033
lag 5	0.03301	0.03279	0.03120	0.03299
lag 6	-0.02063	-0.02087	-0.02069	-0.02071
Ljung-Box:				
Q(6)	11.18	11.18	11.03	11.18
Q(12)	15.58	15.57	15.62	15.57
Q(24)	34.22	34.30	34.26	34.22
Squared Residuals				
Autocorrelation:				
lag 1	0.01723	0.01563	0.02451	0.01641
lag 2	-0.03845	-0.03907	-0.03560	-0.03857
lag 3	0.11451	0.11584	0.11370	0.11480
lag 4	0.00282	0.00052	0.00170	0.00262
lag 5	-0.05454	-0.05340	-0.05546	-0.05458
lag 6	0.00348	0.00284	0.00629	0.00331
Ljung-Box:				
Q(6)	6.39	6.45	6.40	6.40
Q(12)	7.80	7.88	7.83	7.82
Q(24)	18.14	18.45	17.79	18.16

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.25
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Portfolio P1

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00145	0.05823	0.06464	-0.02424
Variance	1.00476	1.35196	1.30359	0.28410
Skewness	-0.04488	0.73038	0.72524	0.61175**
Kurtosis	4.45715	6.01535	6.00991	4.84180**
χ^2	32.65900	22.57400	31.38100	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04511	0.06867	0.08772	0.33444**
lag 2	-0.06098	-0.06973	-0.06077	0.05783
lag 3	0.03110	0.03968	0.04349	0.09558
lag 4	0.11082	0.12275	0.12338	0.13329
lag 5	-0.00856	0.00211	0.00506	0.03209
lag 6	-0.03513	-0.04774	-0.04694	-0.03578
Ljung-Box:				
Q(6)	7.26	10.18	10.98	51.35**
Q(12)	11.13	17.61	18.35	57.10**
Q(24)	31.07	40.89*	41.61*	80.89**
Squared Residuals				
Autocorrelation:				
lag 1	0.00084	-0.02626	-0.02318	0.08171
lag 2	-0.02429	-0.02599	-0.02773	-0.03500
lag 3	0.01540	0.01385	0.01783	0.06458
lag 4	-0.01350	-0.00487	-0.00283	0.01224
lag 5	-0.05885	-0.04185	-0.04068	-0.03303
lag 6	-0.06522	-0.04976	-0.04953	-0.03659
Ljung-Box:				
Q(6)	3.14	2.08	2.06	5.22
Q(12)	27.4**	46.57**	46.87**	58.10**
Q(24)	34.56	52.94**	53.26**	66.21**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.26
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Portfolio P2

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01431	0.02116	0.00329	-0.09154
Variance	0.99734	1.06704	1.03334	2.66050
Skewness	-0.31037	-0.55101	-0.45665	0.07304
Kurtosis	4.66925	6.39312	5.67046	2.94616**
χ^2	25.13100	24.70500	16.18200	
Dependence Residuals				
Autocorrelation:				
lag 1	0.02580	0.05820	0.03738	0.14961
lag 2	-0.00542	0.00026	-0.00367	0.05729
lag 3	0.08068	0.06389	0.06984	0.08131
lag 4	-0.02934	-0.02863	-0.02921	-0.00925
lag 5	0.01011	0.00598	0.00808	0.02015
lag 6	0.03925	0.03173	0.03357	0.04417
Ljung-Box:				
Q(6)	3.47	3.33	2.98	12.36
Q(12)	8.88	8.16	8.04	18.05
Q(24)	24.34	22.24	22.57	39.07*
Squared Residuals				
Autocorrelation:				
lag 1	0.00442	0.03083	0.02227	-0.06617
lag 2	-0.00393	-0.00947	-0.00691	-0.03248
lag 3	-0.01131	-0.02069	-0.01867	0.01310
lag 4	-0.02940	-0.03817	-0.03658	-0.03652
lag 5	-0.00718	-0.01584	-0.01338	-0.01268
lag 6	-0.00312	-0.02154	-0.01811	0.03113
Ljung-Box:				
Q(6)	0.39	1.30	0.98	2.88
Q(12)	3.11	2.47	2.52	9.98
Q(24)	5.12	4.13	4.28	14.46

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.27
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Portfolio P3

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01500	0.00994	-0.01071	-0.02134
Variance	0.99945	1.01068	1.00232	0.34272
Skewness	-0.017759	-0.100101	0.00094	-0.06648
Kurtosis	1.42797	1.84489	1.47238	1.86774**
χ^2	19.59100	34.36400	16.75000	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04103	0.05515	0.05279	0.24338**
lag 2	-0.10090	-0.09672	-0.09998	-0.03571
lag 3	0.03070	0.03354	0.03630	0.03663
lag 4	-0.03184	-0.03286	-0.03173	-0.01280
lag 5	0.01900	0.02034	0.01828	0.03052
lag 6	0.11625	0.11664	0.11943	0.10529
Ljung-Box:				
Q(6)	9.92	10.25	10.64	26.35**
Q(12)	14.56	14.67	15.07	29.78**
Q(24)	35.24	35.07	35.32	46.65**
Squared Residuals				
Autocorrelation:				
lag 1	0.01321	0.03982	0.01015	0.07182
lag 2	0.01270	0.02617	0.03411	0.02364
lag 3	-0.01947	-0.01111	-0.00692	-0.00794
lag 4	-0.02361	-0.02933	-0.01931	-0.03948
lag 5	-0.02627	-0.02955	-0.02595	-0.04570
lag 6	0.01254	0.01275	0.03214	0.02525
Ljung-Box:				
Q(6)	0.76	1.53	1.22	3.59
Q(12)	9.96	9.82	11.80	15.35
Q(24)	18.97	17.08	20.52	22.37

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.A.28
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NASDAQ Portfolio ALL

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01077	0.02511	0.02217	0.08776*
Variance	1.00065	1.04660	1.04525	0.55837
Skewness	-0.18443	-0.50520	-0.39276	-0.26850
Kurtosis	3.93394	5.82820	5.12165	4.58731**
χ^2	29.53400	39.47700*	24.99900	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04904	0.07683	0.06274	0.31814**
lag 2	-0.05635	-0.05192	-0.05649	0.05308
lag 3	0.05429	0.04553	0.04993	0.09558
lag 4	0.00865	0.00148	0.00395	0.04815
lag 5	0.01242	0.01104	0.01162	0.04496
lag 6	0.04696	0.04268	0.04473	0.06524
Ljung-Box:				
Q(6)	3.91	4.50	4.20	43.29**
Q(12)	6.69	7.19	6.90	45.03**
Q(24)	24.36	23.25	23.59	61.05**
Squared Residuals				
Autocorrelation:				
lag 1	0.01179	0.04709	0.03555	0.08241
lag 2	-0.02089	-0.00606	-0.00837	-0.08180
lag 3	0.02287	0.00060	0.00819	0.06038
lag 4	0.00435	-0.01217	-0.00767	0.03220
lag 5	-0.03313	-0.03008	-0.03101	-0.02633
lag 6	-0.04486	-0.04545	-0.04554	-0.00109
Ljung-Box:				
Q(6)	1.52	1.92	1.61	4.38
Q(12)	4.71	2.88	3.14	9.63
Q(24)	7.12	5.10	5.43	12.95

