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# The Time Series Behavior of Intradaily Stock Prices.

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# THE TIME-SERIES BEHAVIOR OF INTRADAILY STOCK PRICES

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## ABSTRACT

This dissertation investigates the time-series properties of intradaily stock prices. It provides a model of the return generating process that is capable of incorporating not only such institutional constraints as the specialist's bid-ask spread, but also the presence of dependence in the conditional variance. It extends the literature by introducing a conditional error distribution, the power-exponential, that adequately accounts for not only leptokurtosis but also peakedness in the empirical distribution. Evidence is presented that suggests intradaily returns are best modelled as a mixture of distributions. Furthermore, it documents the inability of information proxies, such as volume or the number of trades, to account for the presence of autoregressive conditional heteroscedasticity in the data. And lastly, it examines the robustness of variance ratio statistics to test the null hypothesis of a random walk in the presence of higher order dependence.

## INTRODUCTION

The statistical properties of speculative price changes remain a central focus of financial research. This stems from the historical development of the major theories for investment decisions and capital asset pricing. These include the mean-variance analysis and portfolio theory of Markowitz (1959), the Capital Asset Pricing Model of Sharpe (1964), Litner (1965), and Mossin (1966), the Arbitrage Pricing Model of Ross (1976), and the Option Pricing Model of Black and Scholes (1973).

The assumptions about the distributional properties of the price series are essential to any of the above theories. The two most prevalent models are the martingale and the random walk. The martingale is the less restrictive of the two, requiring only that the conditional expectation of next period's price (based on the current information set) is this period's price. The random walk model, on the other hand, requires that the probability distribution of price changes is independent of current and past prices. The greater use of the random walk model by previous authors created considerable problems for the efficient markets literature. These problems have only recently been enunciated by LeRoy (1989). They arose, in part, from the recognition of the role of higher moments, particularly the second, in portfolio theory. The price series was conceptualized as the outcome of repeated drawings from some particular probability distribution. Eventually, this led to the empirical assumption of independent and identically distributed random variables.

A growing body of literature, as evidenced by the work of Akgiray (1989), Bollerslev (1987), and Hsieh (1989a), has begun to question the degree of independence found in the observed series of speculative price changes. Traditionally the focus has been on the independence of the first moment, or mean, of the distribution. Emphasis is now shifting to the findings of dependence in the second moment, or variance. This leads back to the question of whether the martingale provides a better description of the data than the random walk, since the latter requires the assumption of independence. Akgiray (1989) and Bollerslev (1987), among others, have suggested that the independence assumption may be erroneous. Their focus has primarily been on the changing variance, a point well documented by previous authors,[1] and the ability to model the return generating process as a nonlinear stationary time series. Their insight comes from investigating the role of the conditional variance in modelling the distributional properties of the return series. However, they use daily and longer intervals with the returns being based on the end of day price.

Amihud and Mendelson (1987) and Harris (1989), however, argue that the beginning and end of day trading mechanism is very different from that of the rest of the day. Hence, the end of day price may not be a true representation of the trading process. Their evidence suggests that

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[1] In fact, the more recent work deals with conditional variances while earlier work by Press (1967) and Clark (1973) dealt with the nonstationarity of the unconditional variance. A related issue is the relationship between the unconditional variances for different time intervals dealt with by Young (1971), Schwartz and Whitcomb (1977), and Perry (1982). Lo and MacKinlay (1988, 1989) generalize this latter concept to include the heteroskedasticity in the conditional variances, thereby tying together the two lines of inquiry.

those two periods of the day are more volatile than other times of the day. On a similar note, French and Roll (1986) find a higher volatility in asset prices during exchange hours as compared to non-exchange hours. They offer both mispricing (noise) and the incorporation of private information as possible explanations. Grossman (1976, 1978) and Grossman and Stiglitz (1976, 1980) provide a rational expectations framework for the incorporation of private information in the price. They focus on the cost of being informed versus remaining uninformed. For competitive equilibrium to exist, the information possessed by the informed trader must be transmitted through the price with noise. Hence the possibility exists that increased volatility arises from trading based on the inferences derived from particular transactions. In fact, French and Roll suggest that trading itself may induce volatility.

Mandelbrot (1971) first raised this question while setting forth the conditions under which price could not be arbitraged efficiently. He argues that arbitraging activities may increase the variance of the return series as traders attempt to eliminate the observed dependencies in the mean. Given finite horizon anticipation, he notes that 'the only way in which arbitraging can decrease the correlation of $P_f(t+1) - P_f(t)$ is by making its high frequency effects strong',[2] where $P_f(t)$ is the price of the stock at time t. Therefore, the volatility observed in the returns of speculative assets may occur in part because of trading

[2] Mandelbrot (1971), p. 235.

itself. In fact, the volatility could increase with the improved anticipation of the market participants.[3]

In this dissertation, we investigate the time series properties of intraday returns based on ten and thirty minute time intervals. Our primary focus is on the best model capable of incorporating not only correlation in the mean or first order dependence, but also higher order dependence, especially second order or dependence in the variance. Dependence in the mean of intraday returns has generally been attributed to the specialist bid-ask spread and other market microstructure elements [e.g., Ho and Stoll (1983) and Hasbrouck and Ho (1987)]. Theoretical and empirical work has recently focussed on the autocorrelation as a way to distinguish between different components of the spread [e.g., Roll (1984) and Stoll (1989)]. However, no empirical work has been done concerning higher order dependencies and there is no theory presently available for addressing such dependency. Nevertheless, capital asset pricing models have always incorporated the variance in the pricing equation, so there is a natural interest in establishing the effect that higher order dependency has on the return generating process.[4]

[3] Mandelbrot also discusses some of the implications for low frequency effects, which he had previously labeled the Joseph effect. This has relevance for the findings of Poterba and Summers (1988) on the mean reversion in stock prices and earlier works by Shiller (1981) and others questioning the high volatility of stock prices in relation to movements in the dividend and interest rate series. Mandelbrot's work also anticipates that of French, Schwert, and Stambaugh (1987) who document the positive relationship between expected risk premiums and volatility. None of these questions will be addressed here.

[4] Hsieh (1989a) notes that intertemporal asset pricing models have Euler equations involving conditional expectations of marginal utilites across both assets and time periods. Hence, conditional variances and covariances could show up in the demand equations.

In Chapter 2, we review the relevant literature on both the distributional as well as microstructural properties of the data. The literature is roughly divided on the basis of the estimation interval used, thereby contrasting the results of the intradaily work with the daily and higher intervals. In Chapter 3, we describe the data and provide the preliminary analysis of the ten and thirty minute return series. Evidence for the existence of higher order dependence in the two return series is presented and discussed. In Chapter 4, we examine those models that best fit the data based on the likelihood ratio and goodness of fit results. In Chapter 5, we consider the best models and test whether the use of volume[5] or the number of transactions can explain the observed presence of autoregressive conditional heteroskedastic or ARCH effects. We then turn to a discussion of the various forms of the variance ratio test in Chapter 6. We provide Monte Carlo results for the unconditional variance ratio test based on data generated from an ARCH process. We also examine the relevance of the variance ratio test to the ten and thirty minute return series from our sample of stocks. We then conclude the dissertation in Chapter 7 with a discussion of the implications of our results and areas of future research.

[5] Lamoureux and Lastrapes (1990) provide evidence that the GARCH effects observed in daily data can be explained by using volume as a proxy for the information arrival rate.

# CHAPTER 2

## LITERATURE REVIEW

The literature on speculative price changes can be classified into two divisions based on the time interval used in the analysis. The first area contains the work using daily or longer periods and is generally concerned with the statistical properties and models of speculative price changes. The other is the sub-daily investigations with an emphasis on the effects of transaction costs in explaining the return generating process. [6] The first division has the longer history beginning with the work of Bachelier (1900). The major theories of asset pricing have their foundations here, especially with respect to static equilibrium results and the frictionless trading assumptions. The second division has its roots in the work on market microstructure, beginning with Demsetz's (1968) discussion of the specialist as a supplier of immediacy and perhaps going back as far as Tobin's (1958) analysis of liquidity preference or even Keynes's (1936) attack on the classical theory of macroeconomic equilibrium.[7]

Both areas begin to overlap as the estimation interval approaches one day. Nevertheless, far less work has been devoted to understanding the properties of transaction data, in part because of the lack of a

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[6] Transaction costs include information collection as well as such institutional arrangements as the bid-ask spread, the 1/8 rule, and limit orders.

[7] Two issues of note here are the classical theory's reliance on market participants having perfect information and Keynes' explicit recognition of transaction costs in his theory of money demand.

theoretical model (particularly an equilibrium one) capable of incorporating transaction costs into the dynamics of the trading process. The following review first discusses the works based on daily or longer intervals and then moves to the sub-daily and market microstructure literature.

## A. DAILY, WEEKLY, AND MONTHLY INTERVALS

### Statistical Properties and Models of Price Changes

Beginning with the work of Bachelier (1900) and continuing with the papers of Mandelbrot (1963), Fama (1963, 1965a), Mandelbrot and Taylor (1967), Press (1967), and Clark (1973) a number of alternative theories exist for the statistical distribution of speculative price. Bachelier posits that successive price changes can be modeled as arithmetic Brownian Motion, which is the continuous time version of a normally distributed sequence of random variables. However, because of the economic restriction that stock prices cannot be less than zero this requires modification. Samuelson (1973) proposes geometric Brownian motion, or in discrete time, normally distributed log price relatives. The underlying assumption here is that the same probability distribution applies to every dollar's worth of a stock's value no matter what the price. Furthermore, this leads to the independence of the price ratios for any nonoverlapping interval, hence today's price change is independent of current and past prices.

To reiterate, the two basic assumptions of the random walk are: (1) that price changes are independent random variables and (2) that

they have the same distribution (i.e., identically distributed). The second assumption is where the early work of speculative price changes concentrates, beginning with Mandelbrot (1963). He argues that the empirical evidence on price changes provides enough departure from normality as to warrant the use of another, more general family of distributions called the Stable Paretian. It should be noted that one of the major concerns of the time was the notion of stability under addition, or the property that random variables will retain the same probability distribution after summing the observations. For distributions with finite variances, the normal, or Gaussian, is the only one for which this holds. The Stable Paretian family contains infinite variance members that also retain this property.

Fama (1963) further develops the work of Mandelbrot. Empirically, their rejection of the normal or Gaussian distribution is based on the observed thick-tails or leptokurtosis found in stock returns or log price relatives. The characteristic function of the Stable Paretian has four parameters, $\alpha$, $\beta$, $\delta$, and $\gamma$ which allows for a more general specification of the underlying distribution. The scale parameter is $\gamma$, $\delta$ is the location parameter, which corresponds to the mean when the characteristic exponent, or $\alpha$, is greater than one, and $\beta$ is a measure of skewness. When $\alpha$ equals two, the normal or Gaussian distribution is attained. However, Mandelbrot argues that the more relevant range for $\alpha$ is between one and two, thereby maintaining the existence of an empirical mean but not the variance. Fama (1965a) finds that for a sample of 30 stocks from the Dow-Jones Industrial Average the characteristic exponent of the daily return series is on average less

than two. Also of note is his finding concerning the general shape of the empirical distributions. He states that, in comparison to the normal, there is an 'excess of observations within one-half standard deviation of the mean. On the average there is 8.4 per cent too much relative frequency in this interval. The curves of the empirical density functions are above the curve for the normal distribution.'[8] Lastly, he rejects two other explanations for the thick-tails. The first is a mixture of several different normal distributions with the same mean and different variances and the second is the possibility of non-stationarity of the parameter estimates.

The main criticism of the Stable Paretian hypothesis is that, given a characteristic exponent of less than two, the variance is either undefined or infinite. Hence, the standard mean-variance portfolio theory has to be redefined if such a distribution is assumed.[9] Other authors chose to investigate further the other explanations for the thick-tails. Press (1967) pursues the mixture of normal distributions using a Poisson process as the mixing variable. Using a procedure defined as cumulant matching that is very similar to the present day method of moments estimation procedure, he analyzes ten stocks from the Dow Jone Industrial Average using monthly data. He finds that the estimated cumulative density function fits the empirical cumulative density function in most cases. Clark (1973) chooses to use a

[8] Fama (1965a), p. 49.

[9] Fama (1965b) presents portfolio results when the distribution of the assets is described by the Stable Paretian hypothesis. However, Frankfurter and Lamoureux (1987) show that the normality assumption out performs the Stable Paretian even when the monthly data is generated from a stable distribution.

subordinated stochastic process first proposed by Mandelbrot and Taylor (1967) on cotton futures. He argues that the price series evolves at different rates for the same interval of time. He uses a lognormal-normal process to describe the distribution of the price changes. The lognormal process is the directing process or the variable to which the normal price changes are subordinated. Comparison of the results with the Stable Paretian indicates acceptance of the finite-variance subordinated stochastic model.

Blattberg and Gonedes (1974) suggest that the Student-t distribution may provide a better fit to daily data than the symmetric Stable Paretian model. One reason for their argument is that as t-distributed data are aggregated they will converge to a normal distribution by virtue of the Central Limit Theorem. On the other hand, under the Stable Paretian hypothesis, aggregated data will retain the same characteristic exponent as the original observations. Hence, the aggregation property of the Student-t agrees with the findings that monthly data are approximately normal. However, given the evidence of Fama on the peakedness of daily data, there is some doubt as to whether daily data can be considered t-distributed. Nevertheless, the authors find, based on log-likelihood ratios, that the Student-t distribution provides a better fit than the stable model.

Kon (1984) concentrates on the stationarity assumption of previous authors to investigate the relevance of a discrete mixture of normals model for daily data. He finds that for a sample of 30 Dow Jones stocks the discrete mixture assumption is more descriptive of the data than a Student-t. Akgiray and Booth (1987) use weekly and monthly data to

contrast the finite mixtures with a mixed jump diffusion process. They present evidence that the mixed diffusion jump process is a better description of the data. In related work, Bookstaber and McDonald (1987) introduce the generalized beta of the second kind or GB2 distribution. They note that this model is more flexible since it contains the log-normal and log-t as limiting cases. Using daily data and a bootstrapped sample, they argue that it provides a better fit to the data than the log-normal.

In general, the consensus is that monthly data are approximately normal and that weekly and daily data exhibit such departures from normality as to require other models.[10] The common thread in the above work is the reliance on independent increments and to a lesser degree unconditional distributions. Also of note is the attempt to address the leptokurtosis of the return series either by explicitly choosing distributions that contain thick-tailed members, e.g. the Stable-Paretian and Student-t, or by postulating a mixture of distributions or processes that can produce the thick-tails, e.g. the mixture of normals and mixed diffusion-jump.

Later work has begun to focus on the assumption of independence. Dependence in the mean, or first order, has always generally been ruled out for daily or longer intervals. However, dependencies with respect to

[10] Greene and Fielitz (1977) posit the existence of long term dependence in stock prices by applying the rescaled range or R/S methodology made popular by Mandelbrot (1972). However, Aydogan and Booth (1988) provide counter evidence that the technique is not sensitive enough to measure the relatively small level of dependence that may exist. Note however the earlier reference to mean reversion found in footnote 3.

the higher moments, especially the variance, have recently come to the fore. Rather than addressing the non-stationarity of the unconditional variances in the manner of Press (1967) or Clark (1973), these works rely on an autoregressive conditional heteroskedastic (ARCH) model first proposed by Engle (1982).

For instance, Bollerslev (1987) uses a generalized ARCH methodology with conditionally Student-t distributed errors to model monthly stock price indices. His motivation is twofold. The first reason is to address the remark of Mandelbrot (1963) concerning the persistence of large and small price changes. Given such tendencies in speculative price changes, the existence of higher order dependence is implied. Secondly, the use of the Student-t distribution for the conditional errors allows for a distinction between the conditional leptokurtosis and the conditional heteroskedasticity, either of which could explain the observed unconditional leptokurtosis. Somewhat of interest is his finding that the Student-t conditional distribution can be accepted as an accurate description of the monthly S&P 500 stock price index. This contrasts with Akgiray (1989) who applies the same analysis, except with normally distributed conditional errors, to equally-weighted and value-weighted daily stock price indices. If anything, given the work of earlier researchers, one would expect that a priori the results of the two studies would be reversed since monthly data exhibit an unconditional distribution much closer to the normal. In any case, both studies support the premise that stock returns exhibit statistical dependencies that may result from nonlinear stochastic processes generating security prices. International evidence for higher order

dependence is provided by Akgiray, Booth and Loistl (1989) using a German daily price index for common stocks and Booth, et. al. (1990) using a Finnish daily price index for common stocks.

Directly related to this issue is the work of Lamoureux and Lastrapes (1989). They find that the presence of ARCH in daily data could arise from a mixture of distributions, with the mixing variable being the information arrival rate. They use daily volume as a proxy for this information arrival and find that the ARCH effects disappear in their sample. Their work is an interesting integration of the price-volume relation [See Karpoff (1987)] and the hypothesis presented by Clark (1973) that the price series evolves at different rates for the same interval of time. An extant question is the degree to which this explanation holds using sub-daily data.

## B. INTRA-DAILY AND TRANSACTION INTERVALS

### 1. Statistical Properties and Models of Price Changes

While researchers have generally found little evidence of autocorrelation in the mean for daily data, a large part of the intradaily literature simply documents the correlation of returns and the patterns of dependency. For instance, Osborne (1962) partly uses transaction data while looking at the relation between price changes and volume. He finds that individual transactions are for approximately 1.5 round lots, but has little else to say about them. Most of his paper is devoted to the distributional structure of daily volume, which he finds to be roughly lognormally distributed. However, in later work with

Niederhoffer (1966), he presents the first systematic study of transaction data. These authors provide frequency tables of successive price changes for a sample of six Dow Jones Industrial Average stocks for the twenty-two trading days of October 1964. They note a number of interesting observations, such as the 'stickiness of even-eighths' and the tendency towards reversal or what later authors document as negative serial correlation. They conclude that this is a result of the specialist system of market making and in particular arises from the fluctuation of transaction prices between the bid and ask prices. They also note how, 'in the short run, the limit orders on the book will act as a barrier to continued price movement in either direction.'[11] Morever, they provide a number of runs test to verify the existence of other 'regularities'.

Simmons (1971) analyzes transaction data in order to review the role of the random walk model. He notes that such a model requires that successive transactions be statistically independent. After reviewing the work of Niederhoffer and Osborne (1966), he raises the question of whether their results stem from the superimposition of an arbitrary local mechanism upon a return generating process that otherwise appears to be a random walk. He argues that after taking into account the correlation due to the bid-ask spread, the shifts in price that result from market's overall evaluation are serially independent.

Using transaction price and volume data over a twenty day period for 71 NYSE common stocks in early 1968, he details the dependencies using an autoregressive model up to lag five. Assuming that the

[11] Niederhoffer and Osborne (1966), p. 905

disturbance process is stationary, he applies an ordinary least squares (OLS) estimation which is asymptotically valid. Unfortunately, he does not discuss how he aggregated the stocks or whether he simply applied the model to successive stocks. In any case, he finds evidence consistent with an second order autoregressive model.

He then proceeds to analyze the results after eliminating zero price changes which are hypothesized to result from limit orders. However, his results show little improvement. He then turns to a number of runs tests to document the persistence of zero ticks and also large price changes, the latter being attributed to the lack of limit orders either above or below a certain price. He concludes the paper with a short note on volume, finding little correlation between successive transaction volume and also with price changes.

Garbade and Lieber (1977) postulate the same model but concentrate on the time interval between trades, arguing that as the interval increases transaction prices will converge to a random walk. They assume that transactions are independent with respect to the time of execution and whether initiated by a buyer or seller. They find that if they restrict the time interval between transactions to five or ten minutes their model cannot be rejected, but over shorter intervals transactions tend to cluster in time.

The data they use consist of transactions on two stocks for September 1975, IBM and Potlatch. By assuming the time between transactions $t_k$ is independent which implies that $t_k$ is exponentially distributed, they note that the cumulative probability function for $t_k$ is $F(t_k) = 1\text{-}\exp(-\mu t_k)$, with $\mu$ as the mean order arrival rate. Hence the

number of transactions in an interval of length $\tau$ will be Poisson distributed with parameter $\mu\tau$. They develop a model where the observed price is the sum of the equilibrium or true price and a random term. By assuming the true price follows a Gaussian random walk, they derive expressions for the conditional distributions of a price reversal model. The method of maximum likelihood is used to estimate the ratio of the variances of the equilibrium and transient price terms. However, they are unable to directly test the distribution of elapsed time since they have transactions which are recorded to the nearest minute only. Using an approximation they find evidence that sequential transactions are not independent. In the case of a heavily traded stock such as IBM their work suggests that 70% of the transactions are independent, while for an infrequently traded stock such as Potlatch only 63% are independent. They argue that the dependence could be a result of the breaking up of block trades.

Epps (1976) proposes an ARMA process as a way to account for the dependence in the return series. His concern is with the correlation of the returns with the transaction volume. Using data from both bonds and stocks, he finds that an ARMA(1,1) model fits fairly well. However, he does note that his results suggest that the bond market has larger conditional variances than the stock market. He argues that this is a result of the relatively thin trading in the bond market and the presence of the specialist in the stock market.

Oldfield, Rogalski, and Jarrow (1977) develop an autoregressive jump process as an empirical description of transaction data. They start with a model composed of a geometric Brownian motion, calendar time,

diffusion process and a gamma distributed, autocorrelated jump process. The gamma distribution is a more general form which encompasses both the exponential and the Poisson density functions. The conditional variance of the model contains separate components for the diffusion and jump processes, if it is assumed that N, the number of jumps in an interval of length s, is constant. By assuming a gamma distribution for the jump process, the unconditional density can be derived for the case where N is variable. They note that the unconditional mean and variance are then a function of s and not N.

Using transaction data recorded to the nearest minute (the same constraint as Garbade and Lieber), they look at the empirical results for a group of twenty NYSE stocks over the 22 trading days of September 1976. Noting the usual references to the effects of the bid-ask spread and large block transactions, they report summary statistics for the first four moments and autocorrelations up to lag four of returns and the time intervals between transactions. They then proceed to test a number of hypotheses concerning the distributional validity of their model.

The first is whether the process contains a diffusion component. While holding N equal to one, s is increased from one to five minutes. If the process does not contain a diffusion component then the mean and variance will remain unchanged. Their evidence suggests that the variance is constant and not a function of s, the time interval. They note that this raises questions as to the validity of the geometric Brownian motion process and hence the subordinated model for the sample data. Next, the authors test the autoregressive jump process assumption.

By increasing N, the mean and variance of the autoregressive process should increase. Therefore, by comparing the observed means and variances with the theoretical moments, using F-statistics and Bartlett's test respectively, evidence is found in favor of the autoregressive jump process.

The third hypothesis concerns the use of the gamma distribution as the proper density function for the time between transactions. This requires that the intervals between transactions are independent, which they validate by looking at the skewness adjusted serial correlation coefficients. Maximum likelihood estimates of the parameters are obtained for sums of transactions, in part because of the use of a continuous distribution to fit discrete data and also because of the limitations of the data being recorded to the nearest minute. A number of goodness of fit tests are then applied to the theoretical and empirical distributions (including the Kolmogorov-Smirnov, Cramér-Von Mises, and the Anderson-Darling statistics) comparing the gamma and exponential. They find results consistent with the gamma in contrast to Garbade and Lieber's finding of an exponential. Lastly, they test whether the conditional density of returns given N jumps is normal. Their findings are somewhat inconclusive in this respect.

Hasbrouck and Ho (1987) estimate the autocorrelation structure of transaction returns and then present a model of the return generating process that incorporates these dependencies. In particular, they find evidence of positive autocorrelation in transaction returns, in the returns computed from quote midpoints, and in the arrival of buy and sell orders. With the addition of limit orders and a first order

autoregressive model of the price adjustment process, they represent the return generating process as a second order autoregressive, moving average process, i.e. an ARMA(2,2). These results are for an aggregated sample of stocks.

Epps (1979) raises the question of dependence and non-stationarity in short run price movements. He finds evidence for this in the autocorrelation and cross-correlation results of auto industry stocks. He suggests that instability exhibited by the correlations over different time intervals results from either the dependency or the nonstationarity. He finds that the variance for different hours of the day differ, suggesting nonstationarity. He also shows that correlations exist between the lag price changes in one stock and those of another, raising the possibility of information lags from one stock to another. He argues that this may result from a differential number of limit orders between stocks which limit the speed of adjustment to new information.

Harris (1986) studies the weekly and intradaily patterns in stock returns using transaction data. In particular, he looks at intraday returns over 15 minute intervals in order to better characterize the day of the week effect. His data set consists of transaction data recorded to the nearest minute (Fitch tape format) for all NYSE stocks traded between December 1, 1981 and January 31, 1983. Data for days following trading holidays are excluded. First, he documents the consistency of close-to-close returns for an equally-weighted portfolio of stocks in this sample with that of previous authors. He then notes the discrepancy between his results for the close-to-open and the open-to-close returns

and those of Rogalski (1984). This is attributed to the cross-sectional differences in the day of the week effect. He notes that these differences in trading and non-trading intervals are based on size.

Next, he investigates the weekday differences in intraday price patterns, finding a difference in the mean return for the first 45 minutes of trading on Mondays and other days of the week. These differences occur not only through time but also cross-sectionally. He notes that mean returns are larger in absolute value for the beginning and end of the day than in the middle, an observation consistent with the work of Wood, McInish, and Ord (1985). In the appendix he describes the accrual method used to compute the 15 minute portfolio returns. This method is said to be less sensitive to non-synchronous trading problems. Two interesting points in this regard are the use of the beginning of the day price in the denominator and the fact that this method introduces autocorrelation into the series.

Transaction data have also been used to support the mixtures of distribution hypothesis for daily data. Harris (1987) discusses a number of issues with regard to daily volume and price changes and then introduces additional predictions about the mixture model by assuming that transactions occur at a uniform rate in event time and that the number of transactions is proportional to the number of information events. His argument is that if the same properties do not exist when the measurements are taken over transaction intervals, then the results support the mixtures of distribution theory. Two of his more interesting predictions are that the autocorrelation in the transaction time series will be stronger than that found in daily series and normality will be

attained when the distribution of price change is divided by the square root of the daily number of trades. An implication of the assumption of a uniform rate for transactions in event time is that the number of information arrivals within different transaction intervals of fixed length is constant. This leads to hypotheses about price changes and volume approaching normality as the interval increases, as long as those same variables are uncorrelated with each other and there exists no autocorrelation.

The data set consists of 50 NYSE stocks traded between December 1, 1981 and January 31, 1983. He presents a number of statistical results using the cross-security medians of the data. Generally these results support the hypotheses that he has set forth. He finds that the skewness and kurtosis of daily data are not entirely due to those properties being found in transaction data. In his conclusion, he notes two possible explanations, one being that the process that generates transactions is closely related to the rate of information arrival, and the other, which he attributes to Roll and French (1986), being that trading is self-generating.

Harris (1989) looks at the price anomaly of the last transaction of the day. He finds that the price tends to rise at the end of the day and is most obvious on the last transaction. He suggests that a possible explanation is the change in the frequency of bid and ask prices. However, he has no reason as to why the last trade of the day might consistently be an ask price, which also indicates that it was initiated by a buyer. Amihud and Mendelson (1987) present related work on the differences between open-to-open returns and close-to-close returns.

They posit that the opening transactions are a result of a call market while the closing prices result from the behavior of the specialist or market maker. They use transaction data from 30 New York Stock Exchange stocks. They find that the open-to-open returns exhibit a greater variance, thicker tails, and greater peakedness than the close-to-close returns. They also document different serial correlation patterns in the two series.

Wood, McInish, and Ord (1985) investigate the characteristics of trade size, trading frequency, price changes, and trading interval for a large sample of NYSE firms over the periods of September 1971 through February 1972 and the entire 12 months of 1982. They use an equally weighted market index based on minute by minute transaction data. Some discussion is given of alternative measures for a market index which would take into account the fact that all firms do not trade each minute of the sample. However, because of the introduction of autocorrelation they use the simpler method. This index is then aggregated across days by each particular minute to obtain an idea of the trading pattern during the day.

Their findings suggest that the mean and variance of returns at the beginning and end of the day are higher than those during the rest of the day, even after overnight returns are excluded. If these periods are dropped from the sample they find the index is much closer to a normal distribution in terms of its skewness and kurtosis. Hence, they posit that a mixture of distributions is observed when one uses daily or longer intervals with the mixtures corresponding to an overnight, opening, intraday, and end-of-day distribution. The autocorrelation

results for daily (including overnight returns) and thirty minute intervals are interpreted as resulting from differences in the intraday versus overnight return distribution and infrequent trading.

A number of trading statistics are presented on the number of trades, price, size of trades, interval between trades, and the absolute value of price changes, with the categories subdivided by market equity, trading frequency, price changes, and intraday versus overnight trades. Correlation exists between the number of zero price changes and the frequency of trading, the absolute value of price changes and the trading size, and the trading interval and the absolute value of the price changes. [12]

## 2. Transaction Costs and the Return Generating Process

The evidence presented in the previous section suggests that there are a number of dependencies in intra-daily price changes. The exact nature of these relations is not yet clear in terms of the different time intervals used. Many of these effects may have their origin in the institutional structure of the market. For instance, the bid-ask spread, limit orders, and the 1/8 rule all affect the statistical properties of

[12] In a subsequent discussion, Tauchen (1985) suggests using robust measures of location and dispersion, such as the median and interquartile range. He notes that traditional diffusion models may not be correct here but still remain applicable over larger time scales, somewhat analogous to the breakdown of celestial mechanics when applied on an atomic scale. Lastly, he points out that the correlation between large price changes and the time between trades cast doubt on the mixtures of distributions models, which assume that the mixing process is independent of the price-change distribution.

transaction data. These in turn underly theories that attempt to model dealers inventory, ordering, and information costs, the effects of block trades, and the speed of price adjustment to unexpected information.

Of interest here is the differential costs that exist for various traders and the role this plays with respect to the volume and frequency of transactions. The asset pricing models, such as the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Model (APT), have made use of the notion of competitive equilibrium but this has generally taken place in a world without transaction costs. For instance, the CAPM predicts that the unsystematic risk of a stock will not be priced due to the ability to diversify away this component with an appropriately selected portfolio of stocks. The APT is based on the notion that arbitrage will eliminate any profitable trading opportunities and maintain the same equilibrium risk-adjusted expected return for all traded assets. The frame of reference here is on the average investor and the opportunities presented to them given their information and transaction cost constraints. The lower transaction costs of floor traders, specialists, and large institutions suggest not only a higher propensity to trade, but also trading on information that may reflect only the firm specific risk of a particular company. Otherwise, the no arbitrage equilibrium could not attain.

Indeed the role of the specialist can be viewed as one of attempting to bring the intertemporal demand and supply of a particular asset into equilibrium. Given that he stands ready to transact at the quoted bid and ask prices, he must continually adjust these quotes to the random number and size of the orders that arrive at the market.

Hence, intradaily data should be marked by a variance which reflects the basic uncertainty of the firm-specific information that traders possess and the specialist's attempts at ascertaining the appropriate prices for equating the intertemporal supply and demand.

Black (1986) has labeled this process 'noise'. Such a concept leads to such possibilities as the over reaction hypothesis since instantaneous adjustment of prices to new information is only a Walrasian construct and also unsuitable to the fragmented manner in which orders (in terms of volume) arrive in the market. Hence, the study of transaction data should allow for a better understanding of the process of price change in speculative markets.

Recent work by Easley and O'Hara (1987) challenges the random walk model of stock returns as an accurate depiction of transaction data. They argue that the price process follows a martingale relative to the market maker's information set. Also, since the sequence of past trades is important in determining whether the present transaction represents an information event, the distribution of $p_{t+1}$ conditional on $p_t$ is not independent of the past price series, where $p_t$ is the price of the stock at time t.

Other authors have attempted to interpret the data in terms of information arrival or the impact of information events. French and Roll (1986) investigate the volatility of returns during trading and non-trading hours. They note for instance that the variance of returns from open to close is six times larger than the variance from close to open over a weekend. Their explanations include: more public information arrives during normal business hours, volatility is increased by trading

which represents private information, and lastly the trading process produces noise. By comparing daily return variances with those over longer intervals, the authors suggest that 4-12% of the daily return variance is a result of mispricing or noise. They also note that this does not explain the large difference between trading and non-trading variances which they attribute to differences in the incorporation and arrival of information.

The data consist of daily returns for all NYSE and AMEX stocks over the period 1963 to 1982. The data are divided into ten two year subperiods and ratios of the multiple day to single day variances are calculated. A further test is performed on the relation of firm size to the variance differential but the results do not support the hypothesis. By making a number of simplifying assumptions concerning the independence and distribution of returns, French and Roll argue that the following relationship holds:

$$66\sigma_N^2 + 6\sigma_T^2 = 1.107(18\sigma_N^2 + 6\sigma_T^2)$$

where $\sigma_N^2$ is the non-trading variance per hour and $\sigma_T^2$ is the trading variance per hour. Thus, the trading variance per hour is postulated to be 71.8 times the non-trading variance per hour.

They discuss the difference between private and public information by stating that public information is known at the same time it affects stock prices. Private information, on the other hand, becomes known only through trading. The variance ratios then reflect the production of most private information during normal business hours or informed trading by investors for more than one day. The other explanation is that trading produces noise. Hence each day's return represents an information

component and an error component, which may be independent or positively correlated. Since daily returns are used, this explanation assumes that some of the noise is not corrected during one day. If it is corrected, then intra-day variances would increase but not daily variances.

These hypotheses are then tested using the time around exchange holidays as the testing period. If the trading noise hypothesis is correct then the variance should fall while the exchange is closed and it should not be recovered in the subsequent days as opposed to if trading on private information was producing the higher variance. The evidence from this test supports both the noise and private information hypotheses. To further distinguish the two explanations autocorrelation are computed for the daily data. Trading noise will produce negative autocorrelation, but the authors note that so will the bid-ask spread and day of the week effects. Hence, they argue that negative correlation beyond lag one is consistent with the trading noise hypothesis. Their evidence is consistent with this explanation.

As a further test of the importance of the trading noise hypothesis daily variances are compared with those for longer holding periods, up to six months.[13] The view here is that the importance of mispricing and bid-ask spread errors will decrease as the holding period increases. They find that these errors cause a significant fraction of the daily variance. By assuming that daily returns are made up of a rational information component, a mispricing component, and a bid-ask spread error, a lower bound for the variance is computed. In the

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[13] This relationship has been discussed previously in footnote 1.

appendix, further results are deduced on the correlation between information and mispricing.

Patell and Wolfson (1984) look at the speed of adjustment of stock prices to dividend and earnings announcements. They look at three statistics in particular, the mean, variance, and serial correlation of consecutive price changes. Here the authors use aggregate cross-sectional statistics. After reviewing the distinct properties of transaction data, in particular negative serial correlation, they note the apparent anomalies that have been documented with respect to earnings announcements and how their work is not necessarily comparable to the previous studies.

Their sample consists of 571 earnings and dividends releases for 96 firms during 1976 and 1977. The firms are predominantly from the NYSE and the stock price data are from the CBOE/Berkeley Options Transactions Data Base, which records the stock price to the nearest second every time an option trade is executed or quotes are revised. They use the Value Line Investment Survey forecasts as their estimate of the expected earnings.

To test for changes in the mean intraday returns a Wilcoxon single sample test and a Mann-Whitney test are used. The former compares the announcement day return to a norm of zero while the latter tests whether the announcement day results are stochastically larger than the control sample. Using a simple trading rule based on whether the actual earnings announcement exceeds or falls short of the expected earnings announcement, they document significantly different returns for the

period thirty minutes after the actual announcement. Roughly the same results are found for the dividend declarations.

In order to test for the effects on the variance, the authors compile a multinomial frequency distribution for one-hour and overnight price changes for each firm. An extreme price change is then defined as one that falls in either of the 5% tails. Because of the differences in absolute value of the beginning and end of day changes with the midday results separate critical values are used for each hour for each firm. A normal approximation to the binomial is then used to arrive at the appropriate Z-statistic. The evidence suggests a disproportionate number of extreme changes occur during the hour of the earning announcement but not the dividend announcement.

Serial correlation tests are performed on the pooled data for consecutive stock price changes up to lag 10 and also over intervals of one, two, three hours, and one day. The evidence is consistent with previous evidence of negative serial correlation and also the evolution from an autoregressive process to a random walk as the time interval increases. Here, the authors wish to determine the extent to which announcements interrupt the reversal pattern. They use Chi-square tests of two-by-two contingency tables to determine the point at which the process is affected by the announcement and the elapsed time until it returns to its normal pattern. They find significant differences in the relative frequency of continuations after the earnings announcement but not much of an effect in the dividend sample. Similar results are found when the relative frequencies are measured in terms of calendar time intervals rather than actual transactions.

In concluding they note that their tests are basically non-parametric and hence do not require any assumptions about the distributional forms or particular asset pricing models. They also point out that their sample consists of large, actively traded firms and hence should have shorter adjustment periods to new information than smaller, less actively traded ones. Finally, the authors discuss the possible implications for trading strategies based on the observed differences in the adjustment periods for the mean returns (an interval of five to ten minutes) as opposed to the adjustment periods for the variance and serial correlation (intervals of several hours).

Barclay and Litzenberger (1988) study the intraday effects of new equity issue announcements. Their results suggest that new information is received by investors at different rates. This lends support to the possibility of differential information costs among traders and also lags in the adjustment of price to new information. [14]

Several papers have attempted to explicitly model the return generating process while taking account of the various transaction costs that exist in actual trading. Cohen, et. al. (1978a) try to develop an economic model of the return generating process. The change in price is linked to shifts in a negatively sloped demand curve through two processes - idiosyncratic tenders and aggregate demand shifts. They predict that stocks with less trading volume will be more volatile than high volume stocks due to the relationship between the variance and the

[14] Copeland (1976) derives a sequential information arrival model where each trader receives news at different times and hence trading occurs in sequence as each individual adjusts his demand curves.

value of the stock. In a subsequent paper (1978b) they relax a number of assumptions in order to assess the effects of a limit order book on the return generating process. Using a simulation study, they find that transaction returns will exhibit greater negative serial correlation the longer the limit orders stay on the book due to the tendency for randomly arriving transactions to bounce between the bid-ask spread.

Perhaps the most ambitious attempts at incorporating actual price behavior into a theoretical framework are two papers by Goldman and Beja (1979) and Beja and Goldman (1980). In the first paper, the authors model the price change in terms of the instantaneous rate of price adjustment between the observed price and the true equilibrium one. They detail several interrelationships between these two variables based on the speed of the market's response and the length of the time interval while also discusssing the implications of these effects on the time-variance relationship. They posit that return fluctuations will be dominated by the noise in the market over the short run and the asset's underlying value in the long run. In the second paper, they examine the distinction between the state of the environment and the state of the market. The former is loosely associated with fundamental values while the latter incorporates the role of speculation in the market process. Their basic idea is that prices reflect disequilibrium values over short intervals and traders will attempt to estimate the trend, thereby causing prices to either deviate more from equilibrium or converge to it, depending on the degree of trading due to fundamental demand.

This is in perfect agreement with the work of Mandelbrot (1971). He shows that with finite horizon anticipations the attempts at

arbitrage will in fact cause the price series to exhibit higher volatility. As the anticipation of the price trend increases so will the variance. Given the above discussion of the differential costs of various traders, this concept appears especially suited to the trading of large stocks on the NYSE.

In summary, the various institutional structures in the trading process make theoretical modelling quite complex and as a result tend to cloud any inferences which may be derived from their application. Present empirical evidence raises a number of questions concerning the nature and structure of intradaily returns, with the possibility of higher order dependency being one of them.

# CHAPTER 3

## PRELIMINARY DISTRIBUTIONAL AND DESCRIPTIVE ANALYSIS

In this chapter we investigate the distributional properties of intraday returns based on ten and thirty minute time intervals. Our primary objective is to examine the data and describe the distributional properties of the two series in terms of the first four moments. We test whether the series can be described by (1) a normal distribution or (2) a white noise process.[15] Furthermore, we compare the effect of aggregation on the estimation of the moments, particularly the kurtosis. We also test for differences in the unconditional means and variances between the period marked by the opening and closing of the market and the rest of the day. Lastly we provide evidence for the existence of not only correlation in the mean or first order dependence, but also higher order dependence, especially second order, or dependence in the variance.

In the first section we set forth the type of data, the period covered, the sample we use, and the manner and rationale for creating the dummy variables. In the second section, we discuss the statistics we use in the empirical analysis and the corresponding hypotheses. We

[15] A white noise process is defined as one whose autocovariances are zero at all lags and it can be classified as second-order stationary, i.e. its mean and covariance functions do not depend on time. However, such a definition does not imply independence. A 'strict' white noise process is one where the values of the original series are statistically independent over time. If such is the case, then the squared and absolute return series are also strict white noise.

present our results with a discussion of the tables and conclusions in the last section.

## A. DATA DESCRIPTION

The data we use for this study consist of transaction by transaction price, volume, bid-ask quotes, and time stamps provided by the Institute for the Study of Security Markets from August 31, 1987 to October 1, 1987. The period used is restricted by the availability of data and the presence of the October stock market crash in 1987. A random sample of thirty stocks is chosen from the 100 most actively traded stocks on the NYSE for 1987. This is then reduced to fifteen stocks on the basis of whether actual transactions exist for the creation of ten and thirty minute return series (Five minute intervals are attempted but only two stocks from the sample contained enough observations based on the above criterion). Table 3-1 contains a list of the stocks used in our analysis. The last transaction in each ten minute interval is used to calculate the return series.

We calculate the return series as first log price differences, which we denote as $r_t$. We use the log price relatives because they eliminate any effects that the price level may have on simple price changes and they are close to the actual percentage price change when the changes are within ± 15%. We make a distinction between the overnight return and the intraday returns in the creation of the time series. The overnight return is kept the same no matter if the series contains ten minute or thirty minute intervals. This is done to maintain

the different aspect of that return from the others in the series. Hence, the ten minute interval dataset contains 919 observations with 22 overnight returns and 897 intradaily ones, while the thirty minute dataset contains the same 22 overnight returns and 299 intradaily ones for a total of 321.

Since previous studies show that intraday returns are affected by the specialist bid-ask spread and that the overnight return is distinct from the rest of the day [ e.g., Wood, McInish, and Ord (1985) and Harris (1989)], we create two binary dummy variable series to account for this behavior. The ask dummy variable indicates whether or not the return is calculated from a transaction at the bid followed by a transaction at the ask. The end of day dummy variable indicates whether the return occurrs overnight, in the last period of the day, or in the first period of the day.

In creating the ask dummy variable series we use the following procedure detailed in Hasbrouck (1988). First, all those transactions that can be classified as a bid or ask price based on the midpoint of the prevailing quotes are identified, those above the midpoint being an ask and those below being a bid. We then turn to known contemporaneous transactions to identify any unknown ones which occur at the same time. Next we use the subsequent transaction to determine the classification. Hence, if the quote is a bid and an ask of 15 and 15 1/4 and a midpoint transaction ocurrs at 15 1/8 with a later transaction at 15 1/4, then the 15 1/8 is considered a sale that occurrs at the bid.

The last classification method is based on a subsequent quote revision. Here, if a midpoint transaction is immediately followed by a

quote revision then the revision is used to infer the type of order. For instance, given the previous example, if the midpoint transaction is followed by a quote revision of 15 1/8, 15 3/8, then the transaction is considered a sell or occurring at the bid. Hasbrouck uses these methods to classify approximately 98% of his sample. We are able to classify only 92% of our sample, and this led to the following procedure. Those returns that occur as a result of a trade at the bid followed by a trade at the ask are given a value of one; all others are given values of zero. Hence, the ask dummy represents those returns that possibly contain a positive component due to the bid-ask spread.

## B. DESCRIPTIVE AND TEST STATISTICS

We use a number of statistics in the preliminary investigation to provide a description of the ten and thirty minute returns series. These include the mean and median as measures of location, the standard deviation and interquartile range as measures of dispersion, and the skewness and kurtosis as measures of the shape of the distribution. Two procedures are used to test the null hypothesis of a normal distribution in the original return series. The first is based on the Kolomogorov D-statistic, which is defined in terms of the maximum absolute difference between the empirical distribution function and the theoretical distribution function. It is given by:

$$D_n = \sup_x | S_n(x) - F_0(x) | ,$$

where $S_n$ represents the empirical distribution function and $F_0$ is the theoretical distribution function, which in this case is the normal. We use Stephens' (1974) modification of the statistic since the mean and variance of our theoretical distribution are unknown. The second testing procedure is based on the Kiefer-Salmon (1983) statistics, which are defined in terms of the sample skewness and kurtosis coefficients. The skewness statistic is:

$$S = (n/6)*(u_3 - 3u_1)^2$$

and the kurtosis statistic is:

$$K = (n/24)*(u_4 - 6u_2 + 3)^2,$$

where $u_i$ is the corresponding $i^{th}$ sample moment about the mean and $S$ plus $K$ is the $KS$ statistic. The $S$ and $K$ statistics are distributed $\chi^2$ with one degree of freedom and the $KS$ is distributed $\chi^2$ with two degrees of freedom. The null hypotheses are that the skewness and kurtosis are not different from the normal values for those two moments, i.e. $u_3 = 0$ and $u_4 = 3$.

We test whether the population means for the intradaily and overnight returns are different from zero by using the normal approximation to the t-distribution and also test whether they are different from each other by using the Satterthwaite t-statistic approximation with the degrees of freedom based on the sample observations. These statistics are also used to test the same hypotheses for the squared returns since they represent a simple measure of the variance.

The next set of statistics deal with the null hypothesis of strict white noise for the original return series and the presence of dependency in the squared and absolute return series. This set includes Fisher's kappa and Bartlett's Kolmogorov-Smirnov statistics, which both test the null of strict white noise for the original returns in the time domain. The Box-Pierce portmanteau test with modifications by Ljung and Box (1978) is used to test for the above hypothesis in the frequency domain[16] and also to determine the presence of any nonlinear dependency when applied to the squared and absolute return series.[17] The general form of the Ljung-Box portmanteau Q statistic is:

$$Q = n(n+2) \sum_{i=1}^{M} r^2(i)/(n-i),$$

where n is the number of observations, $r(i)$ is the autocorrelation coefficient with a lag of i, and M is the maximum number of lags. The statistic is distributed as a $\chi^2(M\text{-}p\text{-}q)$ where $p$ is the order of the autoregressive component and $q$ is the order of the moving average. The null hypothesis is that the series is a white noise process.

[16] Fuller (1976) has a description of the two time domain tests on pages 282-287. Both are based on an analysis of the periodogram which is generally used to search for cycles in the data. Fisher's kappa uses the largest periodogram, while Bartlett's is based on the normalized cumulative periodogram. The null hypothesis for Fisher's kappa is: $X_t = u + e_t$ (white noise) versus $X_t = u + A\cos\omega t + B\sin\omega t + e_t$, where $\omega$ is unknown.

[17] A discussion of the application of this statistic to the squared residuals can be found in McLeod and Li (1983). Another statistic used to test for nonlinear dependence is the $TR^2$ statistic, a variant of the Lagrange multiplier test under asymptotic normality.

The final statistic used is a Pearson $\chi^2$ goodness of fit test. This is defined as:

$$Q_{k-1} = \sum_{i=1}^{k} (y_t - nP_{io})^2 / nP_{io},$$

where k is the number of mutually exclusive cells into which the data are subdivided, $P_{io}$ is the theoretical probability of an observation occurring in that cell, n is the number of observations, and $y_t$ is the standardized returns.[18]

Kendall and Stuart (1977, p. 463) argue that the best way to determine the class boundaries is to use an equal probabilities method where $P_{io}$ is equal to 1/k. In order to determine the number of classes they provide the following formula:

$$k = b\{ 2^{\frac{1}{2}}(n-1)/(\lambda_\alpha + G^{-1}[P_0])\}^{2/5}$$

where b is between 2 and 4, n is the sample size, $\alpha$ is the size of the test, $\lambda\alpha$ is the upper $\alpha$-percentage point of the standard normal distribution, $P_0$ is the approximate power function for the maximization, and $G^{-1}$ is the inverse of the standard normal distribution function. The statistic $Q_{k-1}$ is distributed as $\chi^2(k-1-m)$, where m is the number of estimated parameters. We use this $\chi^2$ test to determine the model that best fits the empirically determined conditional distribution, which is based on the estimated degrees of freedom.

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[18] The $y_t$ may also represent the standardized residuals when the procedure is used to test the fit of each model.

## C. DISCUSSION AND RESULTS

### 1. Ten minute data

We begin our analysis by examining the descriptive statistics for the ten minute data. From Table 3-2, we first notice the wide range of values for the mean returns. For instance, DOW has a mean return of .00009641 which translates into an 8.09% monthly return and an 96.3% yearly return. On the other hand, GM experienced a ten minute average return of -.00007355 which becomes a -6.17% monthly return and a -73.5% yearly return. Seven of the stocks have a negative average return, while eight are positive. The standard deviations of the returns range from a high of 0.5339 for PAC to a low of 0.2245 for ATL.

The median return for all the stocks is zero, while the values for the interquartile range indicate a large dispersion for some of the stocks, such as PAC, and almost none in the case of BAX. In terms of skewness, six of the stocks have a negative value indicating the distribution is skewed to the left with the highest being GM and nine have a positive value indicating a longer tail to the right with the highest in this case being RJR. All the stocks exhibit leptokurtosis or thick-tails which is consistent with previous work on stock prices, whether daily or intradaily.

In terms of the tests for normality, we turn to Table 3-3. All of the samples reject normality using the Kolomogorov D-statistic, which is not suprising given the nature of the test as a goodness-of-fit test based on the empirical distribution function. We further examine this issue by looking at the Kiefer-Salmon statistics for skewness and

kurtosis. In terms of skewness, the high value of the *S* statistic for ten of the stocks leads to the rejection of the null hypothesis of a zero third moment or a symmetric distribution. The *K* statistic for normal kurtosis rejects the null hypothesis in all but one case, which is the same result as the combined *KS* statistic. Hence, any assumption of a normal unconditional distribution can be thoroughly rejected for all of the stocks except PAC, where the evidence for rejection in not quite as strong. Since rejection of the normality hypothesis does not indicate whether the returns are simply independent white noise processes, we examine the values for Fisher's kappa (K) and Bartlett's (B) statistic. Using Fisher's kappa statistic we would reject the null hypothesis of white noise for only two of the stocks, while Bartlett's test rejects the null for eleven out of the fifteen stocks.

Our next table, Table 3-4, provides the results of several tests for an end of day effect in both the mean and variance. The first two columns give the results for the test that the means for the intraday and end of day returns are significantly different from zero. We cannot reject the null hypothesis of a zero mean intraday return for any of the stocks in our sample, but we can reject the null for the end of day returns in eight of our fifteen companies. These companies also exhibit a statistical difference between the means of the two periods, thereby providing some evidence for a mixture of distributions model based on different means. However, as can be seen from the table, there is very strong evidence that the major difference between these two periods is in the variance. The results of these tests indicate rejection of the null hypotheses in all cases. Hence, there is very strong evidence of a

non-stationary unconditional variance in the return series for the entire sample and an indication that standard estimation techniques are not appropriate.

In Table 3-5, we examine the degree of autocorrelation in the mean while also checking for non-linear dependence, or dependence in the variance. To accomplish this, we use the Ljung-Box statistics on the original returns r, the squared returns $r^2$, and the absolute returns $|r|$. The results for the original return series are in agreement with Bartlett's test, rejecting the null hypothesis of strict white noise in eleven out of the fifteen stocks. Hence, at least in terms of the actual return series, out of our sample of fifteen stocks, only DIG, DOW, PHI, and RJR exhibit a return-generating process that cannot be distinguished from a white noise process or one with no first order dependency.