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.1
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 1

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01309	0.06578	0.01250	-0.01639
Variance	0.93076	0.93719	0.94825	0.74756
Skewness	0.65650**	0.70837**	0.70125**	0.63390**
Kurtosis	2.11600**	2.45043**	2.38132**	2.08542**
χ^2	77.97160**	161.35230**	275.27270**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.02717	0.05031	0.11608	0.12209
lag 2	-0.04039	-0.02603	-0.01517	-0.02458
lag 3	0.03242	0.03613	0.04072	0.03927
lag 4	0.03600	0.03959	0.03459	0.03200
lag 5	-0.02734	-0.02726	-0.02346	-0.02222
lag 6	0.00889	0.01455	0.01166	0.00498
Ljung-Box:				
Q(6)	1.98	2.51	6.13	6.61
Q(12)	7.03	8.02	11.73	11.66
Q(24)	16.52	17.64	21.56	21.10
Squared Residuals				
Autocorrelation:				
lag 1	-0.01234	-0.04017	-0.03331	0.01307
lag 2	-0.01807	-0.04313	-0.04395	-0.01803
lag 3	0.06844	0.05990	0.05502	0.05756
lag 4	-0.00560	-0.00357	-0.00243	-0.00013
lag 5	0.02307	0.00789	0.01252	0.01758
lag 6	-0.08091	-0.07999	-0.08132	-0.07997
Ljung-Box:				
Q(6)	4.40	4.85	4.60	3.77
Q(12)	18.10	18.28	20.76	18.62
Q(24)	23.62	23.46	26.41	24.60

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.2
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 2

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00797	-0.00986	0.00592	0.00695
Variance	1.00012	0.81035	1.07465	0.94992
Skewness	0.65858**	0.64462**	0.71449**	0.66528**
Kurtosis	3.45634**	3.50911**	3.49846**	3.44423**
χ^2	184.64770**	205.81250**	187.34660**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.03623	0.04433	0.03760	0.03596
lag 2	-0.05883	-0.06728	-0.06767	-0.06003
lag 3	-0.01279	-0.01522	-0.01525	-0.01274
lag 4	-0.02211	-0.02227	-0.02160	-0.02153
lag 5	-0.05693	-0.05301	-0.05256	-0.05651
lag 6	-0.04081	-0.04525	-0.03623	-0.04015
Ljung-Box:				
Q(6)	3.71	4.33	3.86	3.70
Q(12)	11.18	11.12	11.64	11.28
Q(24)	28.75	28.89	29.69	28.84
Squared Residuals				
Autocorrelation:				
lag 1	-0.01345	-0.03524	-0.01591	-0.01214
lag 2	0.00848	-0.03231	-0.01550	0.00778
lag 3	-0.05649	-0.06962	-0.05551	-0.05513
lag 4	0.02475	-0.00810	0.03422	0.02836
lag 5	-0.02222	-0.01431	-0.01172	-0.02129
lag 6	0.07556	0.08399	0.08211	0.07667
Ljung-Box:				
Q(6)	3.69	5.20	4.18	3.74
Q(12)	5.46	7.57	6.09	5.48
Q(24)	11.58	14.49	13.12	11.67

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.3
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NSYE Stock 3

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.02012	0.02076	-0.00234	-0.00743
Variance	1.01063	0.99320	1.07139	0.84087
Skewness	-0.02578	-0.15668	-0.13620	-0.02399
Kurtosis	2.45949**	3.04241**	2.91879**	2.63599**
χ^2	94.16480**	212.63070**	227.97160**	
Dependence Residuals				
Autocorrelation:				
lag 1	-0.00285	0.03083	0.03312	0.03511
lag 2	-0.08951	-0.09478	-0.09416	-0.07709
lag 3	-0.01511	-0.02539	-0.02423	-0.01647
lag 4	-0.02939	-0.03452	-0.03284	-0.02593
lag 5	0.04778	0.04497	0.04574	0.03835
lag 6	0.03621	0.04000	0.04056	0.02609
Ljung-Box:				
Q(6)	4.54	5.50	5.49	3.66
Q(12)	8.19	9.14	9.15	7.18
Q(24)	24.02	25.46	25.79	23.25
Squared Residuals				
Autocorrelation:				
lag 1	0.00690	0.01991	0.01699	-0.00159
lag 2	-0.02498	-0.00309	-0.00568	-0.04162
lag 3	-0.00119	-0.01250	-0.01002	-0.03549
lag 4	-0.07558	-0.06789	-0.06936	-0.07943
lag 5	0.03215	0.02071	0.02534	-0.00427
lag 6	0.02414	0.03477	0.03660	0.00604
Ljung-Box:				
Q(6)	2.87	2.44	2.59	3.35
Q(12)	8.59	7.38	7.85	6.00
Q(24)	15.60	12.43	13.22	12.95

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.4
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NSYE Stock 4

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.05045	0.04231	-0.04403	-0.05412
Variance	1.01059	1.14675	1.44548	1.02447
Skewness	2.23183**	2.25276**	2.34523**	2.30399**
Kurtosis	15.24740**	15.11240**	15.94530**	15.86990**
χ^2	471.86360**	499.13640**	514.19320**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.09529	0.08807	0.09246	0.09976
lag 2	0.04534	0.03689	0.04307	0.04569
lag 3	-0.00043	-0.00682	-0.00794	-0.00352
lag 4	-0.05218	-0.04298	-0.04537	-0.05500
lag 5	-0.00196	0.00198	-0.00404	-0.01054
lag 6	0.00411	-0.00305	-0.00441	0.00178
Ljung-Box:				
Q(6)	4.95	3.93	4.48	5.40
Q(12)	10.78	9.48	10.21	11.41
Q(24)	21.72	19.26	19.62	21.89
Squared Residuals				
Autocorrelation:				
lag 1	-0.02167	-0.01794	-0.02238	-0.02547
lag 2	-0.00891	-0.00463	-0.00857	-0.01170
lag 3	-0.01574	-0.00323	-0.00746	-0.01948
lag 4	-0.02418	-0.01928	-0.02015	-0.02524
lag 5	0.03105	0.02771	0.03422	0.02861
lag 6	-0.02524	-0.02478	-0.02232	-0.02391
Ljung-Box:				
Q(6)	1.07	0.76	0.97	1.14
Q(12)	2.92	2.80	3.04	3.23
Q(24)	4.26	3.90	4.23	4.45

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.5
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NSYE Stock 5

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.03062	-0.02288	-0.02527	-0.03076
Variance	1.00625	0.92770	1.01002	1.01308
Skewness	0.19558	0.20049	0.19450	0.19583
Kurtosis	1.26839**	1.27949**	1.29203**	1.26945**
χ^2	82.23300**	71.86360**	51.26710**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.12440	0.12310	0.12398	0.12432
lag 2	-0.01148	-0.01149	-0.01126	-0.01147
lag 3	-0.01176	-0.01239	-0.01178	-0.01179
lag 4	-0.05887	-0.05988	-0.05975	-0.05895
lag 5	-0.02808	-0.02934	-0.03014	-0.02821
lag 6	-0.02414	-0.02436	-0.02430	-0.02416
Ljung-Box:				
Q(6)	7.32	7.29	7.37	7.32
Q(12)	10.32	10.29	10.30	10.32
Q(24)	22.27	22.21	22.08	22.27
Squared Residuals				
Autocorrelation:				
lag 1	0.03090	0.02239	0.02332	0.03023
lag 2	-0.02890	-0.03101	-0.03719	-0.02922
lag 3	0.01676	0.01595	0.00830	0.01650
lag 4	-0.01665	-0.01624	-0.01929	-0.01666
lag 5	0.03807	0.03765	0.03506	0.03799
lag 6	-0.03234	-0.03280	-0.03263	-0.03237
Ljung-Box:				
Q(6)	1.73	1.60	1.67	1.72
Q(12)	5.31	5.25	5.30	5.30
Q(24)	24.74	24.71	24.46	24.73

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.6
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NSYE Stock 6

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00216	0.03813	0.04445	-0.01211
Variance	1.04411	0.98496	1.02055	0.79661
Skewness	0.59927**	0.55122**	0.54091**	0.75259**
Kurtosis	2.22407**	2.18071**	2.13998**	3.01297**
χ^2	32.09090	44.59090*	20.8693	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00887	0.03947	0.04899	0.21724**
lag 2	-0.02664	-0.01858	-0.01529	0.03402
lag 3	0.09515	0.09645	0.09701	0.10500
lag 4	0.09211	0.09307	0.09423	0.11793
lag 5	0.02631	0.02878	0.02994	0.03479
lag 6	-0.01307	-0.00969	-0.01011	-0.04453
Ljung-Box:				
Q(6)	6.86	7.43	7.83	27.23**
Q(12)	8.47	9.16	9.55	29.62**
Q(24)	24.41	25.53	26.29	54.40**
Squared Residuals				
Autocorrelation:				
lag 1	-0.03649	-0.03649	-0.03835	0.03616
lag 2	-0.02573	-0.02986	-0.03382	0.06183
lag 3	0.07048	0.06244	0.06032	0.12201
lag 4	-0.01265	-0.00876	-0.00909	0.06590
lag 5	0.01620	0.00810	0.00776	0.07438
lag 6	-0.01667	-0.01574	-0.01640	0.03414
Ljung-Box:				
Q(6)	2.73	2.32	2.38	11.10
Q(12)	4.84	4.42	4.32	17.58
Q(24)	12.58	11.63	11.66	28.46

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.7
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 7

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00311	0.05025	0.07391	0.00324
Variance	0.99447	0.85092	1.04412	0.99448
Skewness	0.81510**	0.84021**	0.83536**	0.81510**
Kurtosis	3.01936**	3.27484**	3.28034**	3.01938**
χ^2	81.94890**	117.17610**	67.74430**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00897	0.03247	0.05083	0.00897
lag 2	-0.02586	-0.02418	-0.02113	-0.02586
lag 3	0.00384	0.00725	0.00734	0.00384
lag 4	0.00168	0.00367	0.00677	0.00168
lag 5	0.11469	0.11742	0.11987	0.11469
lag 6	0.14332	0.14065	0.14124	0.14332
Ljung-Box:				
Q(6)	12.39	12.68*	13.46*	12.39
Q(12)	26.79**	25.49*	25.86*	26.79**
Q(24)	36.85*	35.61	35.95	36.85*
Squared Residuals				
Autocorrelation:				
lag 1	0.01037	-0.02420	-0.01939	0.01037
lag 2	-0.05203	-0.05228	-0.05145	-0.05202
lag 3	-0.01409	-0.00754	-0.00780	-0.01408
lag 4	-0.06109	-0.06089	-0.05926	-0.06109
lag 5	0.07653	0.07439	0.07822	0.07654
lag 6	0.07475	0.07830	0.07897	0.07476
Ljung-Box:				
Q(6)	6.52	6.72	6.80	6.53
Q(12)	8.02	8.64	8.75	8.02
Q(24)	13.04	14.45	14.35	13.04

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.8
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 8

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.03668	0.11523*	0.09999	0.01334
Variance	0.98323	1.07825	1.14861	1.07237
Skewness	1.64908**	1.86522**	1.87820**	1.89795**
Kurtosis	7.30906**	8.98135**	9.23166**	9.35347**
χ^2	70.30110**	93.59660**	75.27270**	
Dependence Residuals				
Autocorrelation:				
lag 1	-0.01743	0.01745	0.06988	-0.00105
lag 2	0.05763	0.05985	0.06882	0.06096
lag 3	0.01015	0.00056	0.00318	-0.00530
lag 4	-0.02083	-0.02081	-0.01767	-0.01071
lag 5	0.01699	0.00764	0.00716	0.00861
lag 6	-0.02727	-0.03118	-0.02806	-0.04682
Ljung-Box:				
Q(6)	1.85	1.91	3.84	2.19
Q(12)	6.29	5.89	7.32	5.76
Q(24)	17.44	17.17	19.45	18.38
Squared Residuals				
Autocorrelation:				
lag 1	-0.02973	-0.02752	-0.02574	-0.02405
lag 2	0.01408	0.01716	0.01991	0.03649
lag 3	-0.02455	-0.02743	-0.02403	-0.01657
lag 4	0.00208	0.00620	0.00868	0.02750
lag 5	-0.01856	-0.02675	-0.02590	-0.01644
lag 6	-0.00315	-0.01099	-0.01048	0.00311
Ljung-Box:				
Q(6)	0.73	0.96	0.89	1.15
Q(12)	1.31	1.57	1.48	1.54
Q(24)	3.52	3.98	3.95	6.02

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.9
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 9

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02254	0.04597	-0.00553	0.02161
Variance	1.00352	0.98868	1.03596	1.02312
Skewness	0.26135*	0.24319*	0.34243**	0.26068*
Kurtosis	2.11367**	2.23012**	3.12158**	2.12006**
χ^2	286.0682**	305.6705**	183.7955**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.10975	0.10876	0.11714	0.10983
lag 2	-0.02262	-0.02097	-0.01351	-0.02241
lag 3	-0.03644	-0.03238	-0.01834	-0.03619
lag 4	-0.07992	-0.07591	-0.07007	-0.07976
lag 5	-0.03488	-0.03429	-0.03578	-0.03491
lag 6	0.01970	0.01935	0.01562	0.01961
Ljung-Box:				
Q(6)	7.82	7.37	7.38	7.81
Q(12)	11.03	10.62	10.73	11.02
Q(24)	25.95	24.64	22.58	25.89
Squared Residuals				
Autocorrelation:				
lag 1	0.01530	-0.00255	-0.03092	0.01353
lag 2	-0.02091	-0.03285	-0.06056	-0.02153
lag 3	-0.03884	-0.04805	-0.07184	-0.03938
lag 4	0.07372	0.06413	0.03356	0.07353
lag 5	0.05847	0.05906	0.05177	0.05868
lag 6	0.01754	0.01395	0.00047	0.01731
Ljung-Box:				
Q(6)	4.07	4.02	4.87	4.08
Q(12)	6.96	6.79	7.33	6.96
Q(24)	29.47	30.06	27.72	29.52