We next turn to an examination of the degree of higher order dependency, in particular second-order. Since our previous tests indicated that the intradaily mean is not statistically different from zero, we use the sum of squared returns as an approximation for the variance. The results for the squared returns indicate that only in the case of DIG and PHI can we not reject the null hypothesis. This finding agrees with the lag-1 autocorrelation results in both the return and squared return series. In the case of the absolute returns, all of the stocks show a significant level of dependence in both tests. Hence, our results for the ten minute data indicate that a model capable of incorporating both linear and non-linear dependence is required.

## 2. Thirty minute data

We now turn to an examination of the thirty minute results. Generally it has been found that as the interval length over which returns are estimated is lengthened, the degree of autocorrelation and departures from normality exhibited by the data are reduced. We find the same effect for this group of stocks. For example, in looking at Table 3-6, we see that the degree of kurtosis for all but three stocks is reduced as we move from ten minute to thirty minute intervals. The same holds true when we look at the actual hypothesis tests for normality found in Table 3-7. For instance, the number of stocks for which the null hypothesis of zero skewness can be rejected drops from ten to six. Also Fisher's kappa statistic leads to a rejection of the white noise hypothesis in only one of the fifteen stocks and Bartlett's test rejects the null in six of the samples. However, the other tests for normality, the D-statistic and the *K* and *KS* statistics reject the null in all the cases. Hence, even at thirty minute intervals, the leptokurtosis in the return series is very evident. Also a quick check of the ratio of the variances between the ten and thirty minute intervals indicate that the thirty minute interval variances are only roughly twice as large as the ten minute ones, thereby rejecting not only the normality assumption but also that of a random walk.[19]

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[19] In order for the random walk hypothesis to be accepted the ratio must be around three. This concept will be further discussed in Chapter 6.

We next turn to Table 3-8 where we have the mean and variance effects based on the end of day dummy. We see that aggregation of the data has reduced the significance of the mean in distinguishing between the two periods. Only two of the stocks, DOW and RJR, exhibit any difference between the periods. On the other hand, the variance effect still exists in twelve of the fifteen stocks.

This leads to the tests for nonlinear dependence in Table 3-9. In terms of the original return series, we see from the Ljung-Box (LB) test that first order dependence is exhibited in only four of the stocks, but second order dependence, based on the results of the squared and absolute returns, remains strong in eleven of the stocks. The lag-1 autocorrelation results provide similar evidence with an indication that one period mean lags remain significant in eight of the cases and twelve of the stocks exhibit higher order dependence for at least lag-1.

In conclusion, the results of this chapter indicate that intraday returns exhibit not only first order dependence, as documented by previous authors, but also second order dependence. We also find that evidence exists to confirm both the finding of a non-stationary unconditional variance and a mixture of distributions hypothesis. However, because of the presence of higher order dependence, we conclude that any model of the return generating process for intradaily returns that assumes independence is inappropriate. We therefore examine in the next chapter a method for dealing with this problem.

TABLE 3-1
LIST OF COMPANIES

| | |
|---|---|
| AME | American Express |
| ATL | Atlantic Richfield |
| ATT | American Telephone and Telegraph |
| BAX | Baxter Travenol |
| BOE | Boeing |
| CHE | Chevron |
| DIG | Digital Equipment |
| DOW | Dow Chemical |
| GE | General Electric |
| GM | General Motors |
| ITT | International Telephone and Telegraph |
| MOB | Mobil |
| PAC | Pacific Gas & Electric |
| PHI | Phillips Petroleum |
| RJR | RJR Nabisco |

**TABLE 3-2**
**TEN MINUTE DATA**
**DESCRIPTIVE STATISTICS**

| | mean (0000) | std dev (00) | skew | kurt | med | IQR (00) |
|---|---|---|---|---|---|---|
| AME | .1841 | .4280 | .4273 | 2.937 | 0.00 | 0.677 |
| ATL | -.0144 | .2245 | .2488 | 3.681 | 0.00 | 0.273 |
| ATT | .4801 | .3349 | .0476 | 0.969 | 0.00 | 0.722 |
| BAX | .8356 | .4100 | .4867 | 2.635 | 0.00 | 0.000 |
| BOE | -.2386 | .2784 | -.1228 | 3.028 | 0.00 | 0.487 |
| CHE | -.6467 | .3059 | .2026 | 1.086 | 0.00 | 0.460 |
| DIG | .2512 | .2397 | .5763 | 3.827 | 0.00 | 0.263 |
| DOW | .9641 | .2792 | .0782 | 2.606 | 0.00 | 0.255 |
| GE | -.0219 | .3398 | -.1861 | 5.000 | 0.00 | 0.408 |
| GM | -.7355 | .2377 | -.3655 | 7.231 | 0.00 | 0.288 |
| ITT | .1510 | .2323 | -.0399 | 3.767 | 0.00 | 0.398 |
| MOB | -.4289 | .3392 | -.1801 | 4.746 | 0.00 | 0.501 |
| PAC | -.4133 | .5339 | -.1027 | 0.245 | 0.00 | 1.231 |
| PHI | .4258 | .2944 | .9781 | 8.840 | 0.00 | 0.224 |
| RJR | .1402 | .3634 | 1.1636 | 8.843 | 0.00 | 0.379 |

**TABLE 3-3**
**TEN MINUTE DATA**
**TESTS FOR NORMALITY AND WHITE NOISE PROCESSES**

| | D stat | *S* stat | *K* stat | *KS* stat | $\kappa$ | *B* |
|---|---|---|---|---|---|---|
| AME | .1905* | 27.88* | 325.20* | 353.08* | 6.033 | .1270* |
| ATL | .1907* | 9.45* | 511.46* | 520.91* | 6.217 | .0738 |
| ATT | .2424* | 0.35 | 35.07* | 35.42* | 6.490 | .1368* |
| BAX | .2611* | 36.17* | 261.78* | 297.95* | 6.360 | .1154* |
| BOE | .2017* | 2.30 | 345.77* | 348.08* | 7.802 | .1602* |
| CHE | .1782* | 6.26* | 44.18* | 50.44* | 6.712 | .1072* |
| DIG | .1081* | 50.71* | 552.83* | 603.54* | 5.813 | .0356 |
| DOW | .1275* | 0.93 | 255.92* | 256.85* | 6.595 | .0348 |
| GE | .1646* | 5.29* | 944.50* | 949.79* | 6.351 | .0773* |
| GM | .1732* | 20.39* | 1977.33* | 1997.72* | 5.087 | .0896* |
| ITT | .2110* | 0.24 | 535.67* | 535.91* | 7.680 | .0910* |
| MOB | .2044* | 4.95* | 850.96* | 855.91* | 5.420 | .0929* |
| PAC | .2376* | 1.61 | 2.15 | 3.76 | 11.025* | .2478* |
| PHI | .1257* | 146.06* | 2955.53* | 3101.59* | 6.938 | .0595 |
| RJR | .1609* | 206.71* | 2957.92* | 3164.63* | 9.165* | .0454 |

The critical values for the D-statistic at the 0.10, 0.05, and 0.01 significance level are .0270, .0295, and .0341 respectively. The $\chi^2(1)$ value for the *S* and *K* statistics at the 0.05 significance level is 3.84. The $\chi^2(2)$ value for the *KS* statistic is 5.99 at the 0.05 significance level. Fisher's kappa critical values are 8.302, 9.006, and 10.600, while Bartlett's test statistic has 0.05 and 0.01 critical values of .06418 and .07692 (An '*' represents significance at the 5% level.)

TABLE 3-4
TEN MINUTE DATA
TESTS FOR UNCONDITIONAL MEAN AND VARIANCE EFFECTS

| | MEAN EFFECT | | | VARIANCE EFFECT | | |
|---|---|---|---|---|---|---|
| | $H_0$: $\mu_i = 0$ | | $H_0$: $\mu_1 = \mu_2$ | $H_0$: $\mu_i = 0$ | | $H_0$: $\mu_1 = \mu_2$ |
| | means of returns (000) | | | means of variances (0000) | | |
| | 0 | 1 | | 0 | 1 | |
| AME | -.097 | 1.51 | | 0.144 | 0.682 | |
| | (0.67) | (2.89)* | (8.76)* | (11.02)* | (14.50)* | (121.12)* |
| ATL | -.032 | 0.40 | | 0.046 | 0.107 | |
| | (0.42) | (1.45) | (2.28) | (11.22)* | ( 7.30)* | ( 15.93)* |
| ATT | -.000 | 0.67 | | 0.098 | 0.299 | |
| | (0.00) | (1.64) | (2.49) | (15.25)* | (13.04)* | ( 71.68)* |
| BAX | -.006 | 1.25 | | 0.148 | 0.419 | |
| | (0.05) | (2.48)* | (5.78)* | (12.17)* | ( 9.59)* | ( 35.62)* |
| BOE | -.046 | 0.27 | | 0.065 | 0.238 | |
| | (0.49) | (0.75) | (0.78) | (11.40)* | (11.55)* | ( 65.23)* |
| CHE | -.079 | 0.12 | | 0.089 | 0.141 | |
| | (0.76) | (0.33) | (0.27) | (16.03)* | ( 7.03)* | ( 6.11)* |
| DIG | -.045 | 0.94 | | 0.049 | 0.161 | |
| | (0.56) | (3.19)* | (10.40)* | (10.72)* | ( 9.66)* | ( 41.79)* |
| DOW | 0.063 | 0.53 | | 0.067 | 0.223 | |
| | (0.66) | (1.54) | (1.72) | (11.91)* | (11.17)* | ( 57.28)* |
| GE | -.102 | 1.29 | | 0.096 | 0.366 | |
| | (0.89) | (3.10)* | (10.41)* | ( 9.40)* | (10.03)* | ( 50.87)* |
| GM | -.109 | 0.39 | | 0.050 | 0.142 | |
| | (1.35) | (1.35) | (2.78) | ( 8.60)* | ( 6.81)* | ( 18.13)* |
| ITT | -.062 | 1.02 | | 0.42 | 0.201 | |
| | (0.79) | (3.58)* | (13.42)* | (10.12)* | (13.33)* | (102.64)* |
| MOB | -.113 | 0.87 | | 0.092 | 0.416 | |
| | (0.98) | (2.08)* | (5.14)* | ( 9.35)* | (11.82)* | ( 78.63)* |
| PAC | -.044 | -.00 | | 0.272 | 0.451 | |
| | (0.24) | (0.00) | (0.00) | (18.75)* | ( 8.64)* | ( 10.93)* |
| PHI | -.039 | 1.10 | | 0.065 | 0.360 | |
| | (0.39) | (3.05)* | (9.24)* | ( 6.96)* | (10.62)* | ( 70.37)* |
| RJR | -.138 | 1.98 | | 0.092 | 0.650 | |
| | (1.12) | (4.48)* | (21.31)* | ( 6.56)* | (12.90)* | (113.93)* |

The corresponding t-statistics for the null hypotheses are presented in parentheses. The 0 columns represent the intraday results and the 1 columns the end of day results. (An '*' represents significance at the 5% level.)

TABLE 3-5
TEN MINUTE DATA
TESTS FOR NONLINEAR DEPENDENCE

| | LB(6) $r$ | LB(6) $r^2$ | LB(6) $\lvert r\rvert$ | AUTOCORRELATION FOR LAG-1 $r$ | $r^2$ | $\lvert r\rvert$ |
|---|---|---|---|---|---|---|
| AME | 35.71* | 22.53* | 49.14* | -.1878* | .1115* | .1537* |
| ATL | 16.76* | 82.32* | 104.15* | -.0696* | .1866* | .2175* |
| ATT | 51.95* | 19.40* | 21.76* | -.1908* | .1270* | .1129* |
| BAX | 28.06* | 14.29* | 30.45* | -.1700* | .0663* | .1257* |
| BOE | 49.87* | 50.85* | 71.22* | -.2241* | .0817* | .0814* |
| CHE | 32.26* | 63.51* | 33.66* | -.1478* | .1560* | .1050* |
| DIG | 8.18 | 7.28 | 50.60* | -.0320 | .0268 | .0978* |
| DOW | 5.02 | 89.06* | 100.34* | .0309 | .2154* | .2462* |
| GE | 14.83* | 172.15* | 133.29* | -.0906* | .3598* | .2764* |
| GM | 17.51* | 218.47* | 199.81* | -.1065* | .3725* | .2931* |
| ITT | 20.07* | 14.89* | 20.82* | -.1342* | .1209* | .1293* |
| MOB | 20.82* | 98.28* | 106.28* | -.1106* | .1643* | .2100* |
| PAC | 146.08* | 20.81* | 16.87* | -.3894* | .0884* | .0944* |
| PHI | 10.89 | 9.56 | 82.99* | -.0676* | .0277* | .1310* |
| RJR | 10.24 | 27.68* | 61.74* | .0255 | .1439* | .1585* |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. (An '*' represents significance at the 5% level.)

**TABLE 3-6**
**THIRTY MINUTE DATA**
**DESCRIPTIVE STATISTICS**

| | mean (0000) | std dev (00) | skew | kurt | med | IQR (00) |
|---|---|---|---|---|---|---|
| AME | .5272 | .6567 | .2256 | 1.454 | 0.00 | 0.691 |
| ATL | -.0413 | .3629 | .0920 | 3.238 | 0.00 | 0.283 |
| ATT | 1.3746 | .4982 | .1944 | 1.220 | 0.00 | 0.741 |
| BAX | 2.3922 | .6470 | .2489 | 1.977 | 0.00 | 0.889 |
| BOE | -.6831 | .3885 | -.3112 | 2.025 | 0.00 | 0.493 |
| CHE | -1.8513 | .4693 | .3902 | 1.546 | 0.00 | 0.471 |
| DIG | .7192 | .4042 | .1095 | 1.653 | 0.00 | 0.458 |
| DOW | 2.7602 | .5028 | -.0839 | 4.637 | 0.00 | 0.505 |
| GE | -.0626 | .5408 | -.3308 | 2.740 | 0.00 | 0.419 |
| GM | -2.1058 | .3704 | -1.0767 | 5.237 | 0.00 | 0.300 |
| ITT | .4322 | .3513 | -.1288 | 2.143 | 0.00 | 0.403 |
| MOB | -.1228 | .4913 | .1268 | 1.296 | 0.00 | 0.515 |
| PAC | -1.1831 | .5886 | -.2705 | 0.667 | 0.00 | 1.242 |
| PHI | 1.2190 | .4756 | .5377 | 3.496 | 0.00 | 0.439 |
| RJR | .4015 | .5670 | .8209 | 3.767 | 0.00 | 0.737 |

**TABLE 3-7**
**THIRTY MINUTE DATA**
**TESTS FOR NORMALITY AND WHITE NOISE PROCESSES**

| | D stat | *S* stat | *K* stat | *KS* stat | $\kappa$ | *B* |
|---|---|---|---|---|---|---|
| AME | .1325* | 2.70 | 26.69* | 29.39* | 4.334 | .1732* |
| ATL | .1348* | 0.45 | 134.38* | 134.83* | 4.611 | .1036 |
| ATT | .1933* | 2.00 | 18.69* | 20.69* | 5.342 | .1159* |
| BAX | .1908* | 3.28 | 49.73* | 53.01* | 4.053 | .1190* |
| BOE | .1736* | 5.13* | 52.18* | 57.32* | 3.958 | .1272* |
| CHE | .1152* | 8.07* | 30.19* | 38.26* | 6.322 | .1455* |
| DIG | .0915* | 0.63 | 34.62* | 35.25* | 9.240* | .0928 |
| DOW | .1011* | 0.37 | 276.53* | 276.90* | 5.143 | .0684 |
| GE | .1120* | 5.80* | 95.97* | 101.77* | 4.217 | .0586 |
| GM | .1349* | 61.44* | 353.06* | 414.50* | 4.304 | .0684 |
| ITT | .1496* | 0.88 | 58.49* | 59.37* | 4.934 | .0603 |
| MOB | .1348* | 0.85 | 21.15* | 22.00* | 4.412 | .0844 |
| PAC | .2245* | 3.88 | 5.44* | 9.32* | 5.755 | .1583* |
| PHI | .1072* | 15.32* | 156.72* | 172.04* | 5.670 | .0496 |
| RJR | .1227* | 35.71* | 182.12* | 217.83* | 4.371 | .0748 |

The critical values for the D-statistic at the 0.10, 0.05, and 0.01 significance level are .0456, .0498, and .0576 respectively. The $\chi^2(1)$ value for the *S* and *K* statistics at the 0.05 significance level is 3.84. The $\chi^2(2)$ value for the *KS* statistic is 5.99 at the 0.05 significance level. Fisher's kappa critical values are 7.230, 7.895, and 9.439, while Bartlett's test statistic has 0.05 and 0.01 critical values of .10785 and .12927 (An '*' represents significance at the 5% level.)

**TABLE 3-8**
**THIRTY MINUTE DATA**
**TESTS FOR UNCONDITIONAL MEAN AND VARIANCE EFFECTS**

| | MEAN EFFECT | | | VARIANCE EFFECT | | |
|---|---|---|---|---|---|---|
| | $H_0$: $\mu_1 = 0$ | | $H_0$: $\mu_1 = \mu_2$ | $H_0$: $\mu_1 = 0$ | | $H_0$: $\mu_1 = \mu_2$ |
| | means of returns (000) | | | means of variances (0000) | | |
| | 0 | 1 | | 0 | 1 | |
| AME | -.138 | 0.79 | | 0.326 | 0.833 | |
| | (0.33) | (0.97) | (1.04) | ( 6.74)* | ( 8.77)* | ( 22.69)* |
| ATL | .003 | -.00 | | 0.115 | 0.193 | |
| | (0.01) | (0.69) | (0.00) | ( 6.20)* | ( 5.27)* | ( 3.57) |
| ATT | .089 | 0.32 | | 0.222 | 0.346 | |
| | (0.28) | (0.53) | (0.12) | ( 8.04)* | ( 6.38)* | ( 4.17)* |
| BAX | .107 | 0.75 | | 0.334 | 0.743 | |
| | (0.26) | (0.94) | (0.51) | ( 6.52)* | ( 7.39)* | ( 13.15)* |
| BOE | -.058 | -.11 | | 0.118 | 0.274 | |
| | (0.24) | (0.23) | (0.01) | ( 6.40)* | ( 7.56)* | ( 14.63)* |
| CHE | -.053 | -.69 | | 0.203 | 0.285 | |
| | (0.18) | (1.20) | (0.98) | ( 7.96)* | ( 5.68)* | ( 2.15) |
| DIG | -.156 | 0.95 | | 0.129 | 0.296 | |
| | (0.62) | (1.92) | (3.97)* | ( 6.77)* | ( 7.93)* | ( 15.93)* |
| DOW | 0.339 | 0.03 | | 0.186 | 0.511 | |
| | (1.07) | (0.05) | (0.19) | ( 4.70)* | ( 6.56)* | ( 13.83)* |
| GE | -.140 | 0.51 | | 0.224 | 0.552 | |
| | (0.41) | (0.77) | (0.76) | ( 5.79)* | ( 7.26)* | ( 14.79)* |
| GM | -.173 | -.36 | | 0.115 | 0.223 | |
| | (0.74) | (0.78) | (0.13) | ( 4.96)* | ( 4.88)* | ( 4.40)* |
| ITT | -.011 | 0.25 | | 0.092 | 0.244 | |
| | (0.05) | (0.58) | (0.30) | ( 6.07)* | ( 8.23)* | ( 20.95)* |
| MOB | -.203 | 0.19 | | 0.190 | 0.437 | |
| | (0.66) | (0.31) | (0.33) | ( 7.17)* | ( 8.38)* | ( 17.80)* |
| PAC | -.051 | -.38 | | 0.322 | 0.435 | |
| | (0.14) | (0.52) | (0.16) | ( 9.13)* | ( 6.27)* | ( 2.08) |
| PHI | -.062 | 0.83 | | 0.172 | 0.432 | |
| | (0.21) | (1.42) | (1.86) | ( 5.30)* | ( 6.77)* | ( 13.18)* |
| RJR | -.303 | 1.36 | | 0.233 | 0.660 | |
| | (0.86) | (1.97)* | (4.59)* | ( 4.96)* | ( 7.15)* | ( 17.06)* |

The corresponding t-statistics for the null hypotheses are presented in parentheses. The 0 columns represent the intraday results and the 1 columns the end of day results. (An '*' represents significance at the 5% level.)

TABLE 3-9
THIRTY MINUTE DATA
TESTS FOR NONLINEAR DEPENDENCE

| | LB(6) | LB(6) | LB(6) | AUTOCORRELATION FOR LAG-1 | | |
|---|---|---|---|---|---|---|
| | r | $r^2$ | $\lvert r \rvert$ | r | $r^2$ | $\lvert r \rvert$ |
| AME | 20.12* | 19.13* | 30.92* | -.2063* | .2123* | .2762* |
| ATL | 10.04 | 28.69* | 37.64* | -.1326* | .2062* | .2351* |
| ATT | 8.52 | 14.34* | 5.46 | -.1310* | .0679* | .0687 |
| BAX | 10.39 | 10.13 | 19.85* | -.1416* | .1676* | .2134* |
| BOE | 12.47 | 23.31* | 24.83* | -.1680* | .2042* | .2144* |
| CHE | 39.12* | 34.59* | 31.52* | -.1910* | .1802* | .2650* |
| DIG | 7.09 | 14.24* | 16.90* | -.0356 | .1405* | .1081* |
| DOW | 4.55 | 13.33* | 35.02* | .0484 | .1811* | .2600* |
| GE | 6.34 | 23.83* | 23.46* | -.0545 | .2087* | .1253* |
| GM | 7.05 | 20.55* | 11.18 | -.0667 | .1002* | .0933 |
| ITT | 3.67 | 5.91 | 5.89 | -.0768 | .0863 | .0914 |
| MOB | 9.58 | 19.88* | 22.92* | -.0732 | .1874* | .1845* |
| PAC | 17.08* | 8.22 | 4.31 | -.1935* | .0343 | -.0023 |
| PHI | 2.72 | 5.10 | 11.17 | -.0298 | .1078 | .1513* |
| RJR | 11.28* | 1.80 | 4.92 | -.0644* | .0237 | .0448 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. (An '*' represents significance at the 5% level.)

## CHAPTER 4

## MODEL ESTIMATION

The finding of non-linear dependence in intradaily returns requires us to use a more general class of processes than standard linear time-series models, such as the autoregressive moving average (ARMA) processes of Box-Jenkins. It also rules out a number of processes used previously in the literature to model security returns, such as the Stable-Paretian, Student-t, and mixture of normals.

Priestley (1980) offers a general state dependent approach for handling non-linearities that includes the bilinear model of Granger and Anderson (1978) and the exponential autoregressive model of Haggan and Osaki (1981). We choose to employ a variant of the bilinear processes known as the autoregressive conditional heteroskedasticity (ARCH) model, since its estimation techiques are well developed. Also, the ARCH model has been proven suitable for modelling the time series properties of returns for longer sampling intervals, such as a day or week.

In the first section of this chapter, we introduce the theory behind both the ARCH model and the more general GARCH model. In the second section, we discuss the specific formulations and rationale for using the conditional distributions, which include the normal, Student-t, and power-exponential. We also introduce the particular classes of ARCH and GARCH and the criterion we use for selecting the model that best fits the data. In the final section, we present our results and a discussion of their implications for the return generating process of stock returns.

## A. ECONOMETRIC THEORY

Engle (1982) first introduces the ARCH model as a means for dealing with a non-stationary variance and second order dependency. He specifically expresses the conditional variance as a function of past values of the random variable. He points out that the conditional means and variances may evolve jointly over time, thereby requiring simultaneous estimation. His ARCH(q) model has the following form:

$$r_t | \Psi_{t-1} \sim N(x_t B, h_t)$$
$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2$$
$$e_t = r_t - x_t B,$$

where $\Psi_{t-1}$ is the information set at time t-1, $x_t$ is the vector of independent variables, the $\alpha$'s and B's are vectors of unknown parameters with $\alpha_0 > 0$ and $\alpha_i \geq 0$, and $h_t$ is the variance of the errors. The conditional distribution of $r_t$, or $r_t | \Psi_{t-1}$, and $e_t$ are assumed to be normal.

Engel makes a number of comments concerning the specification of the conditional variance or $h_t$. First, he notes that large observations, in absolute value, will lead to a larger variance for next period's distribution. Secondly, if the coefficient of the squared lag value is positive, i.e. $\alpha_i > 0$, then successive observations are dependent through higher moments. Thirdly, the first order process will generate fatter tails for the unconditonal distribution than the normal. And lastly, the temporal clustering of outliers may be used to predict their occurrence. The first and third comments arise from the expressions for the

unconditional variance and kurtosis of the error term, $\epsilon_t$. For instance, given q=1, the unconditional variance of $\epsilon_t$ is $\sigma^2$, which equals $\alpha_0(1-\alpha_1)^{-1}$ [See Engle (1982), p. 992]. We can then write $h_t-\sigma^2$ as $\alpha_0(\epsilon^2_{t-1}-\sigma^2)$; therefore the conditional variance is greater than the unconditional variance whenever the squared error last period is greater than its unconditional expectation.[20] Thus, in the same spirit as Mandelbrot's Stable Paretian hypothesis, Engle presents a model that incorporates some of the empirical properties found in the data.