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.10
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 10

Statistics	(N)	(T)	(PE)	(MJ)
<u>Location and Shape: Residuals</u>				
Mean	0.02674	0.00209	-0.05287	0.02605
Variance	1.00558	0.93766	1.03371	1.09020
Skewness	0.14536	0.23694*	0.22661*	0.13857
Kurtosis	2.91572**	3.13413**	3.07097**	2.91438**
χ^2	228.96590**	315.04550**	235.92610**	
<u>Dependence Residuals</u>				
Autocorrelation:				
lag 1	0.10567	0.12079	0.11706	0.10371
lag 2	0.02616	0.03136	0.02875	0.02538
lag 3	0.06206	0.05153	0.05393	0.06338
lag 4	-0.06324	-0.06018	-0.06055	-0.06345
lag 5	0.03572	0.03380	0.03527	0.03607
lag 6	0.06501	0.06120	0.06283	0.06547
Ljung-Box:				
Q(6)	9.02	9.56	9.40	8.96
Q(12)	21.40*	22.28*	22.02*	21.29*
Q(24)	32.34	33.14	33.05	32.26
<u>Squared Residuals</u>				
Autocorrelation:				
lag 1	0.00611	0.04638	0.02641	0.00031
lag 2	0.04009	0.05500	0.05681	0.03712
lag 3	-0.00948	-0.00549	-0.00851	-0.01024
lag 4	-0.06202	-0.06062	-0.05946	-0.06212
lag 5	-0.04436	-0.03456	-0.03178	-0.04514
lag 6	0.01438	0.00145	-0.00124	0.01542
Ljung-Box:				
Q(6)	2.78	3.61	3.06	2.73
Q(12)	6.75	7.21	6.39	6.75
Q(24)	14.74	15.54	14.44	14.72

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.11
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 11

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01401	0.06473	0.08242	0.01587
Variance	1.00562	1.03773	0.99781	1.06166
Skewness	0.32098**	0.27773*	0.28477*	0.31826**
Kurtosis	0.78155**	0.94230**	0.87463**	0.78892**
χ^2	168.31250**	160.35800**	126.06250**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.12019	0.12092	0.11910	0.12037
lag 2	0.04934	0.06063	0.05483	0.05050
lag 3	0.06670	0.06871	0.06679	0.06717
lag 4	-0.03309	-0.02343	-0.02732	-0.03255
lag 5	0.07279	0.07159	0.07213	0.07264
lag 6	0.02762	0.01830	0.02113	0.02688
Ljung-Box:				
Q(6)	10.18	10.37	10.02	10.23
Q(12)	17.24	17.36	17.05	17.28
Q(24)	27.92	28.87	28.35	28.00
Squared Residuals				
Autocorrelation:				
lag 1	-0.00989	-0.01468	-0.00654	-0.01195
lag 2	-0.00684	-0.03464	-0.02219	-0.01029
lag 3	-0.04188	-0.06481	-0.05703	-0.04365
lag 4	0.03109	0.00213	0.01010	0.02996
lag 5	0.03872	0.02545	0.03222	0.03785
lag 6	-0.04659	-0.06055	-0.05273	-0.04752
Ljung-Box:				
Q(6)	2.35	3.57	2.77	2.42
Q(12)	5.07	5.63	5.11	5.10
Q(24)	24.93	25.11	24.65	25.06

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.12
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 12

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02910	0.07357	0.11416*	0.02875
Variance	1.00493	0.99064	1.01247	1.00271
Skewness	0.63272**	0.66085**	0.63273**	0.63280**
Kurtosis	1.88506**	2.07337**	1.97049**	1.88492**
χ^2	52.97160**	60.07390**	32.65910	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01289	0.04558	0.05978	0.01288
lag 2	-0.04899	-0.04332	-0.04252	-0.04898
lag 3	0.01853	0.01346	0.01546	0.01853
lag 4	0.00394	-0.00045	-0.00010	0.00396
lag 5	-0.06616	-0.05642	-0.05830	-0.06620
lag 6	0.01888	0.01410	0.01508	0.01887
Ljung-Box:				
Q(6)	2.74	2.69	3.30	2.74
Q(12)	6.64	6.89	7.36	6.64
Q(24)	19.65	20.02	20.47	19.66
Squared Residuals				
Autocorrelation:				
lag 1	-0.01949	-0.03393	-0.03620	-0.01937
lag 2	-0.00775	-0.03357	-0.02119	-0.00770
lag 3	-0.01519	-0.03939	-0.03546	-0.01511
lag 4	-0.04766	-0.04981	-0.04478	-0.04766
lag 5	-0.03292	-0.04508	-0.04096	-0.03288
lag 6	0.06447	0.06115	0.06293	0.06447
Ljung-Box:				
Q(6)	2.94	4.33	3.82	2.93
Q(12)	10.05	11.65	11.29	10.04
Q(24)	20.41	22.63	22.18	20.41

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.13
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 13

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.00145	0.06133	0.04136	-0.00219
Variance	0.99739	1.04795	1.00766	1.02253
Skewness	0.86294**	0.88449**	0.87066**	0.85864**
Kurtosis	2.75287**	3.08597**	2.86161**	2.74111**
χ^2	35.21590	56.38070**	38.76710*	
Dependence Residuals				
Autocorrelation:				
lag 1	0.02219	0.06199	0.05567	0.02205
lag 2	-0.01385	-0.01432	-0.01260	-0.01340
lag 3	-0.05118	-0.05420	-0.05422	-0.05113
lag 4	-0.01804	-0.01947	-0.01994	-0.01738
lag 5	0.04984	0.05487	0.04983	0.04947
lag 6	0.04585	0.04062	0.04774	0.04544
Ljung-Box:				
Q(6)	2.94	4.30	4.06	2.90
Q(12)	5.50	6.65	6.61	5.43
Q(24)	11.03	12.64	12.22	10.93
Squared Residuals				
Autocorrelation:				
lag 1	-0.01771	0.00199	-0.01120	-0.01942
lag 2	0.01348	0.01953	0.01189	0.01238
lag 3	-0.01429	0.00065	-0.01023	-0.01539
lag 4	-0.03297	-0.02775	-0.03448	-0.03388
lag 5	-0.00134	0.00102	0.00150	-0.00269
lag 6	0.01753	0.02530	0.02726	0.01656
Ljung-Box:				
Q(6)	0.75	0.64	0.83	0.79
Q(12)	2.56	2.56	2.70	2.62
Q(24)	5.38	4.80	5.64	5.40

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.14
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 14