Maximum likelihood estimates of the unknown parameters are based on the sum of the conditional log likelihoods. Denoting $l_t$ as the log likelihood of the $t$th observation and n as the sample size, we have

$$L = 1/n \sum_{t=1}^{n} l_t \text{ , where}$$

$$l_t = -\tfrac{1}{2}\ln(h_t) - \tfrac{1}{2}\epsilon_t^2 h_t^{-1} - \tfrac{1}{2}\ln(2\pi).$$

First and second order derivatives of the function produce the gradient and the information matrix, respectively. Engle demonstrates the block diagonality of the information matrix under suitable symmetric and regularity conditions and shows that any qth order ARCH model satisfies

[20] Engle also derives the formula for the unconditional kurtosis of the first order ARCH process. It is equal to:

$$3\sigma^4 \frac{(1-\alpha_1^2)}{(1-3\alpha_1^2)}$$

Since, the kurtosis of the normal distribution is equal to $3\sigma^4$ the value for the first order ARCH process is always greater than the normal, hence the fat tails in the unconditional distribution.

the regularity conditions if $\alpha_0$ is greater than zero and the $\alpha_i$'s are greater than or equal to zero.[21]

We use an iterative estimation procedure based on the algorithm of Berndt, Hall, Hall, and Hausman (1974) to obtain the maximum likelihood estimates of the $\alpha$'s and B's. This algorithm provides a numerical solution for the first derivatives of the likelihood function with the iterations for the $\alpha$'s and B's being carried out separately because of the block diagonality of the information matrix. Each step produces parameter estimates $\theta^{i+1}$ based on the preceding estimates according to

$$\theta^{i+1} = \theta^i + \lambda_i \left[ \sum_{t=1}^{n} [(\partial l_t/\partial\theta)(\partial l_t/\partial\theta')]\right]^{-1} \sum_{t=1}^{n} \partial l_t/\partial\theta$$

where the $\partial l_t/\partial\theta$ is evaluated at $\theta^i$, the parameter estimates for the i$^{th}$ step, and the $\lambda_i$ is the step length. Three convergence criterion are used. The first is based on the gradient around the inverse of the Hessian matrix, which can be interpreted as the remainder of a Taylor series expansion around the estimated maximum. The second is the change in the calculated log likelihood function and the third is the change in the gradient for each iteration. Weiss (1986) demonstrates the consistency and aysmptotic normality of the maximum likelihood estimates. Hence, standard t-statistics are used to test whether the parameters are significantly different from zero.

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[21] Proofs of these theorems can be found in the appendix of Engle (1982).

Bollerslev (1986) respecifies the ARCH process in terms of a generalized autoregressive conditional heteroskedasticity or GARCH model. He points out that most applications of ARCH have used a linear lag structure, while GARCH will allow for a more flexible one. In the same manner that the ARMA model is a generalization of the AR model for the mean or first moment, so is the GARCH a generalization of ARCH for the variance or second moment. Hence, just as the autocorrelation and partial autocorrelation functions are useful in identifying and checking the times series behavior of the ARMA process for the conditional mean, the same procedure can be used on the squared process for checking and identifying GARCH behavior in the conditional variance. Whereas the ARCH process specifies the conditional variance as a linear function of past sample variances only, the GARCH(p,q) process includes lagged conditional variances as well. Hence, this allows for the possibility of an adaptive learning mechanism based on the past conditional variances.

Bollerslev's generalized autoregressive conditional heteroskedasticity (GARCH) model has a conditional variance equation of:

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

where $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$, and $\beta_i \geq 0$. He notes that for 'p=0 the process reduces to the ARCH(q) process, and for p=q=0 $\epsilon_t$ is simply white noise.'[22] When $\sum_{i=1}^{q}\alpha_i + \sum_{i=1}^{p}\beta_i < 1$ the process is considered stationary and the unconditional variance of the $\epsilon_t$'s is defined as $\alpha_0/(1-\Sigma\alpha_i-\Sigma\beta_i)$ [See Bollerslev (1986)]. Maximum likelihood estimates of the regression

[22] Bollerslev (1986), p.309.

parameters for both the mean and variance equations are obtained using the same iterative procedure outlined above for the ARCH model.

Bollerslev's (1987) second contribution concerned the specification of the conditional density. By allowing for t-distributed conditional errors, he points out that this 'permits a distinction between conditional heteroskedasticity and a conditional leptokurtic distribution, either of which could account for the observed unconditional kurtosis in the data.'[23] This distinction plays an important role in the model's ability to fit the observed data, a point we will discuss further in the following section.

## B. MODEL SPECIFICATION

Since part of our work concerns the differences that existence in the returns based on ten and thirty minute sampling intervals, we employ four basic estimation models with three different conditional distributions. Our first model assumes that there is no nonlinear dependence while still retaining the linear dependency through the use of a moving average process of order one, denoted MA(1). This is consistent with the findings in Chapter 3, where some of the thirty minute returns exhibited little evidence of higher order dependency. The three remaining models all take account of the nonlinear dependence and are denoted as an ARCH(1), ARCH(2), and a GARCH(1,1) process respectively.

[23] Bollerslev (1987), p.542.

In the same manner, we include three conditional distributions to account for the moment structure of the ten and thirty minute return series. These are the normal, Student-t, and power-exponential distributions. Within each model, we first estimate the parameters based on the assumption of conditional normality. This is the original specification of the ARCH process developed by Engle. The formula for the normal conditional density is:

$$N(e_t,h_t) = (2\pi h_t)^{-.5} \exp[-.5(e_t^2)/h_t].$$

The second specification of the conditional density is the Student-t with reference to Bollerslev (1987). The conditional density is defined as:

$$T(e_t,h_t,df) = \Gamma[k]\cdot\Gamma[df/2]^{-1}\cdot[(df-2)h_t]^{-.5}\cdot[1+e_t^2/(h_t(df-2))]^{-k},$$

where $\Gamma[\cdot]$ is the gamma function, df are the degrees of freedom with the restriction that they be greater than two, and $k=(df+1)/2$. Note that as $1/df\to 0$ the t-distribution approaches the normal. Connolly (1989) suggests that for $df>30$ and $\alpha_i$, $\beta_i>0$, time-varying heteroskedasticity explains the leptokurtosis, while if $df<10$, then both non-normality and time-varying heteroskedasticity are possible explanations. However, this observation seems to be more a rule of thumb rather than based on any statistical theory, since traditionally the Student-t is assumed to approach normality at approximately 30 degrees of freedom.

The third distributional assumption we use results from Nelson's (1989) extension of the GARCH model with a conditional density based on the Generalized Error Distribution (GED) or the power-exponential (PE) distribution as defined by Box and Tiao (1973). Its distributional form is:

$$PE(e_t,h_t,df) = .5df\cdot[\Gamma(3/df)]^{.5}\cdot[\Gamma(1/df)]^{-1.5}\cdot h_t\cdot$$
$$\exp(-[\Gamma(3/df)/\Gamma(1/df)]^{df/2}\cdot|e_t/h_t|^{df}),$$

where df are the degrees of freedom. If df=2 we have the normal distribution, while df=1 gives us the double exponential. Box and Tiao (1973) note that (2/df)-1 gives a measure of kurtosis.

Figure 4-1 provides a graphical representation of the differences between these three distributions. There are several important points to note. The first is that where as the Student-t approaches the normal from below, the power-exponential approaches it from above. Hence, in reference to Fama's (1965a) discussion on the peakedness of his daily data [see footnote 8], the power-exponential would seem a priori to provide a better fit to daily data than the Student-t. By reversing our inferences about aggregated daily returns approaching normality, we can argue that intradaily returns should exhibit even greater peakedness while still retaining the leptokurtosis. The second point is that the power-exponential has a large part of its density at the mid-point of the distribution. This is generally consistent with a large number of returns at zero. In fact a comparison of the distributions in Figure 4-1 indicates that the power-exponential with one degree of freedom has

roughly 12.4% of its distribution ± 0.05 standard deviations from the mean as compared to 7.4% for the normal, and 7.1% for the Student-t with 5 degrees of freedom. The last point concerns the distribution of the tail regions. The Student-t distributions exhibit fatter tails than the normal at approximately 1.7 standard deviations from the mean while the power-exponential distributions cross over at about 2.3 standard deviations. Hence, both the Student-t and power-exponential distributions are considered leptokurtotic with the extent depending on their respective degrees of freedom. For the Student-t and the power-exponential distributions the appropriate degrees of freedom are estimated in the maximum likelihood algorithm.

In terms of the actual models we estimate, we retain the two dummy variables discussed in Chapter 3 in both the mean and variance equation. As mentioned, one represents the component of the return (or conditional variance) which results from the bid-ask spread and the other is an end of day dummy. The mean equation also contains a moving average term to account for the autocorrelation found in the mean. Our general mean equation is denoted by:

$$r_t = a_0 + a_1 EOD + a_2 AD + a_3 e_{t-1} + e_t,$$

where the $r_t$ are the ten or thirty minute returns, $a_0$ is the mean intercept, EOD is the end of day dummy, AD is the ask dummy, $e_{t-1}$ represents the moving average process, and $e_t$ are the residuals. The conditional distributions of the residuals include the normal, Student-

t, and power-exponential. This equation represents our basic model that we denote as MA in the ensuing tables.

The variance equation has three functional forms depending on the degree of the ARCH process. The first is the ARCH of order one denoted as AR(1):

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_2 EOD + \beta_3 AD$$

The second if the ARCH of order two denoted as AR(2) with the following specification:

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \beta_2 EOD + \beta_3 AD$$

And the last is the GARCH(1,1) denoted as G(1,1):

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^{½} + \beta_1 h_{t-1} + \beta_2 EOD + \beta_3 AD$$

Since the actual estimation requires the testing of a number of alternative models, likelihood ratio tests are used to determine which nested model fits the data better. The simple MA process is nested within the conditionally normal family, which is in turn nested within either the Student-t or power-exponential distributions. As noted by Akgiray (1989), the test statistic is defined as:

$$LR = -2\{L(\theta_n) - L(\theta_a)\},$$

where $\theta_n$ and $\theta_a$ are the parameter estimates under the null and alternative hypothesis respectively and the $L(\cdot)$ are the corresponding maximum log-likelihood values. The statistic is asymptotically $\chi^2$ distributed with the degrees of freedom equal to the difference between the number of parameters under the alternative and null hypotheses [See Akgiray (1989), p. 68]. Since the Student-t and power-exponential distributions are estimated separately a different test is required to determine the best model among them.[24] We choose the Pearson $\chi^2$ goodness of fit test discussed in Chapter 3 since it provides a statistical comparison of the theoretical distribution based on the estimated parameters and the empirical distribution of the standardized residuals, $e_t/h_t^{1/2}$ or $r_t$. We also examine the standardized residuals to determine how well the final models have eliminated the first and second order dependencies found in the original data.

## C. ESTIMATION RESULTS

### 1. Ten minute data

We begin our discussion with the ten minute data. Table 4-1 provides the log-likelihood values for the four models with the normally distributed conditional errors. The underlined values indicate those models with the highest log-likelihood based on the likelihood ratio test. As can be seen in the table, the simple MA model never does better

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[24] McDonald and Newey (1988) show that the power-exponential and the Student-t are included in a more general family of distributions known as the generalized t or GT. This possibility will be pursued in future work.

than the ARCH models indicating that higher order dependence is present in all the stocks. Table 4-2 has the corresponding $\chi^2$ values. They indicate that the normal distribution provides a poor fit for all the ten minute return series since in all cases the null hypothesis is rejected at the .05 significance level.

We next turn to the Student-t distribution and the log-likelihood and $\chi^2$ values found in Tables 4-3 and 4-4 respectively. Again the evidence suggests that higher order dependency can be found in the data since the MA model is superseded by the other three. The Student-t models also provide a better fit to the data than the normal in 43 of the 60 cases, however we still find that the null hypothesis of a good fit is rejected in all cases. Hence, even though the fat-tailed Student-t distribution does better than the normal it still is unable to provide a very good fit to the data.

We then look at the results for the power-exponential. We again find that the simple MA model is out performed by the other three. We also find that the power-exponential begins to address the empirical data a little better. However in only one case, DIG, are we unable to reject the null hypothesis at the .05 level. We will address this issue in more detail later after we have determined the best model out of the ones we have tested.

In order to determine the best model out of the twelve possible cases, we first use the likelihood ratio test to determine the best models for each conditional distribution. These results are found in Table 4-7. The results are dominated by the GARCH(1,1) and ARCH(2) model. Since the normal results are nested within both the Student-t and

power-exponential we are able to directly compare the log-likelihoods to determine if the normal is better than the other two. The evidence suggests that only PAC returns exhibit a conditionally normal distribution. This result confirms the normality tests of Table 3-3 since this is the only stock where the Kiefer-Salmon tests for normality could not reject the null hypotheses. Because the estimation algorithm does not use a procedure that allows joint estimation of the Student-t and power-exponential distributions, we turn to the $\chi^2$ results to determine the best model. Based on these results we find that in the case of AME, ATT, BOE, ITT, and MOB the Student-t distribution out performs the power-exponential. In the other nine cases the power-exponential is the better model.

Hence, up to this point, we have found that ten minute return data exhibit non-linear dependency and in general conditional leptokurtosis. The evidence also indicates that our assumption about the peakedness of the data is confirmed in nine out of the fifteen stocks sampled. However, we do not find strong evidence in support of a single conditional distribution that is able to model the ten minute return series. We next examine the estimation results for our fifteen stocks based on the best models in Table 4-7.

Table 4-8 contains the parameter estimates for the mean and variance equations. We first examine the mean equation. The two results that immediately stand out are the significant coefficients for the ask dummy, $a_2$, and the moving average dummy, $a_3$. In all cases, these parameters are significantly different from zero further documenting the effect of the bid-ask spread on the observed returns for short time

intervals. In fact, the sign of the coefficients are all in agreement with previous work, with the negative moving average coefficient lending credence to Roll's (1984) hypothesized result concerning the bid-ask spread creating negative serial correlation in the observed returns. The results for the end of day dummy, $a_1$, are less definitive with nine of the stocks showing no effect on the mean return and six showing an effect. These results are in general agreement with those of Table 3-4 where we looked at the effects of the end of day dummy on the unconditional mean and variance. The indication is that there is an end of day effect in the mean but it is not universal to all stocks. We next examine the results for the variance equation.

The first points of interest are the parameters for nonlinear dependence given by $\alpha_1$, $\alpha_2$, and $\beta_1$. All of these coefficients are significantly different from zero except $\alpha_1$ for ITT. In every case the sums are always less than one, indicating a stationary process. In general, the Student-t and normal models have lower measures of persistence in the variance than the power-exponential results. However, there seems to be no definitive pattern in the behavior. The results indicate that ARCH effects do exist in the returns of ten minute intervals.

Further information is obtained by looking at the end of day, $\beta_3$, and ask, $\beta_4$, parameters. Of particular interest is the fact that the end of day parameters are all significantly different from zero. This is in agreement with the results of Table 3-4 on the unconditional variances. Hence, this evidence collaborates previous work by Harris (1989) and Wood et. al. (1985) on the differences between end of day and intradaily

returns. It also extends the literature by finding that the end of day effect is more likely to be found in the variance than in the mean. The ask dummy is less conclusive with six of the stocks showing insignificant results. Hence, the bid-ask effect seems to be predominately in the mean with some stocks exhibiting dependency in the conditional variance. The last column is Table 4-8 provides the estimated degrees of freedom for the conditional distributions. The power-exponential results indicate a high degree of peakedness, while three of the other six stocks are very close to a conditionally normal distribution.

In our last two tables we check the distributional and time series properties of the standardized residuals in order to determine (1) where the models fail to fit the empirical conditional distributions and (2) whether the models eliminate the first and second order dependence in the data. From Table 4-9 we see that the skewness in the data is not significantly different from zero in ten out of the fifteen stocks based on the *S* statistics. However, it may explain some of the high $\chi^2$ values in those stocks where there is evidence of skewness, such as ITT and RJR. Three of these stocks also exhibit a higher measure of skewness in the residuals than in the original data.[25] On the other hand, our measures of kurtosis are all in agreement with the estimated models since PAC is the only one with no evidence of leptokurtosis.

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[25] Hsieh (1989b) argues that the skewness and kurtosis of the standardized residuals should be smaller than those of the raw data if the coefficients of the mean equation are very small. A large increase in the absolute size of those two moments is then seen as evidence against the model.

In the last two columns of Table 4-9, we attempt to ascertain where the models fail to fit the empirical distributions. Since the total $\chi^2$ measure is a sum of k independent $\chi^2$s each of degree one, we sum the corresponding estimates of the $\chi^2$ for the tail and mid-point regions of the distributions, respectively. In eleven out of the fifteen samples, we cannot reject the null hypothesis of an adequate fit in the tail regions and in eight out of the fifteen we cannot reject the null in terms of adequate fit over the mid-region of the distribution. In fact in seven out of the fifteen stocks, both the tail and mid-point regions are in agreement with their respective null hypotheses. Hence, the models for the ten minute intervals are doing a better job of fitting both the leptokurtosis and the peakedness of the data then we originally thought. This raises the possibility that a mixture of distributions with non-linear dependence may in fact be the true underlying process generating the returns.

In Table 4-10, we find that the estimated models do a fairly good job of eliminating the higher order dependence in the data. In nine of the stocks no evidence remains for either first order or second order dependence based on both the Ljung-Box test and lag-1 autocorrelation statistics. In two of the remaining six the only evidence for dependency is in the absolute residuals and in two of the others there is dependence only in the mean. Interestingly, this first order dependence arises in two out of the three stocks where no such dependence existed in the original data. Hence, the use of a general moving average process of order one for all of the stocks may be inappropriate.

In conclusion, we find that the power-exponential conditional distribution with a GARCH(1,1) process is the model that best fits the ten minute return series for the majority of the stocks in our sample. However, the evidence suggests that a more appropriate specification of the process is a mixture of distributions based on a model capable of incorporating nonlinear as well as linear dependence. We shall attempt to address this issue in future research. We now turn to an examination of the thirty minute results.

### 2. Thirty minute data

Table 4-11 provides the log-likelihood values for the four models with normally distributed conditional errors. As opposed to the ten minute results, the simple MA model does better than any of the ARCH models for three of the stocks indicating that higher order dependence may have been eliminated through the aggregation of the data. An examination of Table 4-12 shows that the $\chi^2$ values are generally lower for the thirty minute returns than for the corresponding ten minute ones but are not significant in only three of the possible cases.

The Student-t results in Tables 4-13 and 4-14 indicate that a simple MA model fits several of the stocks better than any of the ARCH models. The $\chi^2$ tests indicate that the null hypothesis of a good fit is rejected in every case for the Student-t models. However, the fit seems to be better overall for the thirty minute data than the ten minute data. The results for the power-exponential distribution are reported in Tables 4-15 and 4-16. An additional stock, ATT, is added to the list of

stocks where the simple MA model fits better than the ARCH models. Hence, there are very strong indications that unconditional leptokurtosis is a result of the conditional leptokurtosis and not of any heteroskedasticity in the data. We will examine this issue in more detail later. The $\chi^2$ results in Table 4-16 indicate that the power-exponential still holds the highest possibility for fitting the data since nine of the cases cannot reject the null hypothesis concerning the goodness of fit.

We next determine the best models for the data based on the likelihood ratio test and the $\chi^2$ goodness of fit results. Table 4-17 indicates that three of the fifteen thirty minute returns are best modelled as conditionally normal distributions. These are the returns for AME, CHE, and PAC. If we look back at Table 3-7 we see that all exhibited excess kurtosis, but only CHE rejected the null hypothesis of no skewness. The evidence in Table 3-9 shows that nonlinear dependence existed in the AME and CHE series but not in the PAC returns. This is in agreement with the estimated models since the first two are a GARCH(1,1) and an ARCH(2) respectively, while the third is a simple MA. Interestingly both AME and CHE had the lowest estimated degrees of freedom for their respective models in the ten minute results while PAC already exhibited normality. Therefore there is agreement between the two time series in terms of the gradual move to normality as the returns are aggregated. Also of note is that AME remained a GARCH(1,1), CHE became an ARCH(2), and PAC a simple MA as we aggregated the results. So there is a movement toward normality not only in the shape of the distribution but also in the loss of nonlinear dependence.

The Student-t distribution yields the best model for three stocks, ATT, BAX, and ITT. The ten minute results for ATT indicated a GARCH(1,1), with the thirty minute results indicating an ARCH(2). It retained the general distributional shape while exhibiting less second order dependence. The BAX returns, on the other hand, flatten out from a power-exponential to a Student-t while still keeping the estimated GARCH(1,1) albeit lower in magnitude. Lastly, the ITT results indicate the same general shape for both the ten and thirty minute intervals, while losing their nonlinear dependence all together in the thirty minute returns. Hence, the pattern developing is that each stock has its own empirical characteristics with the aggregation leading to a reduction in the nonlinear dependence and/or a shift toward conditional normality.

Nevertheless, as was found for the ten minute results, the power-exponential continues to provide the best fit, in this case for nine of the fifteen stocks. However, the results for two stocks, BOE and MOB, are contrary to our previous observation. BOE goes from an ARCH(2) to an ARCH(1) but actually becomes more peaked as it is aggregated. One possible explanation for this behavior is that the high first order negative autocorrelation in the mean for the ten minute data was cancelling out in the larger returns and creating more returns close to zero as they were aggregated. There seems to be no way to predict this peculiar behavior and for now we simply document it as an idiosyncrasy of that particular stock. In the case of MOB, not only do the returns become more peaked but they also have a greater degree of nonlinear dependence. However, the significance of that nonlinear dependence is

called into question by the fact that its parameter estimate is not significantly different from zero. We discuss this further in the next section. The remaining stocks all exhibit the same general behavior mentioned previously. For instance ATL, GE, and CHE go from a GARCH(1,1) to an ARCH(2) with the last stock becoming normal as noted above. Three stocks, DIG, DOW, and RJR remained power-exponential GARCH(1,1) for both return series, while GM and PHI went from a power-exponential GARCH(1,1) process to a power-exponential MA process.

We next examine the estimated parameters in Table 4-18 alluded to briefly in the prior discussion of the MOB results. The first point of interest is the lack of explanatory power for our two dummy variables in the mean equation. In only two cases, DIG and GE, is coefficient for the end of day dummy significantly different from zero at the .05 significance level and in none of the stocks is the ask dummy coefficient significant. This last point is especially striking since the coefficient for the same dummy was significantly different from zero in every one of the stocks in the sample over the ten minute return interval. Hence, we can infer that the direct effect of the specialist's bid-ask spread on the return series is mitigated by the time thirty minutes have passed. We emphasize the above as a direct effect since for nine of the stocks there is still a significant moving average component to the mean; hence, there may still exist some indirect influence from the bid-ask spread on the return generating out to thirty minutes.

Turning to the variance equation, we see that the end of day dummy still remains strong out to thirty minutes in nine of the fifteen stocks. The ask effect is totally removed in every stock but BAX. Hence,

there is little evidence for the specialist's bid-ask spread significantly affecting the return generating process after thirty minutes have passed. We next examine the parameters measuring the nonlinear dependence, specifically $\alpha_1$, $\alpha_2$, and $\beta_1$. We find there is evidence of second order dependence but it is not always significant at the .05 significance level. Several of the stocks show a significant p=2 ($\alpha_2$) or a q=1 ($\beta_1$) but an insignificant $\alpha_1$. Yet, as we already demonstrated with the use of the simple MA process, when these variables are removed, the model does worse, as measured by the likelihood ratio statistic. The only stocks where there is definitive evidence of ARCH or GARCH effects in the return series are AME, ATL, and CHE. This result suggests that the nonlinear dependence found in the returns using the Ljung-Box or autocorrelation results of Chapter 3 may be of a different form than that modelled here. For instance, Nelson (1989) suggests an exponential ARCH model as an alternative to the standard specification of the conditional variance equation. That possibility will be pursued in later work. The last column in Table 4-18 indicates that several of the stocks still have a peaked midpoint based on the estimated degrees of freedom for the power-exponential distributions. Overall, our results indicate that the ARCH or GARCH effects present in the ten minute time series has been reduced by aggregating to thirty minute intervals.

We examine the fit of the models and whether the first and second order dependencies are eliminated from the return series in the last two tables. Table 4-19 provides the skewness and kurtosis of the standardized residuals along with the Kiefer-Salmon *S* statistic in the

first three columns. Only three stocks have a measure of skewness significantly different from zero. In terms of the kurtosis, four of the stocks have a higher value for their residuals than for the original data. This is perceived as evidence against the model. For three of the stocks, the hypothesized distribution is not rejected using the total $\chi^2$ goodness of fit value. They are DIG, PHI, and RJR. Hence, at least in terms of this test, the thirty minute data do better than the ten minute, where only the model for DIG could not be rejected. Looking at the fit of the tails and midpoint we find that all but one model, ITT, do well in fitting the tails of the distribution, but only four stocks replicate that result with the midpoint. However, that failure does not seem to be the main reason for the lack of fit since most of the rejection continues to come from the other parts of the distribution. This agrees with our results from the ten minute data.

Given the previous discussion, it might be perceived that the thirty minute models are not capable of accurately portraying our particular sample of stocks. However, when we look at the the tests for nonlinear dependence we find that only in the case of GM were we unable to eliminate the higher order dependence and the first order dependence remains only in the case of CHE. Hence, the estimated models are capable of dealing with the time series properties of the data, but do not accurately portray the true distribution.

To summarize, we have found in this chapter that ten minute data show significant bid-ask effects in the mean with less influence being found in the variance. The end of day effect is much more pronounced in the variance than in the mean indicating a degree of volatility not

necessarily associated with the actual returns. This lends support to the French and Roll (1986) hypothesis that the trading process produces noise. The same data exhibit nonlinear dependency and both conditional and unconditional leptokurtosis, as well as peakedness in the distributions. On the other hand, the thirty minute data show a noticeable lack of bid-ask effects, except to the extent that the moving average term in the mean can be considered as such. The end of day effect continued to influence the variance of the returns much more than the mean. The noticeable difference in the two time intervals was the extent to which the shape of the distributions became more normal and the nonlinear dependence decreased as we aggregated the data.