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00325	0.06128	0.05955	0.00170
Variance	0.98878	0.94544	1.07902	0.14840
Skewness	0.84167**	0.91602**	0.84736**	0.83975**
Kurtosis	2.68539**	3.01114**	2.76264**	2.74862**
χ^2	31.38070	68.02840**	26.26710	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01702	0.01267	0.01636	0.01430
lag 2	-0.02015	-0.01579	-0.01900	-0.02112
lag 3	-0.04873	-0.04163	-0.04930	-0.04218
lag 4	0.10214	0.10362	0.10289	0.10686
lag 5	0.01039	0.01755	0.00902	0.01649
lag 6	-0.00606	-0.00452	-0.00801	-0.00562
Ljung-Box:				
Q(6)	4.88	4.73	4.93	5.06
Q(12)	16.67	16.75	16.80	17.48
Q(24)	38.61*	39.50*	38.51*	39.42*
Squared Residuals				
Autocorrelation:				
lag 1	-0.02007	-0.03089	-0.01067	-0.00401
lag 2	-0.01392	0.02462	-0.00145	0.01404
lag 3	-0.04545	-0.02926	-0.03994	-0.03074
lag 4	0.02746	0.04174	0.03771	0.04717
lag 5	0.13064	0.14254	0.13863	0.13267
lag 6	-0.08696	-0.07426	-0.08252	-0.07920
Ljung-Box:				
Q(6)	10.07	10.77	10.47	9.79
Q(12)	12.11	13.95	12.88	13.10
Q(24)	19.49	21.78	20.30	20.75

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.15
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 15

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.01526	0.05274	0.06449	0.01002
Variance	1.00291	0.98997	1.01434	0.11047
Skewness	0.42088**	0.42210**	0.41441**	0.40518**
Kurtosis	1.86321**	2.11166**	2.02362**	2.11663**
χ^2	43.45460*	47.43180*	44.02270*	
Dependence Residuals				
Autocorrelation:				
lag 1	-0.00901	0.04849	0.03248	0.01306
lag 2	-0.07600	-0.06257	-0.06572	-0.07181
lag 3	0.05160	0.05246	0.05160	0.05091
lag 4	0.05750	0.06017	0.05874	0.07106
lag 5	-0.03817	-0.02812	-0.02991	-0.04100
lag 6	0.07446	0.07498	0.07489	0.06841
Ljung-Box:				
Q(6)	6.74	6.82	6.44	6.92
Q(12)	10.61	11.25	10.65	11.44
Q(24)	22.00	22.64	21.91	24.26
Squared Residuals				
Autocorrelation:				
lag 1	-0.01828	-0.00584	-0.01170	0.08395
lag 2	0.03406	0.02716	0.02686	0.05670
lag 3	0.00821	0.01041	0.01137	0.00677
lag 4	-0.05249	-0.04267	-0.04359	-0.04426
lag 5	-0.07219	-0.07180	-0.07352	-0.05622
lag 6	-0.04283	-0.04263	-0.04256	-0.04842
Ljung-Box:				
Q(6)	4.07	3.47	3.63	6.34
Q(12)	9.99	9.52	9.45	11.47
Q(24)	35.94	37.11*	36.83*	34.96

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.16
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 16

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02940	0.07606	0.06670	0.03062
Variance	1.00727	1.08328	1.44874	1.05836
Skewness	1.58066**	2.12137**	2.33298**	1.55544**
Kurtosis	8.99399**	14.48460**	16.41960**	8.76525**
χ^2	355.67050**	449.70460**	307.94320**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.11280	0.11785	0.10459	0.11166
lag 2	0.00360	0.01464	0.01125	0.00271
lag 3	0.02767	0.03858	0.03176	0.02661
lag 4	-0.00497	-0.00002	-0.00281	-0.00553
lag 5	-0.06163	-0.06133	-0.07007	-0.06244
lag 6	0.00452	0.00450	-0.00235	0.00377
Ljung-Box:				
Q(6)	6.19	6.92	6.07	6.12
Q(12)	15.25	14.67	11.53	15.15
Q(24)	24.48	23.62	20.21	24.46
Squared Residuals				
Autocorrelation:				
lag 1	-0.00641	-0.00981	-0.02281	-0.00727
lag 2	-0.01535	-0.00381	-0.01192	-0.01643
lag 3	-0.02000	-0.00509	-0.01110	-0.02132
lag 4	-0.04434	-0.02912	-0.02918	-0.04536
lag 5	-0.04128	-0.02619	-0.02296	-0.04218
lag 6	-0.03961	-0.02593	-0.02581	-0.04048
Ljung-Box:				
Q(6)	2.13	0.84	1.02	2.25
Q(12)	9.76	10.97	7.15	9.46
Q(24)	12.69	11.97	8.02	12.54

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.17
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 17

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.03657	0.02330	0.01515	-0.03748
Variance	1.00435	0.95354	1.05326	1.05109
Skewness	0.24620*	0.53440**	0.53718**	0.23128*
Kurtosis	1.74887**	2.37163**	2.35861**	1.73067**
χ^2	48.28410**	54.25000**	30.38640	
Dependence Residuals				
Autocorrelation:				
lag 1	0.10690	0.08778	0.08821	0.10723
lag 2	0.02553	0.02949	0.03012	0.02502
lag 3	-0.02216	-0.01938	-0.01915	-0.02215
lag 4	0.02747	0.02011	0.02045	0.02788
lag 5	-0.03470	-0.05064	-0.05056	-0.03459
lag 6	0.01501	0.01661	0.01689	0.01407
Ljung-Box:				
Q(6)	5.26	4.36	4.40	5.27
Q(12)	8.42	9.46	9.51	8.34
Q(24)	20.64	21.07	21.09	20.63
Squared Residuals				
Autocorrelation:				
lag 1	0.00351	-0.03005	-0.02966	0.00052
lag 2	-0.01755	0.00475	0.00710	-0.02189
lag 3	-0.03575	-0.00892	-0.00851	-0.03661
lag 4	0.00516	0.04559	0.04626	0.00221
lag 5	-0.08819	-0.04503	-0.04450	-0.08994
lag 6	-0.05847	-0.02711	-0.02689	-0.06042
Ljung-Box:				
Q(6)	4.62	2.10	2.10	4.88
Q(12)	19.58	16.84	16.97	19.45
Q(24)	33.51	25.89	25.91	33.56

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.18
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 18

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00508	0.02891	0.05778	0.00565
Variance	0.99660	0.97958	1.02398	0.98562
Skewness	0.27554*	0.11015	0.20053	0.27334*
Kurtosis	2.30974**	3.10471**	2.63704**	2.32036**
χ^2	32.65910	55.38640**	15.75570	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01562	0.03646	0.03628	0.01572
lag 2	-0.11810	-0.12925	-0.12111	-0.11854
lag 3	0.03476	0.03319	0.03232	0.03480
lag 4	0.06126	0.06626	0.06342	0.06150
lag 5	-0.01709	-0.01139	-0.01467	-0.01681
lag 6	-0.05832	-0.05167	-0.05693	-0.05805
Ljung-Box:				
Q(6)	8.16	9.39	8.75	8.19
Q(12)	19.99	20.16	20.00	20.04
Q(24)	29.27	29.26	29.28	29.32
Squared Residuals				
Autocorrelation:				
lag 1	0.02907	0.08444	0.04853	0.03042
lag 2	0.01793	0.07849	0.04519	0.01952
lag 3	-0.03832	-0.01999	-0.03350	-0.03777
lag 4	-0.01383	-0.01418	-0.00998	-0.01333
lag 5	0.01500	0.00206	0.01059	0.01537
lag 6	0.00184	-0.01659	-0.01032	0.00221
Ljung-Box:				
Q(6)	1.09	5.04	2.08	1.12
Q(12)	9.07	10.08	8.19	9.07
Q(24)	11.91	12.31	10.88	11.91

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.19
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 19

Statistics	(N)	(T)	(PE)	(MJ)
<u>Location and Shape: Residuals</u>				
Mean	-0.02544	0.07065	0.07617	-0.02603
Variance	1.00058	0.84568	1.01408	0.99556
Skewness	0.48082**	0.59757**	0.56865**	0.48168**
Kurtosis	1.92144**	2.47503**	2.34573**	1.92224**
χ^2	32.65910	55.38640**	15.75570	
<u>Dependence Residuals</u>				
Autocorrelation:				
lag 1	0.07195	0.06464	0.06546	0.07196
lag 2	-0.00912	-0.02249	-0.02156	-0.00916
lag 3	-0.04221	-0.03316	-0.03554	-0.04212
lag 4	0.01300	0.02191	0.01976	0.01308
lag 5	-0.04640	-0.05546	-0.05458	-0.04651
lag 6	-0.00064	0.00253	0.00257	-0.00058
Ljung-Box:				
Q(6)	3.35	3.34	3.36	3.35
Q(12)	7.90	7.07	7.26	7.90
Q(24)	13.32	13.34	13.40	13.31
<u>Squared Residuals</u>				
Autocorrelation:				
lag 1	0.03203	-0.00167	0.01063	0.03250
lag 2	0.00768	-0.01913	-0.01478	0.00790
lag 3	-0.01168	-0.01151	-0.01336	-0.01153
lag 4	-0.05179	-0.01506	-0.02026	-0.05156
lag 5	-0.05688	-0.03873	-0.04485	-0.05668
lag 6	-0.04561	-0.02362	-0.02990	-0.04549
Ljung-Box:				
Q(6)	3.31	1.00	1.38	3.31
Q(12)	10.82	9.02	9.61	10.83
Q(24)	19.79	17.82	18.13	19.82

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.20
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 20

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.03757	-0.01932	-0.02074	-0.03810
Variance	1.00811	1.06364	1.0176	1.04283
Skewness	-0.08871	-0.06141	-0.07886	-0.08521
Kurtosis	1.68686**	1.81349**	1.74367**	1.69796**
χ^2	48.56820**	51.40910**	58.65340**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.08966	0.08820	0.08978	0.08936
lag 2	-0.06267	-0.05748	-0.06013	-0.06215
lag 3	0.04794	0.04361	0.04665	0.04731
lag 4	-0.04597	-0.04768	-0.04786	-0.04605
lag 5	0.00666	0.00505	0.00528	0.00655
lag 6	0.13087	0.13062	0.13008	0.13096
Ljung-Box:				
Q(6)	12.05	11.62	11.88	11.99
Q(12)	13.41	13.04	13.31	13.36
Q(24)	25.49	24.41	25.06	25.37
Squared Residuals				
Autocorrelation:				
lag 1	0.08428	0.05588	0.08228	0.07913
lag 2	-0.01484	-0.02483	-0.02276	-0.01539
lag 3	-0.00379	-0.01568	-0.01089	-0.00498
lag 4	-0.01808	-0.03087	-0.02896	-0.01876
lag 5	-0.06524	-0.07210	-0.06978	-0.06595
lag 6	0.05305	0.05182	0.05258	0.05281
Ljung-Box:				
Q(6)	5.28	4.60	5.69	5.02
Q(12)	6.32	5.51	6.60	6.07
Q(24)	10.76	9.76	10.77	10.52

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.21
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 21

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02932	0.01219	0.01299	0.02931
Variance	1.03290	0.87706	1.02541	1.01713
Skewness	0.05656	0.18067	0.06581	0.06178
Kurtosis	1.55996**	1.64831**	1.57509**	1.56705**
χ^2	48.28410**	76.12500**	47.28980**	
Dependence Residuals				
Autocorrelation:				
lag 1	-0.00838	-0.00889	-0.00820	-0.00843
lag 2	0.00380	-0.01720	0.00290	0.00343
lag 3	-0.08279	-0.06543	-0.08150	-0.08221
lag 4	-0.10092	-0.10870	-0.10084	-0.10128
lag 5	0.06483	0.07471	0.06544	0.06503
lag 6	0.07768	0.07621	0.07815	0.07793
Ljung-Box:				
Q(6)	9.83	10.02	9.80	9.85
Q(12)	21.66*	25.22*	21.79*	21.75*
Q(24)	28.45	32.64	28.61	28.55
Squared Residuals				
Autocorrelation:				
lag 1	-0.07377	-0.05237	-0.07452	-0.07336
lag 2	-0.01403	0.03078	-0.01275	-0.01341
lag 3	0.01614	0.03663	0.01604	0.01627
lag 4	-0.03133	-0.00789	-0.03083	-0.03077
lag 5	-0.02056	0.00771	-0.02000	-0.02021
lag 6	0.08332	0.13252	0.08462	0.08549
Ljung-Box:				
Q(6)	5.11	8.18	5.20	5.20
Q(12)	9.74	14.12	9.66	9.81
Q(24)	14.59	22.79	14.61	14.67

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.22
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 22

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.02192	0.02660	0.00729	-0.02131
Variance	1.04616	0.91152	1.03052	1.15209
Skewness	0.37766**	0.36011**	0.36583**	0.39330**
Kurtosis	1.94675	1.96310**	1.89764**	1.96608**
χ^2	23.85230	46.86360*	23.1421	
Dependence Residuals				
Autocorrelation:				
lag 1	0.08043	0.07904	0.08000	0.07937
lag 2	-0.00647	-0.00608	-0.00654	-0.00587
lag 3	-0.10579	-0.10493	-0.10677	-0.10419
lag 4	-0.07060	-0.07068	-0.07099	-0.07258
lag 5	-0.00988	-0.01100	-0.01034	-0.00989
lag 6	0.03999	0.03952	0.03987	0.04011
Ljung-Box:				
Q(6)	8.73	8.58	8.80	8.65
Q(12)	15.56	15.55	15.67	15.43
Q(24)	25.49	25.46	25.49	25.42
Squared Residuals				
Autocorrelation:				
lag 1	0.00220	-0.00459	0.00456	-0.00127
lag 2	-0.02249	-0.02822	-0.02168	-0.02734
lag 3	-0.02532	-0.03109	-0.02695	-0.02917
lag 4	-0.05882	-0.06029	-0.06003	-0.05802
lag 5	0.01023	0.01162	0.01328	0.00459
lag 6	0.06801	0.06003	0.06414	0.06405
Ljung-Box:				
Q(6)	3.36	3.29	3.28	3.27
Q(12)	5.92	6.03	5.90	5.96
Q(24)	10.74	10.66	10.73	10.88