These results raise several interesting questions. The first concerns the extent to which the end of day return can be perceived as simply the summation of all the intradaily returns. Given that there is some evidence of ARCH effects in daily stock returns, for example Lamoureux and Lastrapes (1990), and the degree to which the intradaily returns lose the nonlinear dependence, we hypothesize that the GARCH effects in the intradaily returns may result from a different process than that found in the daily returns. For instance, Lamoureux and Lastrapes found that by using volume as a proxy for the arrival of information, they were able to eliminate the significance of the ARCH parameters. The second question relates to the distributional assumptions and the evidence that a more appropriate model may in fact be a mixture of distributions. We can see from our results that the end and beginning of the day are different from the rest of the day. Harris (1989, 1987), Amihud and Mendelson (1987), and Wood, McInish, and Ord

(1985) have all documented this. However, it seems that the difference is much more pronounced in the variance than in the mean. Hence, the use of the conditional variances becomes a natural method by which to detect these differences and further investigate the behavior of returns as they are sampled from different parts of the day. For instance, does the end of day return series exhibit the same behavior as say a noon day return series? What are the implications for the literature on excess volatility in stock prices if we find that the end/beginning of the day process is much more volatile than that of the rest of the day and seems to be a function of investors reactions to the closing of the market? As we can see, such questions quickly lead to discussions of market structure and the most appropriate way to achieve an efficient allocation of resources. Hence, we seem to have returned, albeit tangentially, to the question of what influence the trading process has on the process that generates returns.

**FIGURE 4-1**
**PLOT OF THE NORMAL, POWER-EXPONENTIAL, AND STUDENT-T DISTRIBUTIONS**
**P=POWER(1.0), R=POWER(1.33), N=NORMAL, S=T(10), T=T(5)**

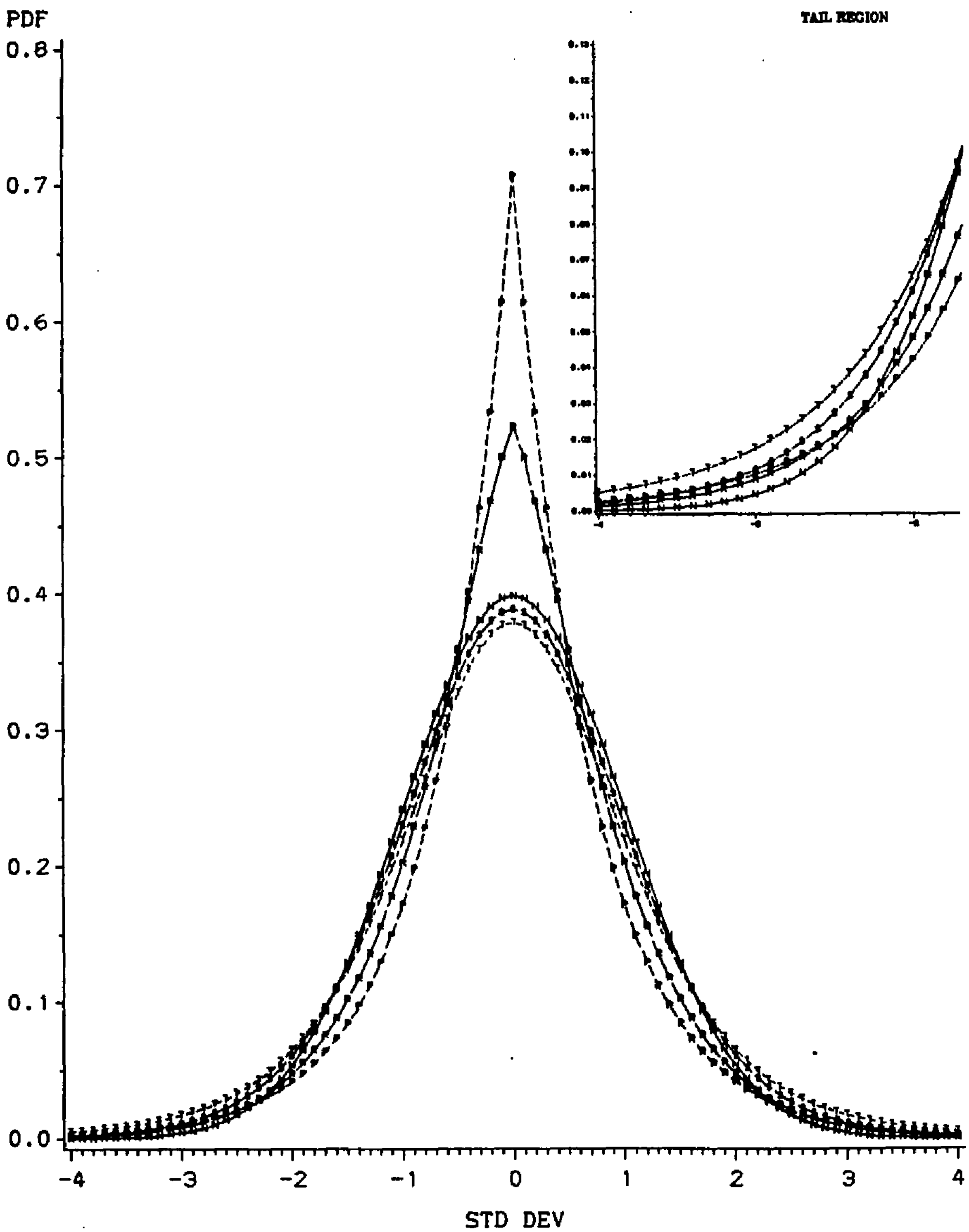


**TABLE 4-1**
**TEN MINUTE DATA**
**NORMAL DISTRIBUTION**
**LOG-LIKELIHOOD VALUES**

| | N-MA | N-ARCH(1) | N-ARCH(2) | N-GARCH(1,1) |
|---|---|---|---|---|
| AME | 3769.78 | 3772.72 | 3774.57 | <u>3780.08</u> |
| ATL | 4288.18 | 4322.05 | 4344.75 | <u>4370.91</u> |
| ATT | 3957.09 | <u>3966.54</u> | 3967.23 | 3962.30 |
| BAX | 3790.54 | 3805.65 | <u>3814.12</u> | 3807.99 |
| BOE | 4160.11 | 4162.74 | <u>4176.24</u> | 4157.17 |
| CHE | 4007.21 | 4023.69 | 4024.52 | <u>4031.39</u> |
| DIG | 4259.00 | 4263.85 | 4261.41 | <u>4273.06</u> |
| DOW | 4106.78 | 4132.91 | <u>4138.50</u> | 4124.07 |
| GE | 3948.47 | 4002.45 | 4007.27 | <u>4010.10</u> |
| GM | 4249.28 | 4312.11 | 4337.91 | <u>4338.82</u> |
| ITT | 4332.72 | 4333.44 | <u>4336.45</u> | 4330.33 |
| MOB | 3962.34 | <u>3987.09</u> | 3988.00 | 3979.55 |
| PAC | 3610.87 | 3616.46 | <u>3620.41</u> | 3599.09 |
| PHI | 4105.73 | 4120.10 | 4123.91 | <u>4125.06</u> |
| RJR | 3945.38 | 3961.01 | 3699.20 | <u>3979.15</u> |

The underlined figures denote the highest value based on the Likelihood Ratio test.

**TABLE 4-2**
**TEN MINUTE DATA**
**NORMAL DISTRIBUTION**
**$\chi^2$ VALUES**

| | N-MA | N-ARCH(1) | N-ARCH(2) | N-GARCH(1,1) |
|---|---|---|---|---|
| AME | 240.88 | 237.55 | 215.60 | 158.76 |
| ATL | 700.08 | 623.95 | 279.80 | 149.93 |
| ATT | 681.07 | 799.85 | 806.94 | 511.68 |
| BAX | 506.28 | 530.64 | 538.21 | 203.05 |
| BOE | 185.63 | 164.70 | 197.31 | 85.91 |
| CHE | 199.24 | 197.26 | 196.10 | 125.23 |
| DIG | 392.56 | 270.31 | 167.59 | 87.16 |
| DOW | 181.49 | 198.08 | 189.20 | 177.87 |
| GE | 755.85 | 626.55 | 640.11 | 181.53 |
| GM | 823.35 | 253.08 | 666.69 | 549.74 |
| ITT | 385.47 | 438.44 | 460.06 | 391.55 |
| MOB | 653.81 | 253.42 | 258.49 | 406.26 |
| PAC | 207.73 | 184.91 | 172.85 | 309.67 |
| PHI | 242.81 | 181.63 | 285.74 | 132.71 |
| RJR | 406.36 | 363.95 | 608.46 | 520.46 |

The $\chi^2(20)$ value at the .05 significance level is 31.41. A '#' indicates that the null hypothesis cannot be rejected.

TABLE 4-3
TEN MINUTE DATA
STUDENT-T DISTRIBUTION
LOG-LIKELIHOOD VALUES

| | T-MA | T-ARCH(1) | T-ARCH(2) | T-GARCH(1,1) |
|---|---|---|---|---|
| AME | 3776.87 | 3780.47 | 3781.06 | <u>3783.67</u> |
| ATL | 4309.89 | 4282.27 | 4377.71 | <u>4407.65</u> |
| ATT | 3961.79 | 3970.25 | 3970.92 | <u>3973.51</u> |
| BAX | 3797.54 | 3817.86 | <u>3824.57</u> | 3820.16 |
| BOE | 4167.63 | 4170.73 | <u>4181.05</u> | 4175.65 |
| CHE | 4024.44 | 4031.85 | 4032.90 | <u>4040.65</u> |
| DIG | 4284.14 | 4291.39 | 4292.81 | <u>4298.49</u> |
| DOW | 4143.91 | 4162.77 | <u>4167.33</u> | 4153.42 |
| GE | 4003.90 | 4020.61 | 4021.20 | <u>4024.18</u> |
| GM | 4298.86 | 4345.88 | 4359.22 | <u>4359.98</u> |
| ITT | 4339.97 | 4342.52 | 4343.73 | <u>4345.97</u> |
| MOB | 3992.77 | <u>4013.34</u> | 4014.34 | 4007.24 |
| PAC | 3610.41 | 3614.50 | <u>3617.17</u> | 3600.55 |
| PHI | 4152.32 | 4162.04 | 4165.19 | <u>4167.19</u> |
| RJR | 3983.16 | 3996.02 | <u>3999.93</u> | 3997.35 |

The underlined figures denote the highest value based on the Likelihood Ratio test.

TABLE 4-4
TEN MINUTE DATA
STUDENT-T DISTRIBUTION
$\chi^2$ VALUES

| | T-MA | T-ARCH(1) | T-ARCH(2) | T-GARCH(1,1) |
|---|---|---|---|---|
| AME | 204.88 | 204.26 | 216.56 | 184.86 |
| ATL | 264.95 | 259.06 | 426.14 | 296.31 |
| ATT | 581.54 | 620.62 | 650.92 | 384.21 |
| BAX | 461.46 | 498.07 | 540.05 | 154.94 |
| BOE | 192.29 | 145.69 | 144.87 | 109.31 |
| CHE | 122.58 | 143.56 | 113.46 | 105.49 |
| DIG | 86.35 | 117.56 | 123.78 | 91.99 |
| DOW | 123.88 | 161.08 | 148.78 | 113.12 |
| GE | 337.90 | 350.54 | 349.62 | 143.76 |
| GM | 381.27 | 356.91 | 229.35 | 192.44 |
| ITT | 462.99 | 467.05 | 591.24 | 418.81 |
| MOB | 428.55 | 305.23 | 295.97 | 403.03 |
| PAC | 191.47 | 189.93 | 203.42 | 244.45 |
| PHI | 196.30 | 171.11 | 204.60 | 114.32 |
| RJR | 442.88 | 422.836 | 547.62 | 230.89 |

The $\chi^2(19)$ value at the .05 significance level is 30.14. A '#' indicates that the null hypothesis cannot be rejected.

TABLE 4-5
TEN MINUTE DATA
POWER-EXPONENTIAL DISTRIBUTION
LOG-LIKELIHOOD VALUES

| | P-MA | P-ARCH(1) | P-ARCH(2) | P-GARCH(1,1) |
|---|---|---|---|---|
| AME | 3778.82 | 3780.68 | 3780.76 | <u>3784.31</u> |
| ATL | 4374.22 | 4330.02 | 4377.76 | <u>4415.97</u> |
| ATT | 3969.16 | 3983.30 | 3989.66 | <u>3993.98</u> |
| BAX | 3823.16 | 3818.08 | 3824.52 | <u>3829.00</u> |
| BOE | 4172.60 | 4174.77 | <u>4180.69</u> | 4173.22 |
| CHE | 4023.03 | 4034.26 | 4034.97 | <u>4040.41</u> |
| DIG | 4284.80 | 4289.54 | 4294.57 | <u>4297.95</u> |
| DOW | 4146.36 | 4146.05 | 4152.68 | <u>4156.30</u> |
| GE | 4002.22 | 4026.68 | 4028.28 | <u>4030.29</u> |
| GM | 4310.31 | 4329.86 | 4339.75 | <u>4342.52</u> |
| ITT | 4339.67 | 4351.02 | <u>4356.17</u> | 4354.61 |
| MOB | 4015.55 | 4015.71 | 4017.62 | <u>4022.59</u> |
| PAC | 3607.37 | 3613.22 | <u>3619.72</u> | 3598.51 |
| PHI | 4143.59 | 4154.79 | 4157.41 | <u>4162.12</u> |
| RJR | 3988.03 | 3978.01 | 3993.28 | <u>3999.28</u> |

The underlined figures denote the highest value based on the Likelihood Ratio test.

**TABLE 4-6**
**TEN MINUTE DATA**
**POWER-EXPONENTIAL DISTRIBUTION**
**$\chi^2$ VALUES**

| | P-MA | P-ARCH(1) | P-ARCH(2) | P-GARCH(1,1) |
|---|---|---|---|---|
| AME | 202.28 | 175.50 | 246.52 | 213.04 |
| ATL | 347.79 | 190.07 | 164.94 | 132.23 |
| ATT | 548.06 | 747.84 | 660.81 | 453.25 |
| BAX | 835.21 | 535.27 | 524.75 | 212.56 |
| BOE | 225.87 | 179.80 | 177.48 | 99.99 |
| CHE | 114.33 | 231.52 | 172.32 | 79.64 |
| DIG | 78.97 | 117.85 | 45.92 | 26.52# |
| DOW | 381.32 | 41.28 | 52.24 | 40.13 |
| GE | 432.80 | 314.45 | 459.77 | 74.24 |
| GM | 331.87 | 369.50 | 392.99 | 135.02 |
| ITT | 368.15 | 551.67 | 502.46 | 367.52 |
| MOB | 1105.49 | 429.52 | 477.62 | 479.02 |
| PAC | 223.60 | 192.15 | 162.28 | 315.32 |
| PHI | 130.01 | 141.54 | 113.94 | 46.78 |
| RJR | 1207.43 | 364.196 | 494.17 | 205.75 |

The $\chi^2(19)$ value at the .05 significance level is 30.14. A '#' indicates that the null hypothesis cannot be rejected.

**TABLE 4-7**
**TEN MINUTE DATA**
**COMPARISON OF BEST MODELS FROM EACH**
**CONDITIONAL DISTRIBUTION**

| | NORMAL | STUDENT-T | POWER-EXP |
|---|---|---|---|
| AME | $3780.02_G$ | $\underline{3783.67}_G$ | $3784.31_G$ |
| ATL | $4370.91_G$ | $4407.65_G$ | $\underline{4415.97}_G$ |
| ATT | $3966.54_{A1}$ | $\underline{3973.51}_G$ | $3993.98_G$ |
| BAX | $3814.12_{A1}$ | $3824.57_{A1}$ | $\underline{3829.00}_G$ |
| BOE | $4176.24_{A2}$ | $\underline{4181.05}_{A2}$ | $4180.69_{A2}$ |
| CHE | $4031.39_G$ | $4040.65_G$ | $\underline{4040.41}_G$ |
| DIG | $4273.06_G$ | $4298.49_G$ | $\underline{4297.95}_G$ |
| DOW | $4138.50_{A2}$ | $4167.33_{A2}$ | $\underline{4156.30}_G$ |
| GE | $4010.10_G$ | $4024.18_G$ | $\underline{4030.29}_G$ |
| GM | $4338.82_G$ | $4359.98_G$ | $\underline{4342.52}_G$ |
| ITT | $4336.45_{A2}$ | $\underline{4345.97}_G$ | $4356.17_{A2}$ |
| MOB | $3987.09_{A1}$ | $\underline{4013.34}_{A1}$ | $4022.59_G$ |
| PAC | $\underline{3620.41}_{A2}$ | $3617.17_{A2}$ | $3619.72_{A2}$ |
| PHI | $4125.06_G$ | $4167.19_G$ | $\underline{4162.12}_G$ |
| RJR | $3979.15_G$ | $3999.93_{A2}$ | $\underline{3999.28}_G$ |

The underlined figures denote the best conditional distribution based on the Likelihood Ratio or $\chi^2$ goodness of fit test. The subscripts denote the corresponding variance specification.

**TABLE 4-8**
**TEN MINUTE DATA**
**ESTIMATION RESULTS**

| | Mean equation | | | | Variance equation | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $a_0$ | $a_1$ | $a_2$ | $a_3$ | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | 1/df |
| | 00 | 00 | 00 | | 00000 | | | | 0000 | 00000 | |
| $AME_T$ | -.056 | .172 | .079 | -.191 | .276 | .073 | --- | .615 | .235 | .181 | .03 |
| | (-3.79) | (2.34) | (3.56) | (-5.17) | (3.03) | (2.59) | | (9.59) | (4.75) | (2.03) | ( 8.15) |
| $ATL_P$ | -.028 | .075 | .038 | -.117 | .015 | .111 | --- | .791 | .030 | .029 | .99 |
| | (-4.21) | (3.02) | (4.22) | (-4.17) | (0.36) | (3.88) | | (18.87) | (2.30) | (0.57) | (15.24) |
| $ATT_T$ | -.041 | .059 | .073 | -.197 | .078 | .099 | --- | .700 | .075 | .159 | .05 |
| | (-3.04) | (1.29) | (4.01) | (-5.13) | (1.22) | (3.04) | | (11.42) | (3.26) | (2.44) | (21.59) |
| $BAX_P$ | -.061 | .164 | .118 | -.203 | .062 | .094 | --- | .735 | .136 | .212 | .71 |
| | (-5.02) | (2.74) | (6.52) | (-6.05) | (1.22) | (3.27) | | (16.13) | (4.10) | (2.97) | (23.55) |
| $BOE_T$ | -.040 | .023 | .059 | -.292 | .307 | .115 | .154 | --- | .140 | .138 | .03 |
| | (-4.67) | (0.67) | (4.92) | (-8.73) | (8.08) | (2.59) | ( 4.67) | | (4.83) | (2.35) | ( 3.07) |
| $CHE_P$ | -.036 | .008 | .062 | -.258 | .077 | .227 | --- | .675 | .051 | .038 | .69 |
| | (-3.50) | (0.20) | (4.23) | (-6.81) | (1.33) | (4.41) | | (11.49) | (2.38) | (0.62) | (13.71) |
| $DIG_P$ | -.046 | .184 | .064 | -.165 | .000 | .175 | --- | .721 | .060 | .089 | .74 |
| | (-6.11) | (4.86) | (5.87) | (-4.64) | (0.00) | (3.58) | | (16.21) | (2.90) | (1.77) | (82.50) |
| $DOW_P$ | -.014 | .135 | .056 | -.118 | .017 | .160 | --- | .716 | .049 | .113 | .83 |
| | (-1.81) | (3.81) | (4.78) | (-3.91) | (0.33) | (3.81) | | (13.91) | (2.19) | (1.96) | (130.9) |
| $GE_P$ | -.018 | .176 | .038 | -.179 | .068 | .203 | --- | .635 | .091 | .140 | .72 |
| | (-1.97) | (3.60) | (2.50) | (-4.97) | (1.28) | (5.04) | | (11.55) | (2.66) | (2.18) | (14.12) |
| $GM_P$ | -.016 | .038 | .075 | -.111 | .030 | .204 | --- | .664 | .041 | .083 | .98 |
| | (-2.60) | (1.31) | (7.99) | (-3.64) | (0.82) | (3.57) | | ( 9.71) | (2.14) | (1.88) | (23.12) |
| $ITT_T$ | -.028 | .081 | .044 | -.189 | .151 | .037 | --- | .398 | .105 | .130 | .14 |
| | (-3.73) | (1.82) | (3.86) | (-5.86) | (2.78) | (0.93) | | ( 3.54) | (3.26) | (2.70) | (18.71) |
| $MOB_T$ | -.038 | .057 | .048 | -.196 | .372 | .303 | --- | --- | .222 | .400 | .15 |
| | (-3.81) | (1.10) | (3.23) | (-6.07) | (7.57) | (4.46) | | | (3.15) | (4.46) | (24.10) |
| $PAC_N$ | -.069 | .028 | .106 | -.500 | 1.13 | .085 | .110 | --- | .161 | .831 | -- |
| | (-5.25) | (0.60) | (5.28) | (-16.3) | (8.48) | (2.19) | ( 2.96) | | (2.63) | (4.23) | |
| $PHI_P$ | -.013 | .071 | .051 | -.103 | .077 | .107 | --- | .659 | .102 | .009 | .88 |
| | (-1.50) | (1.51) | (4.10) | (-3.37) | (1.67) | (3.04) | | (10.78) | (3.89) | (1.67) | (16.50) |
| $RJR_P$ | -.027 | .128 | .056 | -.099 | .147 | .116 | --- | .545 | .245 | .191 | .82 |
| | (-2.76) | (1.91) | (3.64) | (-3.18) | (2.48) | (2.69) | | ( 9.57) | (4.07) | (2.51) | (15.49) |

The t-statistics are in parentheses.

**TABLE 4-9**
**TEN MINUTE DATA**
**DISTRIBUTIONAL TESTS ON RESIDUALS**

| | skew | kurt | $S$ stat | $\chi^2$ Total | $\chi^2$ Tail region | $\chi^2$ Midpoint region |
|---|---|---|---|---|---|---|
| AME | -.039 | 0.569 | 0.23 | 184.86 | 2.03# | 43.85 |
| ATL | .025 | 2.521 | 0.09 | 132.23 | 0.30# | 5.60# |
| ATT | -.031 | 0.539 | 0.15 | 384.21 | 12.29 | 57.25 |
| BAX | .010 | 0.704 | 0.01 | 212.56 | 2.20# | 8.32 |
| BOE | -.013 | 0.832 | 0.03 | 144.87 | 2.73# | 4.01# |
| CHE | .024 | 0.774 | 0.17 | 79.64 | 4.42# | 0.75# |
| DIG | .002 | 1.577 | 0.00 | 26.52# | 2.20# | 0.10# |
| DOW | -.012 | 1.544 | 0.02 | 40.13 | 0.15# | 1.06# |
| GE | -.010 | 0.980 | 1.65 | 74.24 | 3.92# | 23.75 |
| GM | .017 | 2.834 | 4.61* | 135.02 | 9.42 | 2.30# |
| ITT | -.191 | 0.877 | 5.55* | 418.81 | 13.74 | 48.77 |
| MOB | -.214 | 2.221 | 6.95* | 305.23 | 18.45 | 67.32 |
| PAC | -.223 | 0.000 | 7.50* | 172.85 | 0.77# | 11.09 |
| PHI | .031 | 2.315 | 0.14 | 46.78 | 4.04# | 5.82# |
| RJR | .180 | 1.642 | 4.92* | 205.75 | 0.72# | 5.41# |

The $\chi^2(1)$ value for the $S$ statistic at the 0.05 significance level is 3.84. An '*' represents significance at the .05 level. A '#' indicates that the null hypothesis cannot be rejected using the $\chi^2$ goodness of fit tests.

TABLE 4-10
TEN MINUTE DATA
TESTS FOR NONLINEAR DEPENDENCE ON RESIDUALS

| | LB(6) $r$ | LB(6) $r^2$ | LB(6) $\|r\|$ | AUTOCORRELATION FOR LAG-1 $r$ | $r^2$ | $\|r\|$ |
|---|---|---|---|---|---|---|
| AME | 4.86 | 20.16* | 15.16* | -.024 | .003 | .016 |
| ATL | 5.43 | 7.85 | 10.40 | .007 | .073 | .087 |
| ATT | 6.72 | 2.18 | 5.25 | -.018 | .010 | .019 |
| BAX | 7.17 | 2.91 | 4.39 | -.035 | .003 | .027 |
| BOE | 2.21 | 10.44 | 14.11* | .003 | -.036 | -.030 |
| CHE | 6.80 | 7.33 | 7.34 | .060 | -.019 | -.042 |
| DIG | 33.38* | 4.32 | 4.03 | .109* | -.007 | .011 |
| DOW | 16.88* | 5.73 | 6.42 | .079* | .058 | .069 |
| GE | 10.89 | 3.86 | 7.12 | .057 | .047 | .042 |
| GM | 3.84 | 3.97 | 7.96 | .013 | .006 | -.019 |
| ITT | 4.49 | 5.13 | 3.94 | .009 | -.002 | -.001 |
| MOB | 8.74 | 46.92* | 28.11* | .063 | -.046 | -.038 |
| PAC | 3.16 | 12.83 | 14.58* | -.014 | -.007 | -.007 |
| PHI | 8.07 | 2.58 | 5.35 | .032 | .031 | .038 |
| RJR | 4.79 | 3.17 | 7.53 | .050 | -.008 | -.010 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. An '*' represents significance at the .05 level.

TABLE 4-11
THIRTY MINUTE DATA
NORMAL DISTRIBUTION
LOG-LIKELIHOOD VALUES

| | N-MA | N-ARCH(1) | N-ARCH(2) | N-GARCH(1,1) |
|---|---|---|---|---|
| AME | 1182.21 | 1187.71 | 1188.64 | <u>1189.66</u> |
| ATL | 1349.03 | 1355.80 | <u>1363.33</u> | 1359.48 |
| ATT | 1244.68 | 1243.89 | <u>1250.70</u> | 1244.07 |
| BAX | 1173.13 | 1176.29 | 1176.32 | <u>1182.81</u> |
| BOE | 1330.38 | <u>1334.69</u> | 1334.70 | 1329.53 |
| CHE | 1265.19 | 1280.33 | <u>1285.14</u> | 1285.61 |
| DIG | 1317.78 | 1318.67 | 1318.74 | <u>1320.68</u> |
| DOW | 1252.38 | <u>1260.31</u> | 1260.46 | 1260.20 |
| GE | 1228.42 | 1231.61 | <u>1237.30</u> | 1234.81 |
| GM | <u>1345.25</u> | 1345.66 | 1345.66 | 1341.55 |
| ITT | <u>1367.15</u> | 1367.46 | 1367.48 | 1366.37 |
| MOB | 1256.83 | <u>1263.50</u> | 1264.28 | 1264.95 |
| PAC | <u>1198.89</u> | 1198.89 | 1199.36 | 1197.47 |
| PHI | 1264.37 | <u>1269.13</u> | 1268.48 | 1264.18 |
| RJR | 1216.84 | 1217.78 | <u>1222.07</u> | 1222.02 |

The underlined figures denote the highest value based on the Likelihood Ratio test.