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.23
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=353)
NYSE Stock 23

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00654	0.04070	0.03139	0.00412
Variance	1.00171	1.03467	1.01656	0.02668
Skewness	0.38172**	0.23539*	0.32244**	0.43737**
Kurtosis	3.26047**	5.60178**	4.69512**	7.85832**
χ^2	30.10230	34.78980*	21.86360	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01656	0.06268	0.06602	0.11943
lag 2	-0.10421	-0.10773	-0.11847	-0.13546
lag 3	0.09302	0.08042	0.06915	0.04470
lag 4	-0.01028	-0.01585	-0.02282	0.00264
lag 5	-0.04668	-0.03029	-0.01298	-0.04179
lag 6	0.05425	0.04723	0.04135	0.03316
Ljung-Box:				
Q(6)	8.93	9.07	9.11	13.34
Q(12)	11.20	12.41	12.98	17.09
Q(24)	19.54	20.41	21.35	28.37
Squared Residuals				
Autocorrelation:				
lag 1	0.00765	0.07306	0.11568	0.27219
lag 2	-0.05838	-0.02162	-0.01750	0.14558
lag 3	0.02934	0.01545	0.01338	0.10563
lag 4	-0.03951	-0.03493	-0.03879	0.00658
lag 5	0.00541	-0.01702	-0.02550	-0.00259
lag 6	-0.00581	-0.02340	-0.03761	0.01289
Ljung-Box:				
Q(6)	2.12	2.88	6.21	37.91**
Q(12)	12.54	7.98	8.89	45.46**
Q(24)	21.83	15.06	15.28	52.01**

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.24
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Stock 24

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01346	0.02066	0.01318	-0.01493
Variance	1.01353	1.03435	1.01903	1.10126
Skewness	0.36112**	0.41017**	0.39205**	0.34422**
Kurtosis	1.05460**	1.20887**	1.14561**	1.02681**
χ^2	28.25570	26.26710	15.4716	
Dependence Residuals				
Autocorrelation:				
lag 1	0.00352	-0.01868	-0.01276	0.00304
lag 2	-0.00979	-0.02456	-0.01903	-0.00618
lag 3	0.11024	0.11859	0.11494	0.10712
lag 4	-0.02268	-0.02552	-0.02537	-0.02232
lag 5	0.01303	0.01446	0.01387	0.01284
lag 6	0.00300	0.00103	0.00183	0.00384
Ljung-Box:				
Q(6)	4.63	5.67	5.20	4.36
Q(12)	9.86	10.53	10.17	9.64
Q(24)	15.92	16.19	16.03	15.65
Squared Residuals				
Autocorrelation:				
lag 1	0.05662	0.07005	0.07190	0.04540
lag 2	-0.00309	0.00269	0.00310	-0.00928
lag 3	-0.08157	-0.07032	-0.07489	-0.08589
lag 4	-0.04608	-0.03406	-0.03984	-0.04896
lag 5	0.00704	0.02718	0.01664	0.00339
lag 6	0.04472	0.05196	0.05020	0.04405
Ljung-Box:				
Q(6)	5.02	5.16	5.42	4.96
Q(12)	5.40	6.20	6.00	5.39
Q(24)	16.20	16.35	15.85	16.29

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.25
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Portfolio P1

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01368	0.03018	0.02420	-0.00416
Variance	1.00193	1.04291	1.01446	0.32151
Skewness	0.45045	0.39247	0.41959	0.23640
Kurtosis	1.18412	1.44809	1.29380	1.66388**
χ^2	45.15900**	53.68200**	46.72200**	
Dependence Residuals				
Autocorrelation:				
lag 1	0.05186	0.07035	0.0594	0.31861**
lag 2	-0.01172	-0.00943	-0.01161	0.07057
lag 3	0.00796	0.01054	0.00862	0.03377
lag 4	-0.00423	-0.00490	-0.00462	0.01556
lag 5	0.05019	0.04713	0.04874	0.04783
lag 6	0.01289	0.01579	0.01459	0.04392
Ljung-Box:				
Q(6)	2.00	2.72	2.26	39.82**
Q(12)	3.30	3.99	3.55	40.33**
Q(24)	13.50	13.99	13.64	50.80**
Squared Residuals				
Autocorrelation:				
lag 1	-0.01712	0.01832	-0.00241	0.12612
lag 2	0.05355	0.06541	0.05790	0.08694
lag 3	-0.01218	-0.01790	-0.01424	0.01722
lag 4	-0.02076	-0.03013	-0.02316	-0.01604
lag 5	-0.06358	-0.06669	-0.06354	-0.02365
lag 6	0.02862	0.01497	0.02204	0.08192
Ljung-Box:				
Q(6)	3.08	3.76	3.08	11.15
Q(12)	6.64	6.30	6.15	12.08
Q(24)	16.59	14.82	15.38	21.37

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.26
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Portfolio P2

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.02916	0.04872	0.06053	-0.05134
Variance	0.95157	1.03663	1.03118	2.62152
Skewness	0.98861	1.05411	0.99583	1.53204**
Kurtosis	3.92852	4.37668	3.98579	8.66899**
χ^2	34.22200	49.56300**	29.25000	
Dependence Residuals				
Autocorrelation:				
lag 1	0.02304	0.02580	0.02596	0.16139**
lag 2	-0.08873	-0.07790	-0.08701	-0.02122
lag 3	-0.00656	-0.00909	-0.00777	0.00279
lag 4	0.05982	0.06204	0.05881	0.06951
lag 5	-0.04140	-0.04122	-0.04017	-0.02573
lag 6	0.03196	0.03256	0.03180	0.02889
Ljung-Box:				
Q(6)	5.27	4.80	5.14	11.68
Q(12)	11.54	11.30	11.47	21.54*
Q(24)	21.67	21.13	21.41	27.79
Squared Residuals				
Autocorrelation:				
lag 1	-0.01926	-0.02641	-0.02178	-0.04487
lag 2	-0.02901	-0.04472	-0.03166	-0.03774
lag 3	0.04753	0.02893	0.04841	-0.00503
lag 4	0.04114	0.03265	0.03765	0.01185
lag 5	0.00369	-0.00522	0.00098	-0.02659
lag 6	-0.04008	-0.03989	-0.03917	-0.03754
Ljung-Box:				
Q(6)	2.43	2.22	2.42	2.04
Q(12)	20.94	21.34	21.29*	24.38*
Q(24)	29.85	30.22	29.96	31.80

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.27
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Portfolio P3