**TABLE 4-12**
**THIRTY MINUTE DATA**
**NORMAL DISTRIBUTION**
**$\chi^2$ VALUES**

| | N-MA | N-ARCH(1) | N-ARCH(2) | N-GARCH(1,1) |
|---|---|---|---|---|
| AME | 18.10# | 43.28 | 20.11# | 27.23 |
| ATL | 70.87 | 70.47 | 48.00 | 107.78 |
| ATT | 144.60 | 212.41 | 120.12 | 187.23 |
| BAX | 66.25 | 76.49 | 75.98 | 63.54 |
| BOE | 123.43 | 147.31 | 68.56 | 66.86 |
| CHE | 29.74 | 30.84 | 41.38 | 47.50 |
| DIG | 42.98 | 38.17 | 34.75 | 19.31 |
| DOW | 67.46 | 29.44 | 21.71# | 26.43 |
| GE | 43.38 | 62.14 | 27.93 | 50.50 |
| GM | 105.17 | 92.13 | 84.51 | 178.91 |
| ITT | 151.92 | 141.59 | 146.30 | 155.13 |
| MOB | 141.39 | 151.82 | 186.03 | 218.93 |
| PAC | 68.86 | 61.54 | 49.60 | 51.91 |
| PHI | 55.22 | 59.63 | 68.76 | 66.15 |
| RJR | 49.30 | 77.19 | 23.92 | 55.72 |

The $\chi^2(14)$ value at the .05 significance level is 23.68. A '#' indicates that the null hypothesis cannot be rejected.

**TABLE 4-13**
**THIRTY MINUTE DATA**
**STUDENT-T DISTRIBUTION**
**LOG-LIKELIHOOD VALUES**

| | T-MA | T-ARCH(1) | T-ARCH(2) | T-GARCH(1,1) |
|---|---|---|---|---|
| AME | 1179.22 | 1182.59 | 1183.11 | <u>1189.53</u> |
| ATL | 1371.20 | 1376.17 | <u>1380.16</u> | 1377.33 |
| ATT | 1248.74 | 1250.72 | <u>1255.59</u> | 1251.60 |
| BAX | 1182.85 | 1186.77 | 1186.97 | <u>1188.96</u> |
| BOE | 1339.27 | 1341.39 | <u>1343.51</u> | 1342.14 |
| CHE | 1272.17 | 1283.05 | 1284.86 | <u>1286.46</u> |
| DIG | 1315.86 | 1320.91 | 1323.26 | <u>1328.00</u> |
| DOW | 1271.50 | <u>1278.11</u> | 1279.74 | 1279.04 |
| GE | 1241.22 | 1242.28 | 1240.41 | <u>1245.89</u> |
| GM | <u>1365.39</u> | 1362.30 | 1361.90 | 1366.04 |
| ITT | <u>1371.63</u> | 1372.54 | 1372.63 | 1371.29 |
| MOB | 1263.33 | 1559.03 | 1260.88 | <u>1267.06</u> |
| PAC | <u>1198.88</u> | 1196.14 | 1198.98 | 1197.89 |
| PHI | <u>1285.57</u> | 1280.58 | 1285.06 | 1288.13 |
| RJR | 1228.81 | 1228.96 | 1232.27 | <u>1233.74</u> |

The underlined figures denote the highest value based on the Likelihood Ratio test.

**TABLE 4-14**
**THIRTY MINUTE DATA**
**STUDENT-T DISTRIBUTION**
**$\chi^2$ VALUES**

| | T-MA | T-ARCH(1) | T-ARCH(2) | T-GARCH(1,1) |
|---|---|---|---|---|
| AME | 34.05 | 37.76 | 37.56 | 22.62 |
| ATL | 78.29 | 130.05 | 78.19 | 105.68 |
| ATT | 158.04 | 220.43 | 174.99 | 185.53 |
| BAX | 86.62 | 121.93 | 104.17 | 64.75 |
| BOE | 141.89 | 140.99 | 142.19 | 105.27 |
| CHE | 33.15 | 57.33 | 67.16 | 40.47 |
| DIG | 77.09 | 68.56 | 60.64 | 33.95 |
| DOW | 71.47 | 59.93 | 62.14 | 69.16 |
| GE | 54.72 | 69.86 | 162.05 | 68.26 |
| GM | 115.71 | 125.04 | 124.44 | 129.95 |
| ITT | 166.17 | 146.10 | 143.19 | 182.92 |
| MOB | 90.23 | 183.72 | 140.89 | 68.36 |
| PAC | 71.67 | 153.83 | 49.80 | 64.35 |
| PHI | 57.43 | 89.73 | 79.09 | 69.86 |
| RJR | 79.80 | 67.86 | 39.27 | 48.10 |

The $\chi^2(13)$ value at the .05 significance level is 22.36. A '#' indicates that the null hypothesis cannot be rejected.

TABLE 4-15
THIRTY MINUTE DATA
POWER-EXPONENTIAL DISTRIBUTION
LOG-LIKELIHOOD VALUES

| | P-MA | P-ARCH(1) | P-ARCH(2) | P-GARCH(1,1) |
|---|---|---|---|---|
| AME | 1183.94 | <u>1188.12</u> | 1187.54 | 1189.91 |
| ATL | 1363.43 | 1368.26 | <u>1375.01</u> | 1373.68 |
| ATT | <u>1254.87</u> | 1256.24 | 1257.43 | 1255.70 |
| BAX | 1184.70 | 1188.29 | 1190.66 | <u>1200.36</u> |
| BOE | 1341.27 | <u>1345.34</u> | 1344.96 | 1345.19 |
| CHE | 1267.03 | 1282.27 | 1285.78 | <u>1286.36</u> |
| DIG | 1324.15 | 1325.86 | 1325.35 | <u>1327.81</u> |
| DOW | 1261.26 | 1273.99 | 1276.46 | <u>1277.75</u> |
| GE | 1238.25 | 1237.43 | <u>1246.35</u> | 1244.62 |
| GM | <u>1360.87</u> | 1360.92 | 1361.24 | 1360.31 |
| ITT | <u>1373.08</u> | 1373.55 | 1374.24 | 1372.97 |
| MOB | 1264.25 | <u>1268.23</u> | 1269.69 | 1269.74 |
| PAC | <u>1199.45</u> | 1199.43 | 1200.04 | 1201.40 |
| PHI | <u>1287.44</u> | 1287.31 | 1287.96 | 1288.14 |
| RJR | 1228.08 | 1228.54 | 1231.30 | <u>1232.60</u> |

The underlined figures denote the highest value based on the Likelihood Ratio test.

TABLE 4-16
THIRTY MINUTE DATA
POWER-EXPONENTIAL DISTRIBUTION
$\chi^2$ VALUES

| | P-MA | P-ARCH(1) | P-ARCH(2) | P-GARCH(1,1) |
|---|---|---|---|---|
| AME | 12.59# | 45.99 | 25.93 | 27.03 |
| ATL | 56.52 | 60.84 | 49.60 | 56.52 |
| ATT | 178.20 | 206.19 | 199.67 | 233.58 |
| BAX | 80.99 | 196.26 | 231.57 | 399.01 |
| BOE | 68.86 | 78.19 | 51.71 | 80.60 |
| CHE | 21.11# | 31.44 | 44.89 | 38.27 |
| DIG | 18.60# | 25.63 | 32.95 | 17.90# |
| DOW | 19.51# | 39.57 | 41.68 | 44.59 |
| GE | 40.87 | 61.24 | 46.29 | 118.42 |
| GM | 79.29 | 56.32 | 53.11 | 102.87 |
| ITT | 316.64 | 284.54 | 308.31 | 237.79 |
| MOB | 104.57 | 77.89 | 63.64 | 49.10 |
| PAC | 114.70 | 111.50 | 100.36 | 221.54 |
| PHI | 13.89# | 20.81# | 34.35 | 18.20# |
| RJR | 34.15 | 38.68 | 14.59# | 19.91# |

The $\chi^2(13)$ value at the .05 significance level is 22.36. A '#' indicates that the null hypothesis cannot be rejected.

**TABLE 4-17**
**THIRTY MINUTE DATA**
**COMPARISON OF BEST MODELS FROM EACH**
**CONDITIONAL DISTRIBUTION**

| | NORMAL | STUDENT-T | POWER-EXP |
|---|---|---|---|
| AME | <u>1189.66</u>$_G$ | 1189.53$_G$ | 1188.12$_{A1}$ |
| ATL | 1363.33$_{A2}$ | 1380.16$_{A2}$ | <u>1375.01</u>$_{A2}$ |
| ATT | 1250.70$_{A2}$ | <u>1255.59</u>$_{A2}$ | 1254.87$_{MA}$ |
| BAX | 1182.81$_G$ | <u>1188.96</u>$_G$ | 1200.36$_G$ |
| BOE | 1334.69$_{A1}$ | 1343.51$_{A2}$ | <u>1345.34</u>$_{A1}$ |
| CHE | <u>1285.14</u>$_{A2}$ | 1286.46$_G$ | 1286.36$_G$ |
| DIG | 1320.68$_G$ | 1328.00$_G$ | <u>1327.81</u>$_G$ |
| DOW | 1260.31$_{A1}$ | 1278.11$_{A1}$ | <u>1277.75</u>$_G$ |
| GE | 1237.30$_{A2}$ | 1245.89$_G$ | <u>1246.35</u>$_{A2}$ |
| GM | 1345.25$_{MA}$ | 1365.39$_{MA}$ | <u>1360.87</u>$_{MA}$ |
| ITT | 1367.15$_{MA}$ | <u>1371.63</u>$_{MA}$ | 1373.08$_{MA}$ |
| MOB | 1263.50$_{A1}$ | 1267.06$_G$ | <u>1269.74</u>$_G$ |
| PAC | <u>1198.89</u>$_{MA}$ | 1198.88$_{MA}$ | 1199.45$_{MA}$ |
| PHI | 1269.13$_{A1}$ | 1285.57$_{MA}$ | <u>1287.44</u>$_{MA}$ |
| RJR | 1222.07$_{A2}$ | 1233.74$_G$ | <u>1231.30</u>$_G$ |

The underlined figures denote the best conditional distribution based on the Likelihood Ratio or $\chi^2$ goodness of fit test. The subscripts denote the corresponding variance specification.

TABLE 4-18
THIRTY MINUTE DATA
ESTIMATION RESULTS

| | Mean equation | | | | Variance equation | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $a_0$ | $a_1$ | $a_2$ | $a_3$ | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | 1/df |
| | 00 | 00 | 00 | | 0000 | | | | 0000 | 00000 | |
| $AME_N$ | -.019 | .121 | .015 | -.259 | .143 | .305 | --- | .196 | .404 | .000 | -- |
| | (-0.39) | (1.23) | (0.25) | (-3.80) | (2.30) | (2.93) | | ( 1.23) | (3.24) | (0.00) | |
| $ATL_P$ | .025 | .004 | -.033 | -.151 | .056 | .207 | .197 | --- | .055 | .050 | .65 |
| | ( 0.68) | (0.10) | (-.83) | (-2.44) | (3.75) | (2.47) | (2.79) | | (1.54) | (0.30) | (27.01) |
| $ATT_T$ | -.014 | .081 | .009 | -.139 | .167 | .026 | .131 | --- | .194 | .000 | .15 |
| | (-0.27) | (1.21) | (0.16) | (-2.52) | (3.30) | (0.32) | (1.71) | | (1.92) | (0.00) | (10.35) |
| $BAX_T$ | -.071 | .030 | .107 | -.139 | .010 | .063 | --- | .529 | .255 | 1.21 | .14 |
| | (-1.61) | (0.36) | (1.87) | (-2.55) | (0.39) | (1.03) | | ( 4.40) | (2.42) | (3.25) | ( 2.35) |
| $BOE_P$ | .022 | .020 | -.034 | -.136 | .104 | .201 | --- | --- | .096 | .000 | .70 |
| | ( 0.60) | (0.36) | (-.81) | (-2.06) | (4.90) | (1.74) | | | (2.08) | (0.00) | (79.51) |
| $CHE_N$ | -.027 | -.014 | -.023 | -.165 | .083 | .448 | .093 | --- | .077 | .101 | -- |
| | (-0.63) | (-.27) | (-.48) | (-2.33) | (2.86) | (5.53) | (1.87) | | (1.74) | (0.33) | |
| $DIG_P$ | -.035 | .153 | .010 | .019 | .027 | .081 | --- | .632 | .105 | .000 | .73 |
| | (-0.77) | (2.45) | (0.19) | ( 0.31) | (1.03) | (1.30) | | ( 4.61) | (2.61) | (0.00) | ( 9.28) |
| $DOW_P$ | .042 | -.059 | -.038 | -.034 | .098 | .316 | --- | .209 | .238 | .000 | .88 |
| | ( 0.97) | (-.78) | (-.77) | (-0.56) | (1.63) | (1.91) | | ( 0.85) | (1.94) | (0.00) | (13.79) |
| $GE_P$ | -.008 | .190 | -.019 | -.110 | .137 | .096 | .337 | --- | .312 | .000 | .78 |
| | (-0.19) | (2.49) | (-.40) | (-2.03) | (3.08) | (1.24) | (2.14) | | (1.86) | (0.00) | ( 9.45) |
| $GM_P$ | -.009 | -.012 | .000 | -.069 | .073 | --- | --- | --- | .134 | .341 | .68 |
| | (-0.33) | (-.21) | (0.02) | (-1.38) | (5.20) | | | | (2.60) | (1.84) | (44.53) |
| $ITT_T$ | -.033 | .042 | .037 | -.074 | .079 | --- | --- | --- | .154 | .102 | .09 |
| | (-1.00) | (0.70) | (1.00) | (-1.45) | (3.56) | | | | (3.15) | (0.41) | ( 1.82) |
| $MOB_G$ | .061 | .020 | -.086 | -.104 | .051 | .174 | --- | .407 | .161 | .152 | .78 |
| | ( 1.10) | (0.29) | (-1.4) | (-1.65) | (1.13) | (1.83) | | ( 2.29) | (2.19) | (0.37) | (33.53) |
| $PAC_N$ | -.027 | -.038 | .024 | -.265 | .233 | --- | --- | --- | .128 | .842 | -- |
| | (-0.50) | (-.50) | (0.39) | (-4.84) | (4.79) | | | | (1.87) | (1.52) | |
| $PHI_P$ | -.036 | .014 | .042 | -.076 | .192 | --- | --- | --- | .242 | .000 | .94 |
| | (-0.79) | (0.22) | (0.84) | (-1.63) | (3.85) | | | | (2.23) | (0.00) | (11.92) |
| $RJR_P$ | -.059 | .106 | .037 | -.095 | .079 | .004 | --- | .561 | .275 | .000 | .77 |
| | (-1.24) | (1.38) | (0.70) | (-1.96) | (1.28) | (0.07) | | ( 2.99) | (2.70) | (0.00) | (96.04) |

The t-statistics are in parentheses.

**TABLE 4-19**
**THIRTY MINUTE DATA**
**DISTRIBUTIONAL TESTS ON RESIDUALS**

| | skew | kurt | *S* stat | $\chi^2$ Total | $\chi^2$ Tail region | $\chi^2$ Midpoint region |
|---|---|---|---|---|---|---|
| AME | .081 | 0.188 | 0.35 | 27.33 | 0.87# | 3.26# |
| ATL | .176 | 2.251 | 1.63 | 49.60 | 1.47# | 14.60 |
| ATT | .224 | 1.558 | 2.64 | 174.99 | 4.83# | 74.37 |
| BAX | .090 | 1.118 | 0.43 | 64.75 | 3.64# | 30.97 |
| BOE | -.089 | 1.585 | 0.42 | 78.19 | 2.20# | 23.66 |
| CHE | .125 | 0.382 | 0.83 | 41.38 | 1.69# | 7.73 |
| DIG | -.211 | 1.916 | 2.34 | 17.90# | 0.43# | 0.83# |
| DOW | .335 | 5.583 | 5.91* | 44.59 | 2.41# | 5.51# |
| GE | -.287 | 2.012 | 4.34* | 46.29 | 0.48# | 9.07 |
| GM | -1.118 | 5.709 | 65.91* | 79.29 | 0.11# | 35.91 |
| ITT | -.101 | 1.288 | 0.53 | 166.17 | 8.41 | 47.27 |
| MOB | .113 | 0.641 | 0.68 | 49.10 | 0.27# | 24.41 |
| PAC | -.262 | 0.246 | 3.63 | 68.86 | 4.44# | 22.44 |
| PHI | .078 | 2.325 | 0.32 | 13.89# | 2.00# | 2.67# |
| RJR | .464 | 2.289 | 11.33 | 19.91# | 0.78# | 7.28 |

The $\chi^2(1)$ value for the *S* statistic at the 0.05 significance level is 3.84. An '*' denotes significance at the .05 level. A '#' indicates that the null hypothesis cannot be rejected using the $\chi^2$ goodness of fit tests.

TABLE 4-20
THIRTY MINUTE DATA
TESTS FOR NONLINEAR DEPENDENCE ON RESIDUALS

| | LB(6) $r$ | LB(6) $r^2$ | LB(6) $\lvert r \rvert$ | AUTOCORRELATION FOR LAG-1 $r$ | $r^2$ | $\lvert r \rvert$ |
|---|---|---|---|---|---|---|
| AME | 4.46 | 1.39 | 2.90 | -.007 | .037 | .016 |
| ATL | 7.97 | 4.87 | 5.52 | .071 | -.033 | .007 |
| ATT | 4.23 | 1.69 | 3.77 | .006 | -.028 | .020 |
| BAX | 3.57 | 3.04 | 7.62 | -.004 | .018 | .049 |
| BOE | 4.83 | 6.20 | 8.16 | -.006 | -.045 | -.017 |
| CHE | 13.48* | 4.86 | 10.82 | .003 | .017 | -.012 |
| DIG | 9.17 | 4.10 | 3.85 | .054 | .076 | .021 |
| DOW | 8.20 | 0.60 | 5.15 | .084 | .006 | .011 |
| GE | 7.77 | 4.68 | 4.50 | .058 | .095 | -.013 |
| GM | 6.77 | 23.23* | 9.52 | .023 | .038 | .033 |
| ITT | 2.28 | 2.50 | 3.83 | .011 | .052 | .043 |
| MOB | 7.17 | 5.97 | 7.26 | .053 | .019 | -.003 |
| PAC | 9.33 | 5.27 | 5.14 | .025 | .005 | .060 |
| PHI | 3.72 | 3.23 | 3.51 | .048 | .005 | .038 |
| RJR | 11.24 | 7.46 | 9.91 | .005 | -.071 | -.088 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. An '*' represents significance at the .05 level.

# CHAPTER 5

## ARCH EFFECTS AND INFORMATION ARRIVAL

As we noted in Chapter 4, the presence of nonlinear dependence in ten minute return intervals raises the question as to the causes of this dependence. Lamoureux and Lastrapes (1990) posit that the flow of information to the market may dictate the time series behavior observed over fixed intervals of calendar time. Since information is not easily measured, they use contemporaneous daily volume as a proxy for the amount of information that arrives to the market.

In this chapter, we examine the role of information proxies in explaining the ARCH effects observed in the ten minute return series. Since our concern is with a proxy for information, there are several possible variables that we can use in our analysis. One of these, changes in the specialist bid-ask spread, has already been incorporated in our work from Chapter 4. Our results show that for some stocks the specialist bid-ask spread is a statistically significant component of the estimated conditional variance. We should point out that this effect is restricted to the intercept term and not the lagged variance or squared error terms. Two other variables of interest are volume and the number of transactions over a given period. Volume remains of interest over ten minute intervals since it may indirectly affect the setting of the bid-ask spread and the specialist's inventory. The number of transactions, on the other hand, provide a simpler measure of information arrival while eliminating some of the indirect effects associated with the use of volume. We examine the GARCH estimates for

our ten minute time intervals when these two variables have been incorporated in the variance equation.

In the first section of this chapter, we introduce the relevant notation along with a short review of the theory on information arrival. We also discuss the difference between the specification we use for the variance equation and that used by Lamoureux and Lastrapes (1990). In the final section, we present our results and a discussion of their implications for the GARCH effects found in the ten minute interval data.

## A. THEORY AND MODELS

Mandelbrot and Taylor (1967) are the first authors to postulate that the flow of transactions may account for the distributional properties of returns measured over fixed time intervals. They develop a subordinated stochastic process with cumulative volume or number of transactions as the directing process. The variable of interest or stock price, $p_t$, is then measured over a time scale based on the volume of transactions rather than calendar time. As a result, the observed returns or $r_t$, when measured over calendar time, are subordinated to the $p_t$ with the cumulative volume or number of transactions being the directing process.

Lamoureux and Lastrapes (1990) apply this concept to the ARCH process with the information flow acting as the directing process. Using their notation, the $e_t$ are represented as the sum of a random number of

intraday equilibrium price increments, $\delta_{it}$. We can express the above as follows:

$$e_t = \sum_{i=1}^{n_t} \delta_{it},$$

where $n_t$ represents the amount of information that arrives to the market over a particular calendar time interval. By assuming that the $\delta_i$ are independent and identically distributed then the $e_t$, conditional on the $n_t$, are normally distributed, given that the $n_t$ are sufficiently large. This asymptotic normality of the conditional distribution is based on the Central Limit Theorem. Finally, by assuming serial correlation in the daily number of information arrivals, the authors provide a precise measure of the variance of $e_t$ conditional on $n_t$ that captures the nonlinear dependence found in the ARCH process. Hence their conditional variance equation can be written as:

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1} + \beta_4 V_t,$$

where the $V_t$ represents the volume of trading for a given day. Several points need to be further clarified. The first concerns the application of this model to intradaily returns. Given the above assumption concerning the $\delta_i$ the use of other conditional distributions is valid as long as they converge to the normal asymptotically. The second point is that this representation is based on the relationship between ARCH effects and a proxy for information and not the actual information process itself. And our last point is related to the use of

contemporaneous volume in the variance equation. This specification creates a simultaneity bias in the estimation procedure since the conditional variance is based on past values of the variables of interest by definition.

Lamoureux and Lastrapes circumvent this problem by assuming that volume is weakly exogenous as defined by Engle, Hendry, and Richard (1983), i.e., there is no loss of information from estimating the parameters of the model conditional on the contemporaneous volume. However, whether this is actually the case is unclear since exogeneity refers to the effect of the variables in the second or variance equation on the estimation of the parameters in the first or mean equation.[26] In order to avoid this ambiguity, we elect to use lagged variables for the volume and number of transactions. This specification retains the forecasting components of the model while also allowing a test of the information hypothesis. Hence our G(1,1) model will have the following form for the volume analysis:

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 h_{t-1} + \beta_2 EOD + \beta_3 AD + \beta_4 V_{t-1},$$

where $V_{t-1}$ represents lagged volume. The transaction equation has the same form except that $V_{t-1}$ is replaced by $T_{t-1}$. Note that the appropriate specification for the ARCH(1) or ARCH(2) processes can be substituted in the above equation when required. We use those processes with the

[26] A more detail explanation of exogeneity can be found in Engle, Hendry, and Richard (1983). The particular simultaneous equations system must have a number of specific properties for the concept to hold. Of particular note is that block diagonality of the information matrix is not sufficient for weak exogeneity.

underlined log-likelihoods in Table 4-7 as our base models. Estimation is carried out by the same maximum likelihood procedure discussed previously.

## B.ANALYSIS AND ESTIMATION RESULTS

Before we begin the estimation of the two models, we look at graphical illustrations of the estimated conditional variances from the results of Chapter 4 and the associated trading volume. Figures 5-1 through 5-15 contain the intradaily conditional variances and the intradaily volume for each individual stock when they are grouped according to the time of day. For instance, the top graph in Figure 5-1 represents the means of the conditional variances for each ten minute interval of the day as estimated from the associated model in Chapter 4. The corresponding results for the volume are given in the bottom graph.

The first point worth mentioning is the discernible U-shaped pattern that arises in the graphs of the conditional variances. This result is very similar to the pattern of standard deviations found in Wood, McInish, and Ord (1985). A closer inspection of the results indicate that for some stocks the high conditional variance at the beginning of the day decreases gradually until reaching a minimum at around midday, while for other stocks, such as BOE and ITT the minimum is achieved within the first hour of trading. The high to low ratio for the variances ranges from 7 to 2.5 indicating a definite difference in the trading process across the day. Of particular note is the rapid rise in the conditional variance across all stocks in the last half-hour of

trading. These results support the contention of our earlier work concerning a mixture of distributions for the intradaily returns.

Perhaps one of the most interesting findings is the approximate agreement between the best conditional distribution and the patterns found in the graphs. For instance, a rapid drop in the conditional variances is generally associated with the Student-t distribution since the fatter tails are probably a result of the relatively infrequent, yet high variances. On the other hand, those stocks with a power-exponential distribution have a graph with a very gradual decline in the conditional variances. However, these findings are purely observational and further study of the actual relation is left for a later date.

Turning to the graphs of the intraday volume, we find a similar pattern in the beginning of the day results but a noticeable lack of activity at the end of day. Hence, it would seem that the volume-variance relationship is most prevalent at the beginning of the day with an increase in volatility being associated with higher volume. However, the same result does not hold at the end of day. One possible explanation for this result is that the number of limit orders is much higher at the beginning of the day, thereby requiring an associated increase in volume in order to move the price of the stock. On the other hand, the end of day limit orders may be relatively sparse allowing the price of the stock to move quite rapidly with very little volume. This remains simply conjecture since a more in depth analysis of the specialist's activities during these periods is required before any concrete answers can be given.

In terms of the question at hand, the affect of information on the observed ARCH estimates, there would seem to be some support for the idea of a volume proxy, at least at the beginning of the day. However, we must look at our estimation results before we draw any conclusions.[27]

Table 5-1 provides the log-likelihood values and associated degrees of freedom for the estimated volume and transaction results. The underlined values indicate that those are the only models where the estimated log-likelihoods are higher than the models in Chapter 4 using the Likelihood ratio test. Hence, from that standpoint the inclusion of the lagged volume or transaction variable has added no explanatory power to the model. Nevertheless, we still wish to see what affect these variables have on our ARCH estimates since the results of the Lamoureux and Lastrapes work are so conclusively in favor of the information hypothesis.

With this in mind, we turn to Tables 5-2 and 5-3 which have the volume and transaction results respectively. A quick inspection of the last column in Table 5-2 indicates that in no instance does the lagged volume have a statistically significant parameter estimate for $\beta_4$. However, a comparison of the p,q estimates with those for the original models in Table 4-8 indicates that inclusion of the lagged volume does in fact lower the values for the $\alpha_1$'s, $\alpha_2$'s, and $\beta_1$'s. In seven of the fifteen stocks the values for those parameters are reduced to the point that they are not significantly different from zero. Hence, there does

[27] Some of the volume results have noticeable spikes in the middle of the day. These spikes are associated with large block trades during one particular day, especially in the case of Pacific Gas & Electric.

seem to be some relationship between lagged volume and the ARCH process, but the results would indicate that the information hypothesis based on a volume proxy does not hold in the case of ten minute returns.

Table 5-3 contains the results for the transaction variable. An examination of the last column indicates that four of the fifteen stocks have a possible lagged transaction effect. We see that the inclusion of this variable does again change the ARCH estimates, in particular the estimate for $\alpha_1$. Seven of the stocks show parameter estimates that are not significantly different from zero. However, the parameter $\beta_4$ for DOW and GM, the only two stocks with a higher log-likelihood ratio than for the original models, is not significantly different from zero. Hence, the inclusion of the transaction variable, while improving the overall explanatory power of the model for these two stocks, does not explain the GARCH effects. Our conclusion is that the information hypothesis is not supported for either the volume or transaction data at the ten minute return interval.[28]

In our last four tables, we provide results on the overall fit of the preceding models. The indication is that the information proxies affect the time series results of the estimation procedure much more severely than the distributional properties. Many of the models are unable to eliminate the high order dependence in the data, a probable result of the lower $\alpha_1$ estimates. The evidence suggests that multicollinearity is being induced by the inclusion of the 'information' variables. Hence, our use of the volume and transaction proxies is

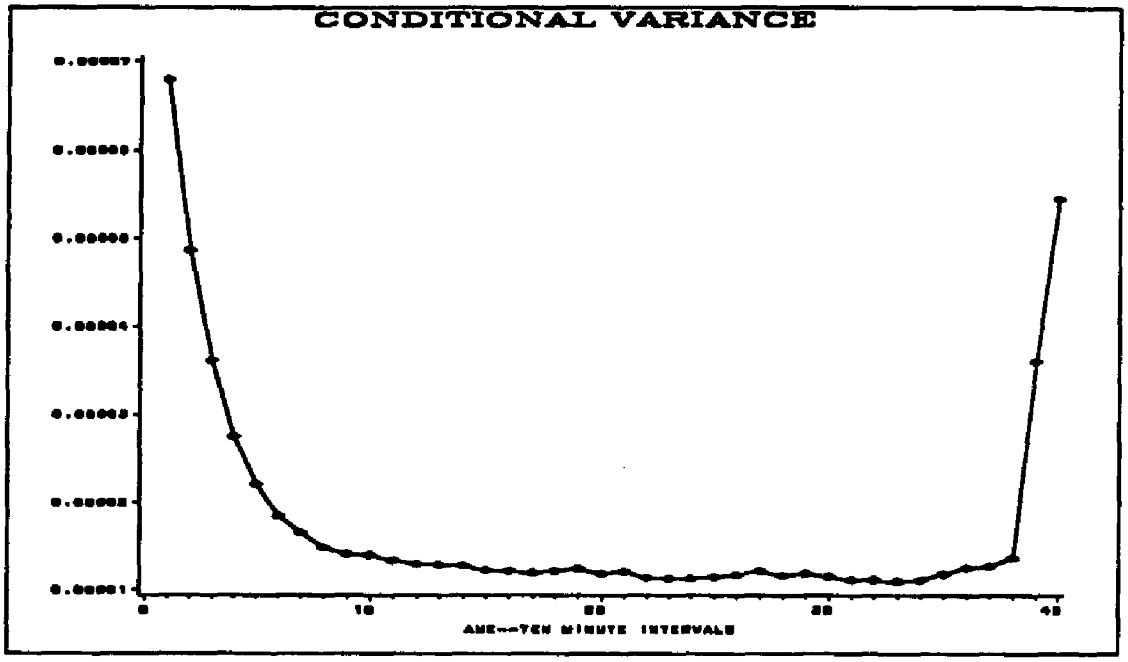
[28] We also perform the estimation with contemporaneous volume and transactions but no significant difference is found in the results.

creating econometric problems that cloud any inferences we can make concerning the role of information in creating the ARCH effects.

In conclusion, the results of this chapter indicate that when an information proxy is specified on the basis of lagged volume or transaction data the overall fit of the model is reduced along with a perceptible drop in the explanatory power. One possible explanation is that the time interval used is too short to reflect trading based on new information. This would then weaken the relationship between information arrival and proxies such as volume or the number of transactions.[29] In any case, the hypothesis that the ARCH effects result from the flow of information to the market is not discredited. We simply have shown that the amount of volume and the number of transactions are not appropriate proxies. Hence, our results along with our preceding discussion of the simultaneity bias inherent in the use of contemporaneous variables indicate that a much more extensive examination of the econometric as well as financial issues inherent in the information hypothesis are in order.

[29] Heiner's (1983) 'competence-difficulty' gap or C-D hypothesis provides some rational for the difficulty of market participants to rapidly assimilate new information.

**FIGURE 5-1**
**AMERICAN EXPRESS**
**CONDITIONAL VARIANCE AND VOLUME**



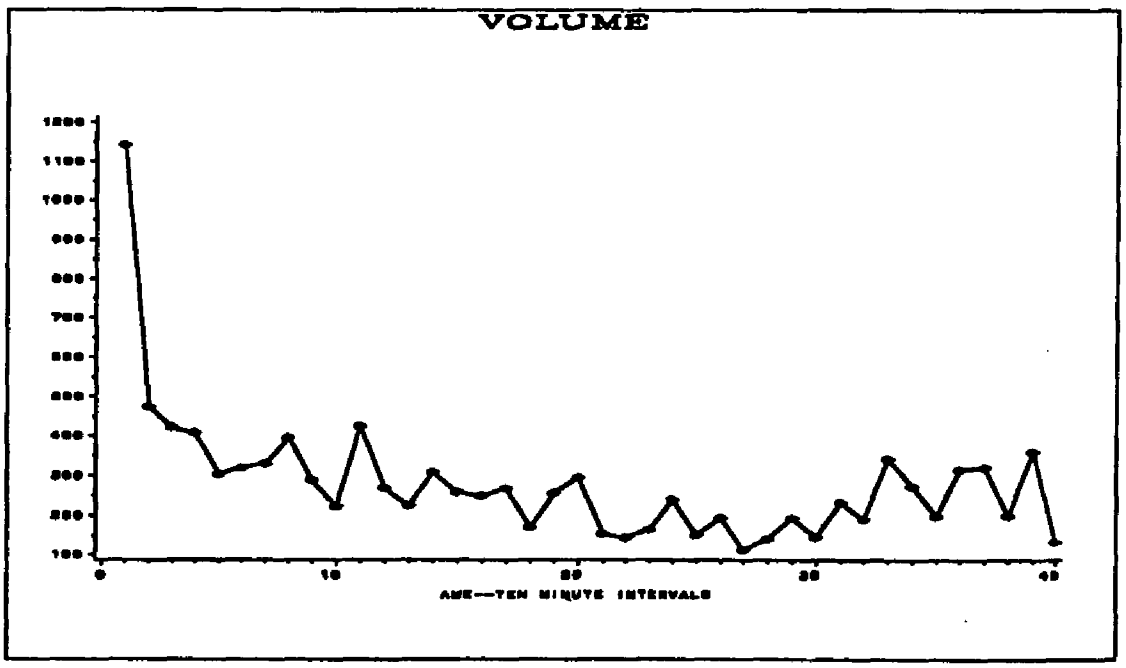
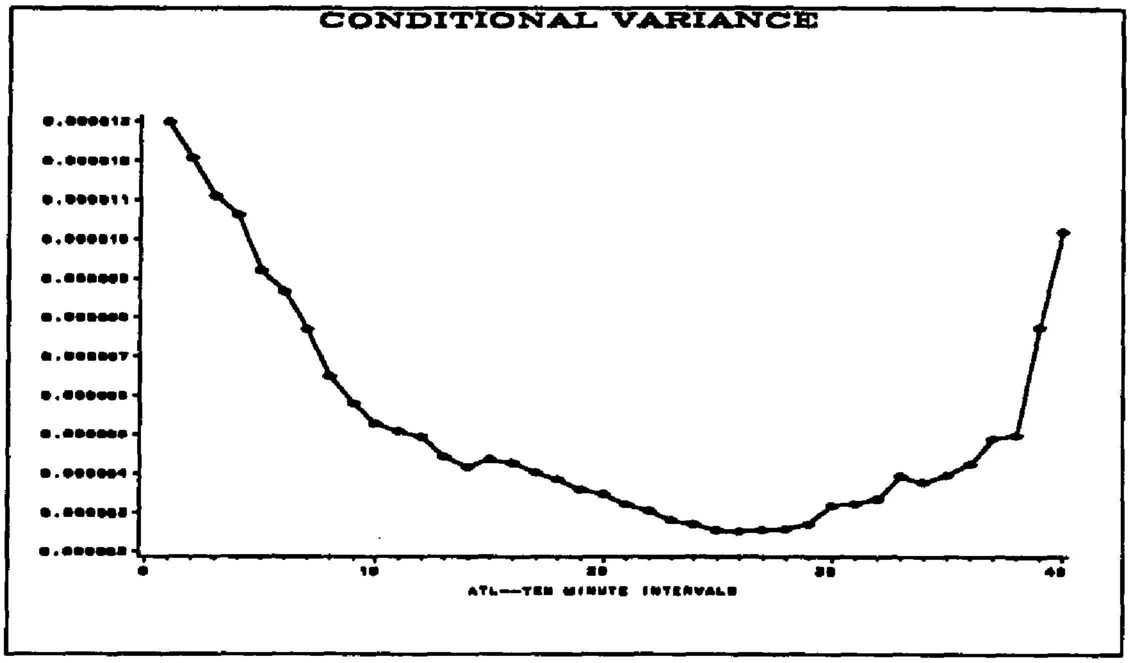



**FIGURE 5-2**
**ATLANTIC RICHFIELD**
**CONDITIONAL VARIANCE AND VOLUME**



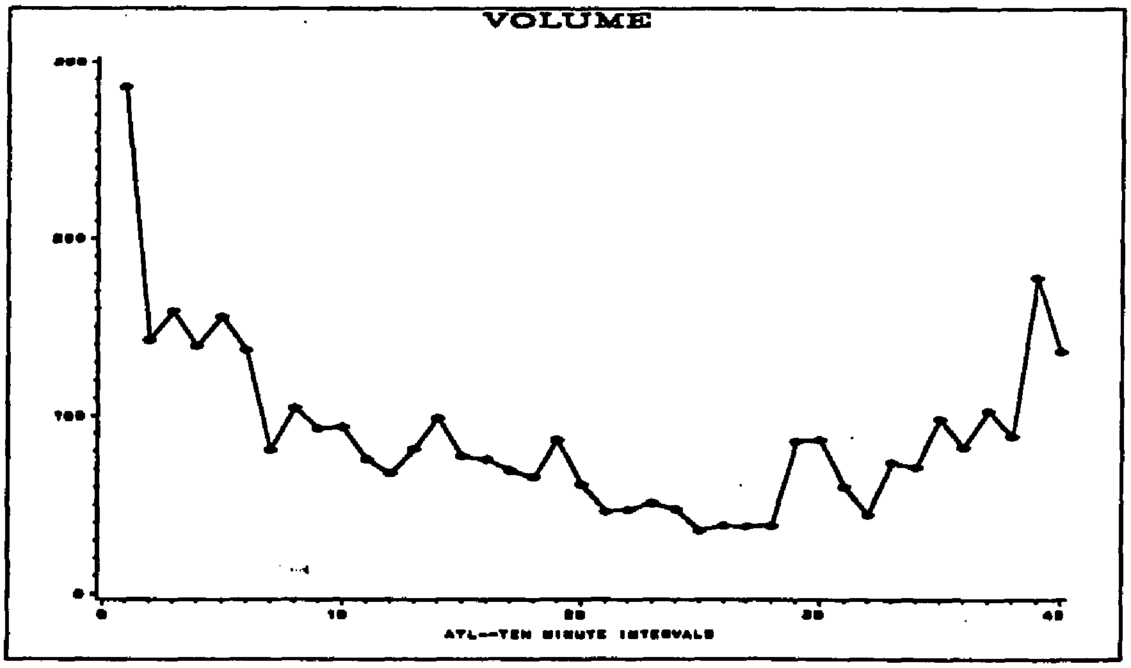
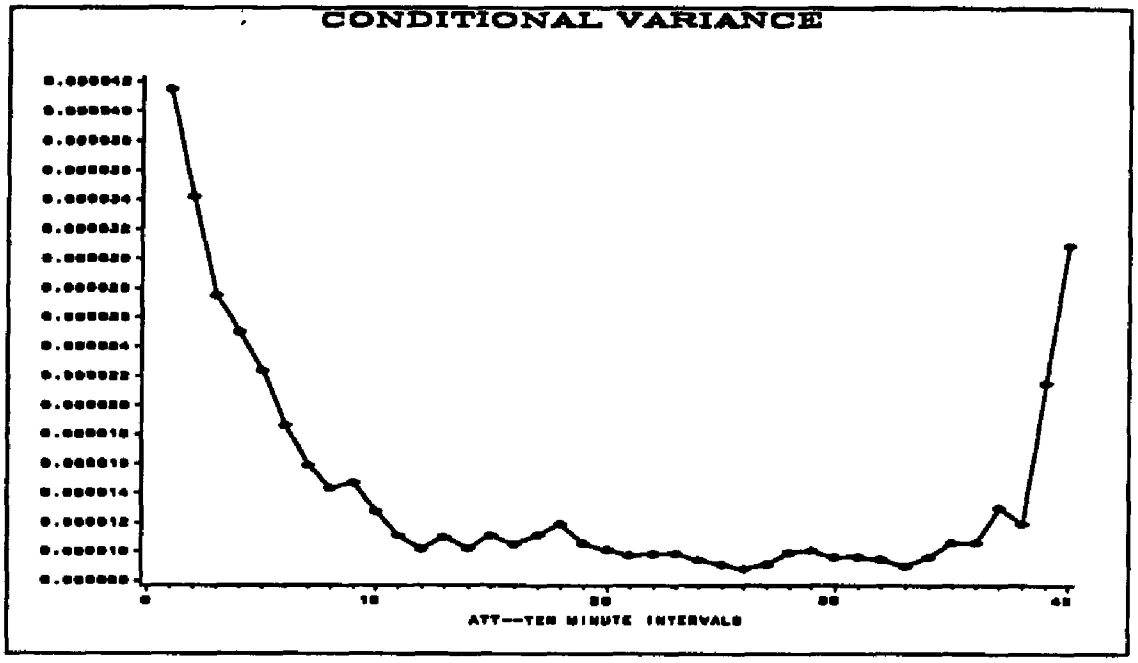



**FIGURE 5-3**
**AMERICAN TELEPHONE AND TELEGRAPH**
**CONDITIONAL VARIANCE AND VOLUME**



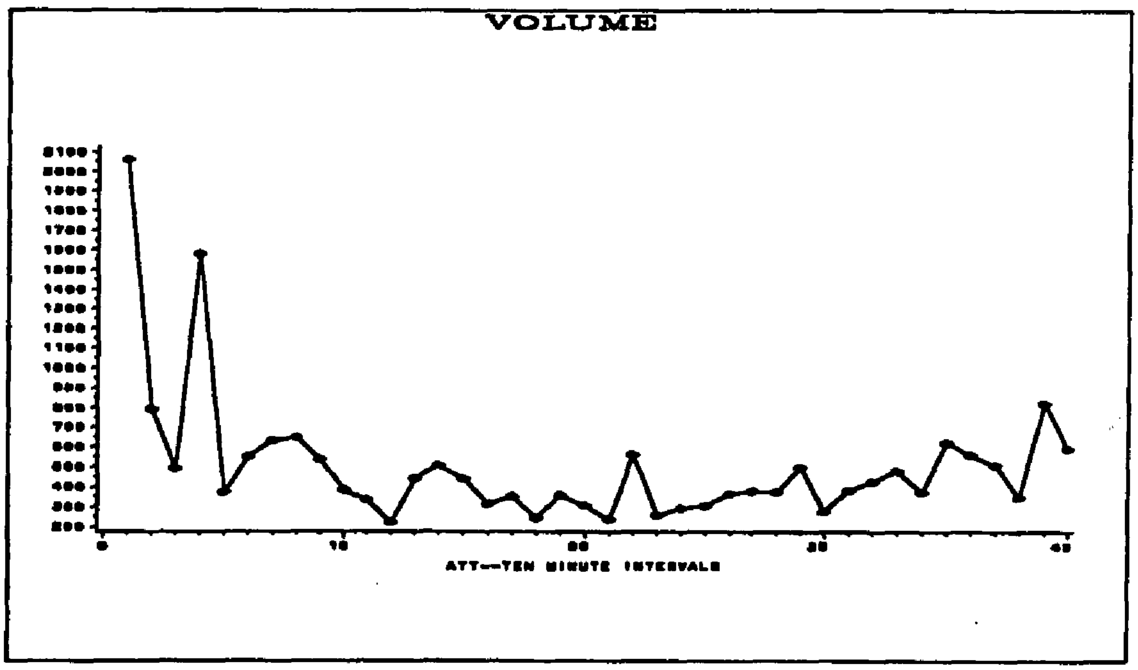
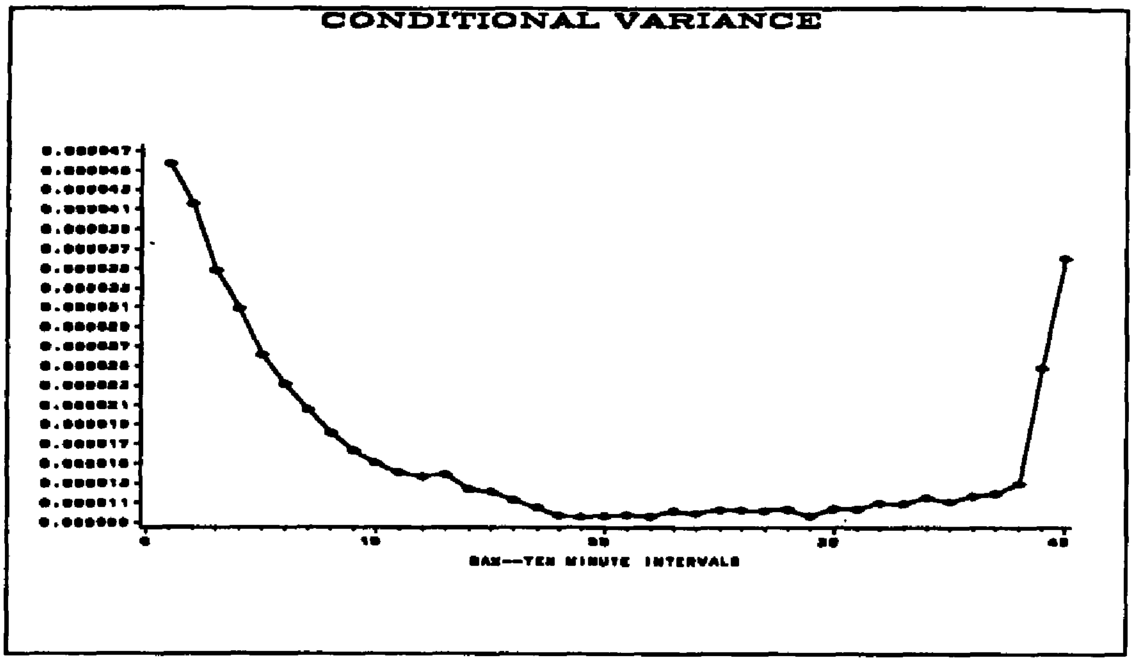



**FIGURE 5-4**
**BAXTER TRAVENOL**
**CONDITIONAL VARIANCE AND VOLUME**



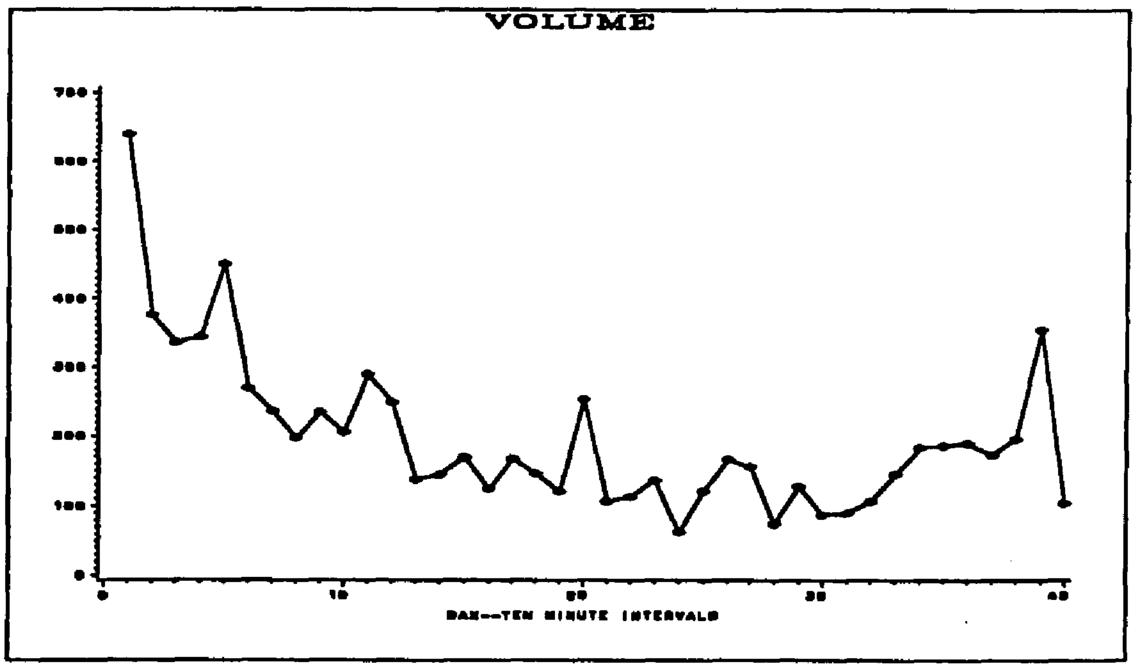
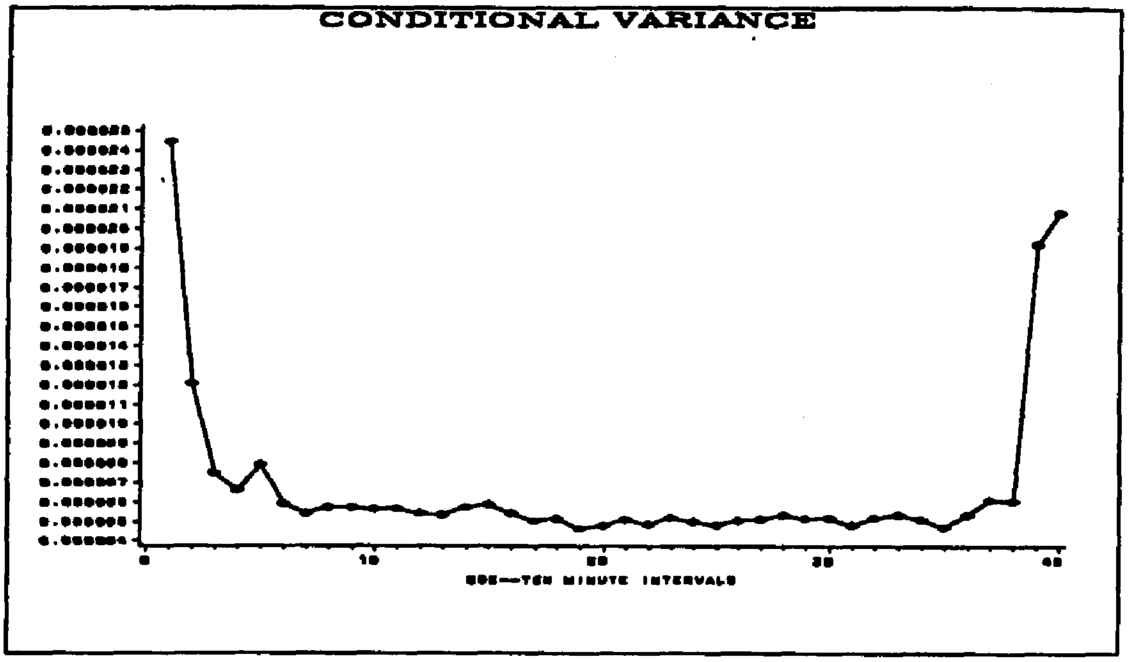