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	-0.01171	0.01903	0.02212	-0.04525
Variance	0.99859	1.03053	1.05067	2.72295
Skewness	-0.307502	-0.34454	-0.344573	0.32194**
Kurtosis	5.39222	6.15709	6.05629	3.82540**
χ^2	38.34100*	57.23300**	21.01100	
Dependence Residuals				
Autocorrelation:				
lag 1	0.01554	0.04971	0.04865	0.08862
lag 2	-0.10077	-0.10380	-0.10198	-0.08504
lag 3	-0.03925	-0.03951	-0.04039	-0.03954
lag 4	0.01109	0.00692	0.00771	0.01442
lag 5	-0.00480	-0.00625	-0.00543	-0.03848
lag 6	0.06772	0.07342	0.07138	0.06277
Ljung-Box:				
Q(6)	5.96	7.24	6.99	7.95
Q(12)	9.73	11.17	10.87	11.91
Q(24)	15.57	17.33	16.92	15.47
Squared Residuals				
Autocorrelation:				
lag 1	-0.01661	-0.01022	-0.01152	-0.08402
lag 2	0.03657	0.05423	0.04777	-0.02476
lag 3	0.00286	0.01214	0.00945	0.01332
lag 4	-0.05448	-0.04648	-0.04837	-0.04978
lag 5	-0.05726	-0.04932	-0.05081	0.00141
lag 6	0.00450	0.02155	0.01655	0.07736
Ljung-Box:				
Q(6)	2.82	2.95	2.75	5.83
Q(12)	4.32	5.19	4.80	16.72
Q(24)	8.61	9.45	9.10	24.48

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

Table C.5.B.28
Empirical Characteristics of Standardized Residuals
(Weekly Returns from 1982-88; n=352)
NYSE Portfolio ALL

Statistics	(N)	(T)	(PE)	(MJ)
Location and Shape: Residuals				
Mean	0.00486	0.01819	0.03552	0.05175
Variance	1.00166	0.96812	1.02902	1.13058
Skewness	0.62035	0.50108	0.55303	0.68102**
Kurtosis	3.57702	4.08838	3.96848	4.24098**
χ^2	36.77800	59.08000**	25.41500	
Dependence Residuals				
Autocorrelation:				
lag 1	0.04515	0.06281	0.06900	0.25905*
lag 2	-0.07297	-0.07314	-0.06536	0.02363
lag 3	0.00420	0.00463	0.00439	0.01434
lag 4	-0.00505	-0.00316	-0.00242	0.01690
lag 5	-0.00185	0.00389	0.00340	0.03153
lag 6	0.05226	0.05829	0.05684	0.05835
Ljung-Box:				
Q(6)	3.62	4.55	4.39	25.78**
Q(12)	8.25	8.92	8.82	31.00
Q(24)	15.88	16.76	16.20	34.34
Squared Residuals				
Autocorrelation:				
lag 1	-0.01576	0.01781	0.00625	-0.01678
lag 2	0.00591	0.02468	0.00777	-0.04007
lag 3	0.04173	0.02140	0.02182	0.02102
lag 4	-0.05703	-0.05781	-0.05768	-0.04609
lag 5	-0.01921	-0.02764	-0.02633	-0.02644
lag 6	-0.02755	-0.02680	-0.02754	-0.02381
Ljung-Box:				
Q(6)	2.29	2.22	1.92	2.05
Q(12)	7.63	7.02	6.99	5.49
Q(24)	14.40	12.49	12.61	9.03

(*) and (**) indicate significance at least at the 5- and 1-percent level, respectively, for the mean (=0), skewness (=0), kurtosis (=0), equiprobable χ^2, structure (=0) and the Q-statistics for various lags. For the autocorrelation coefficients for various lags, (**) indicates that an estimated autocorrelation coefficient is at least three times its standard error. The degrees of freedom for the Q-statistics equal the number of lags minus the number of parameters estimated in the model.

VITA

SALIL K. SARKAR

Department of Finance
College of Business Administration
Louisiana State University
Baton Rouge, LA 70803
(504) 388-6291

P. O. Box 16200
Baton Rouge
LA 70893
(504) 766-7686

AREAS OF INTEREST

Teaching: Business Finance, Investments
Research: Investments, Market Efficiency, Corporate Finance, and Dividend Policy

POSITION DESIRED

Academic: Assistant Professor position at a major or regional university; 50% research and 50% teaching; graduate/undergraduate program.

EDUCATION

Louisiana State University	Finance	1987-	Ph.D
Northeast Louisiana Univ.	Finance	1985-87	MBA
Indian Institute of Tech.	E.E.	1972-77	BS

HONORS

Beta Gamma Sigma (National Honorary Society for Business Graduates)
President's Merit Scholarship (Indian Institute of Technology)
DuPont Summer Fellowship

DISSERTATION

Topic: "Modeling Nonlinear Dynamics in NASDAQ Stock Returns"

EXPERIENCE

Louisiana State University Tch. Assistant 1989-
Teaching Business Finance for several semesters.

Louisiana State University Res. Assistant 1987-

Northeast Louisiana Univ. Res. Assistant 1985-87

Larsen & Toubro Inc. Section Head 1977-85
Responsible for project analysis, design, and commissioning of custom built switchgear panels and control systems.

PUBLICATIONS

"Managements' View on Share Repurchase and Tender Offer Premiums" with James Wansley and William Lane, *Financial Management*, Autumn 1989, pp. 97-110.

PRESENTATIONS AT PROFESSIONAL MEETINGS

"Managements' View on Share Repurchase" with William Lane, presented at the 1988 Annual Meeting of Southern Finance Association, San Antonio, November 1988.

OTHER SCHOLARLY ACTIVITIES

Proficient in FORTRAN, COBOL, BASIC, SAS, SPSS, MINITAB, MICROSTAT, LOTUS 1-2-3, PFS, HG, WORDPERFECT, FRAMEWORK, and FRED. Extensive hands on experience for engineering and business applications on IBM mainframes, VAX/VMS systems, and PCs.

PROFESSIONAL MEETINGS

FMA, ASSA

REFERENCES

Dr. G. Geoffrey Booth
Union National Life Insurance Company
Endowed Professor and Department Chairman
Department of Finance
Louisiana State University
Baton Rouge, LA 70803
(504) 388-6291

Dr. John L. Glascock, Director
Real Estate Research Institute
Department of Finance
Louisiana State University
Baton Rouge, LA 70803
(504) 388-6256

Dr. William Lane
Associate Professor
Department of Finance
Louisiana State University
Baton Rouge, LA 70803
(504) 388-6367

Dr. Gary Sanger
Associate Professor
Department of Finance
Louisiana State University
Baton Rouge, LA 70803
(504) 388-6291

DOCTORAL EXAMINATION AND DISSERTATION REPORT

Candidate: Salil Kumar Sarkar

Major Field: Business Administration (Finance)

Title of Dissertation: Modeling Nonlinear Dynamics in NASDAQ Stock Returns

Approved:

Geoffrey Booth
Major Professor and Chairman

[illegible]
Dean of the Graduate School

EXAMINING COMMITTEE:

Tae Hy Lee

[illegible]

C. Mustafa

Gary Sanger

Joe F. Hair Jr.

Date of Examination:

July 12, 1991