FIGURE 5-5
BOEING
CONDITIONAL VARIANCE AND VOLUME



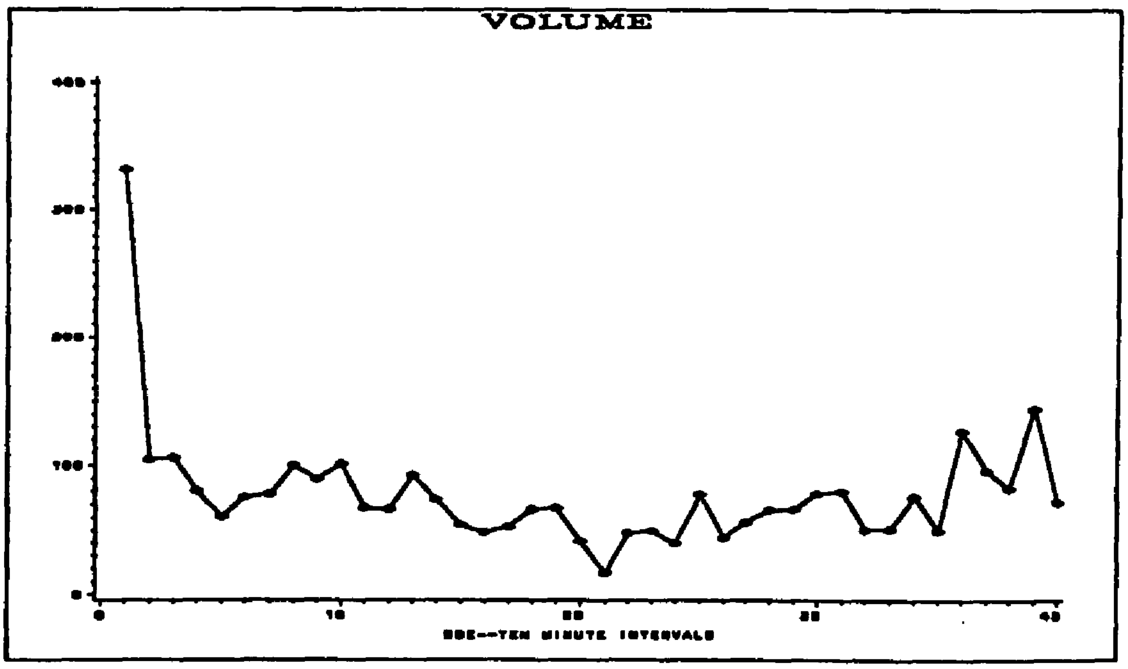
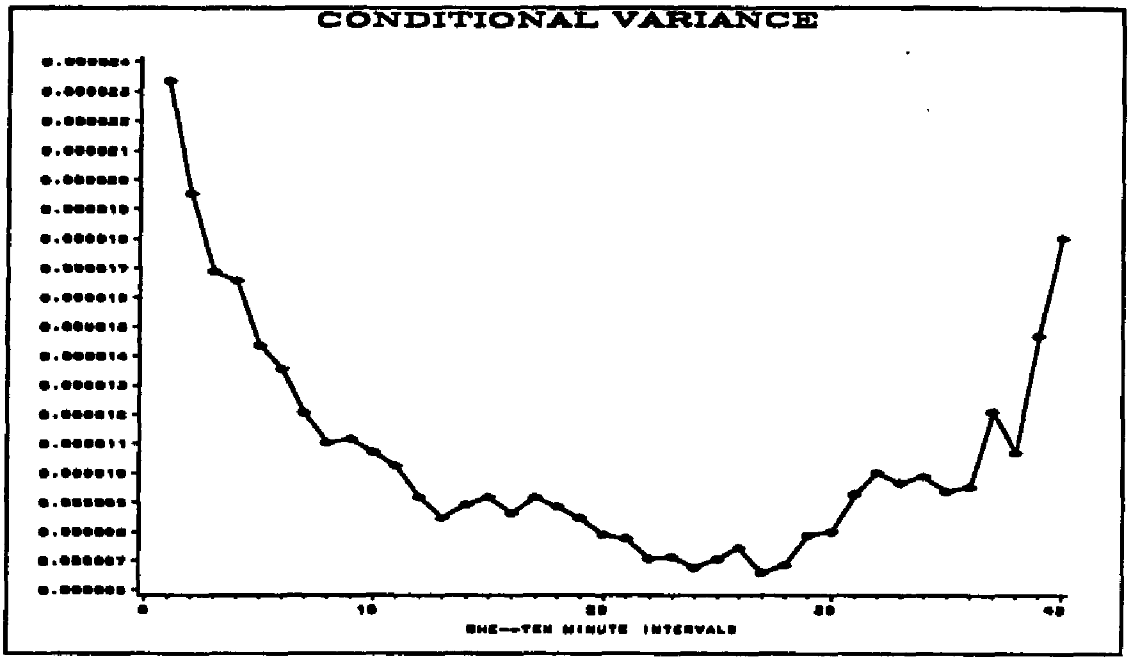



FIGURE 5-6
CHEVRON
CONDITIONAL VARIANCE AND VOLUME



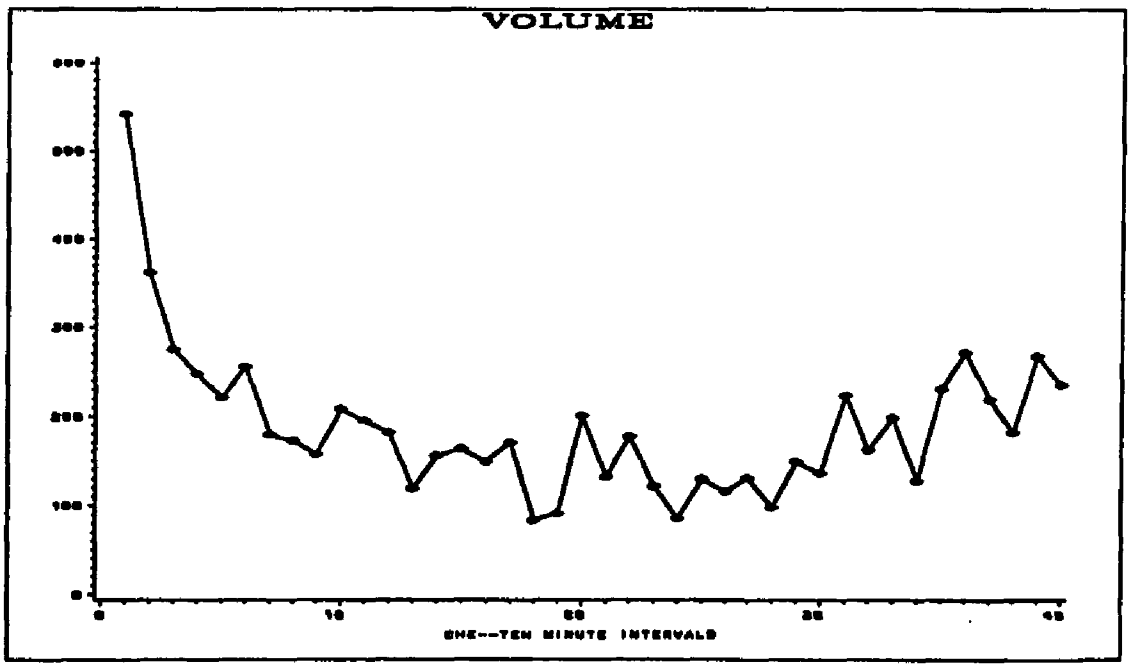



**FIGURE 5-7**
**DIGITAL**
**CONDITIONAL VARIANCE AND VOLUME**

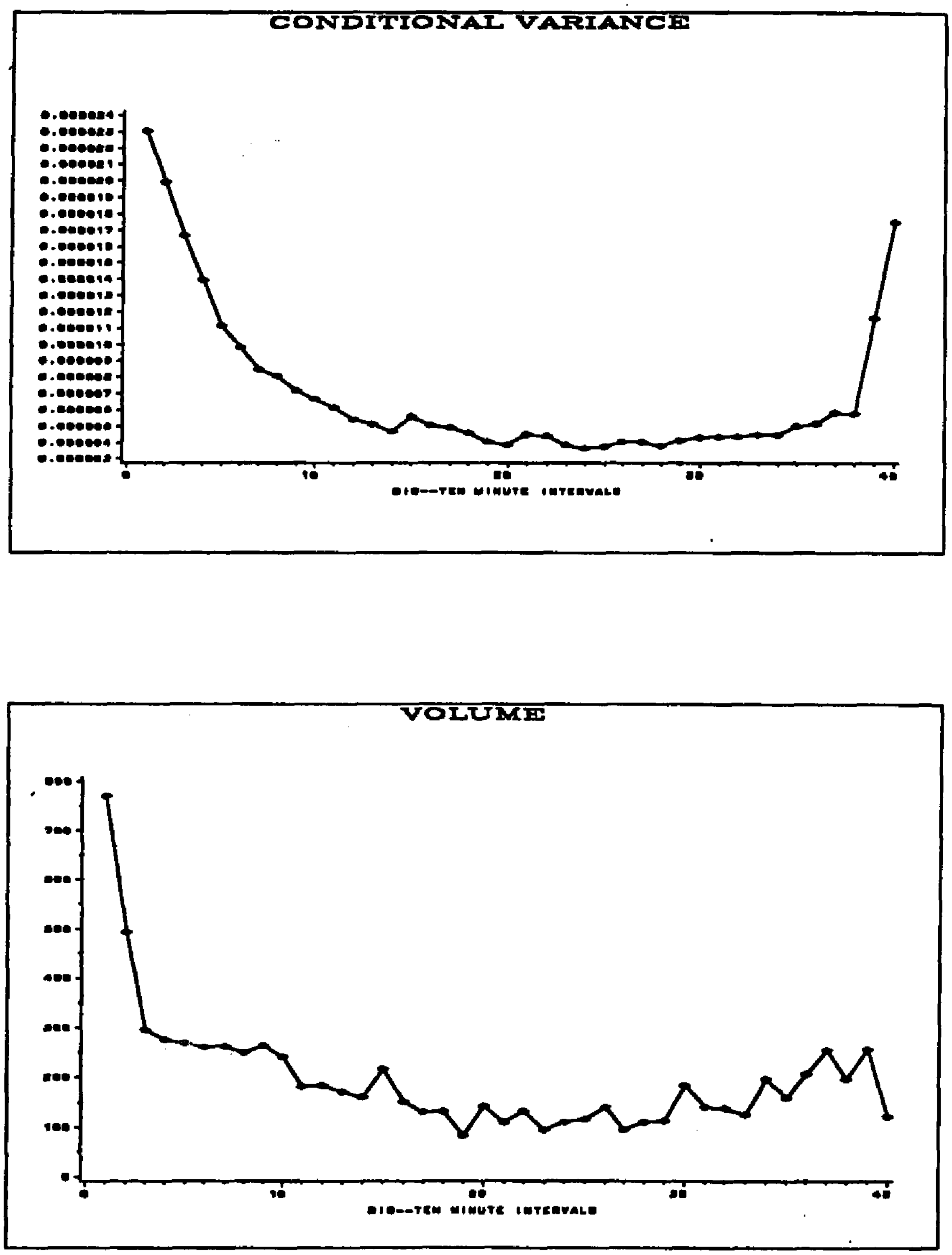
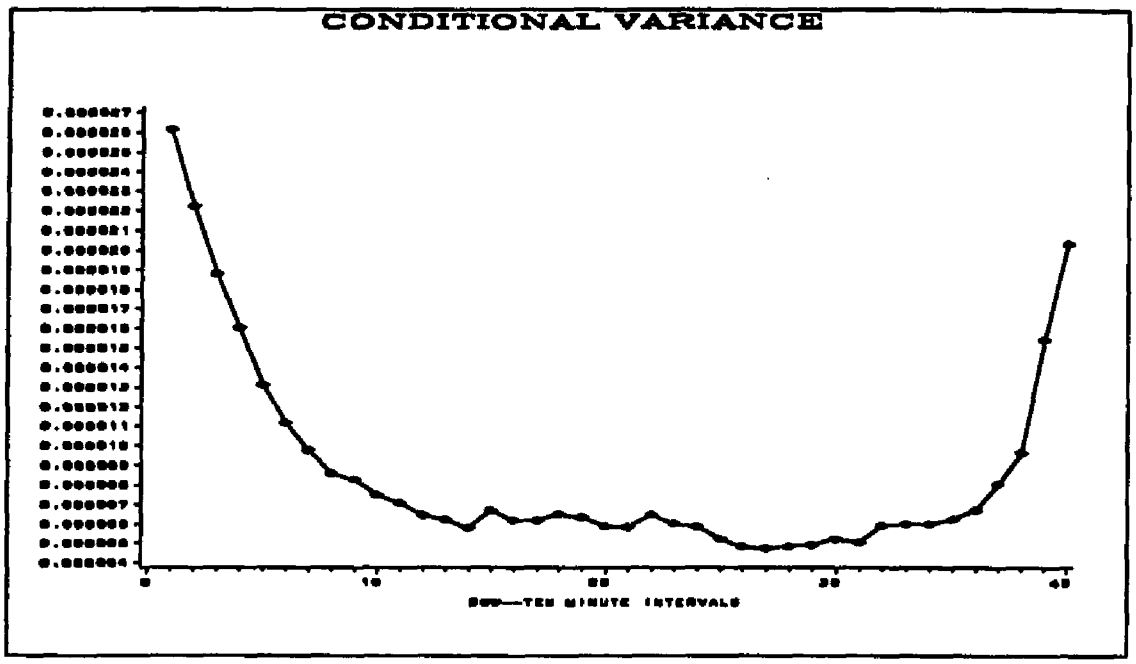


**FIGURE 5-8**
**DOW CHEMICAL**
**CONDITIONAL VARIANCE AND VOLUME**



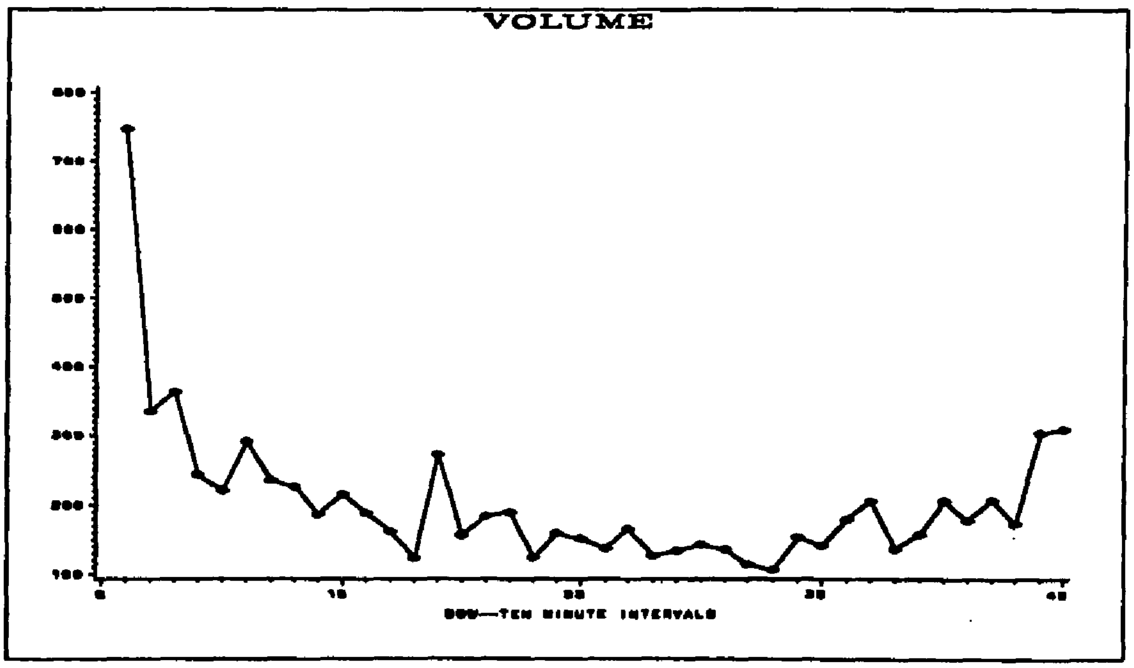
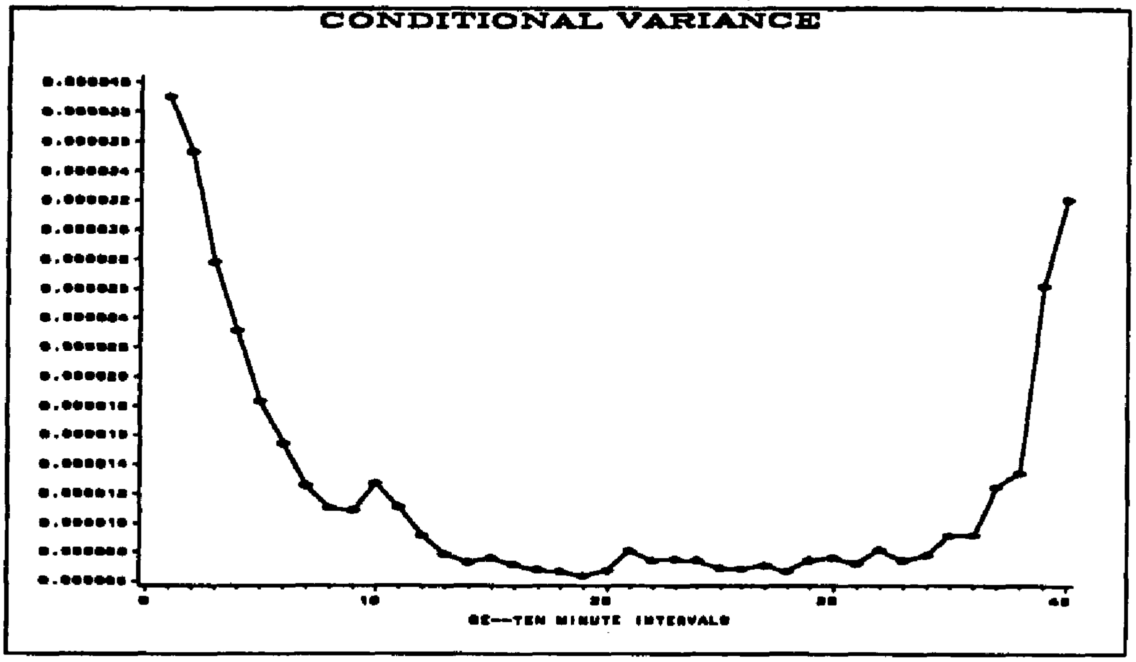



FIGURE 5-9
GENERAL ELECTRIC
CONDITIONAL VARIANCE AND VOLUME



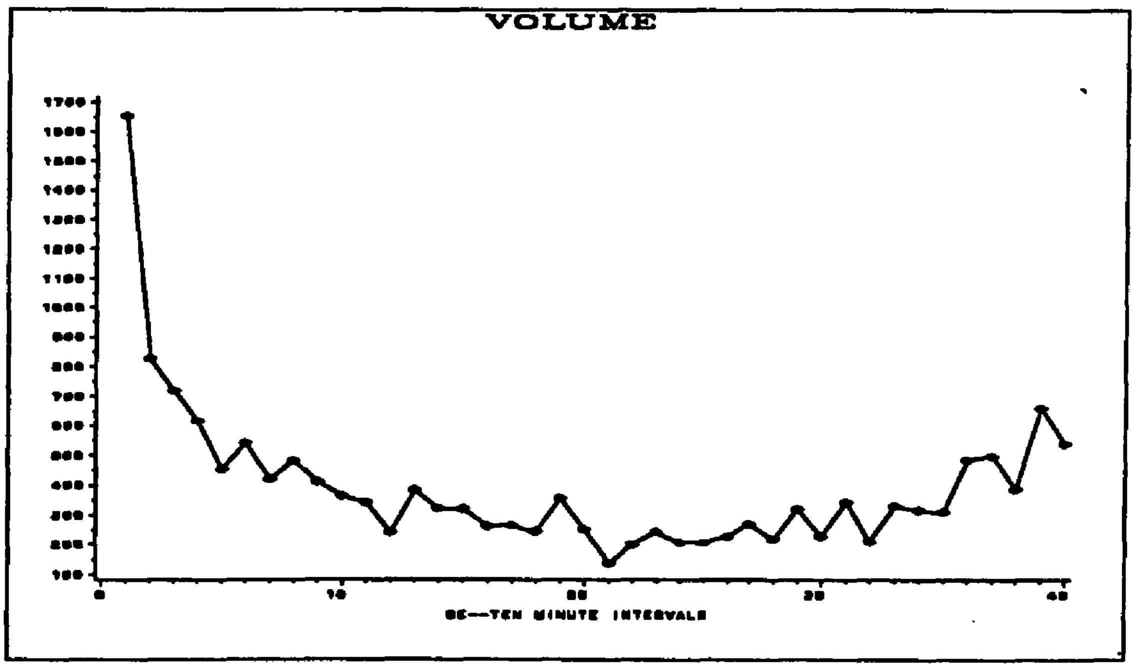
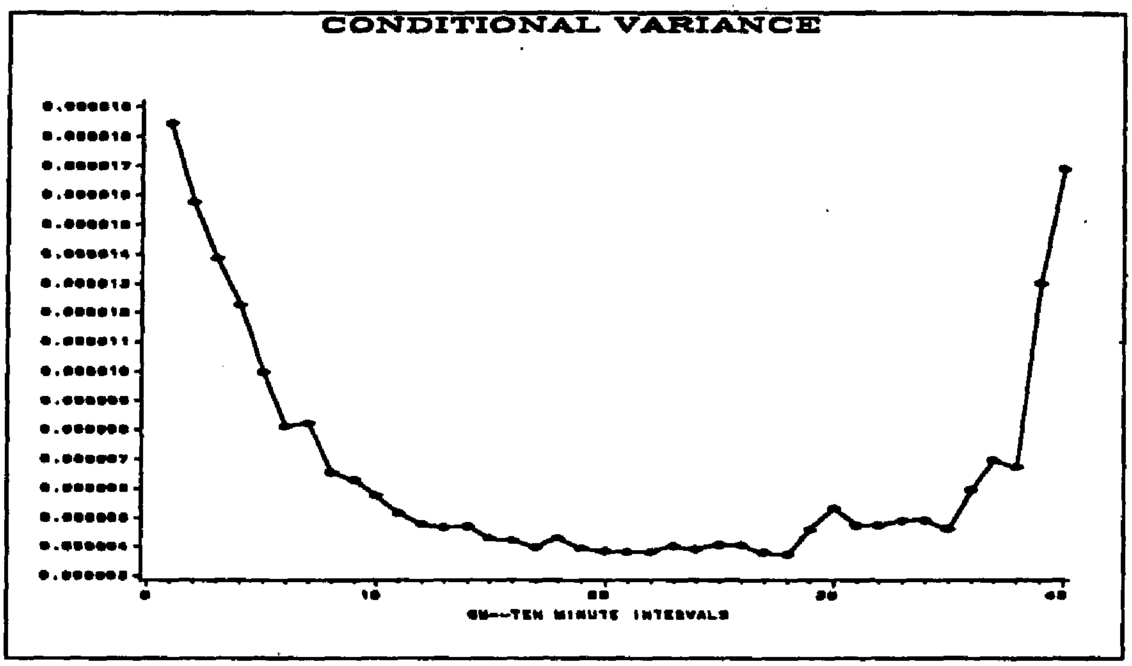



**FIGURE 5-10**
**GENERAL MOTORS**
**CONDITIONAL VARIANCE AND VOLUME**



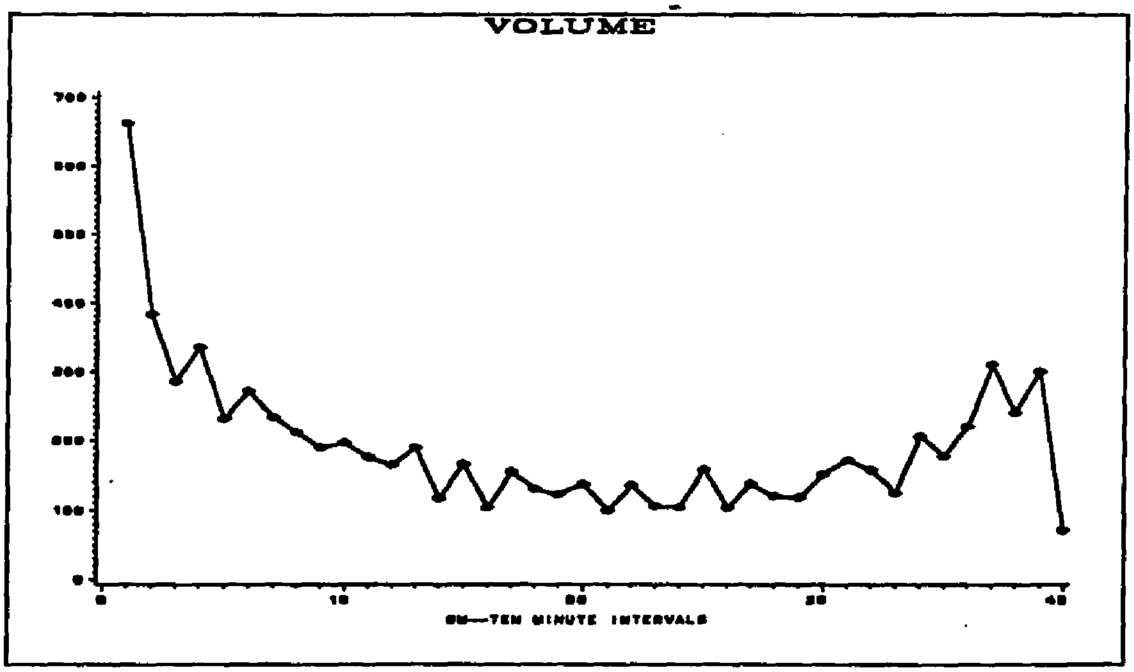
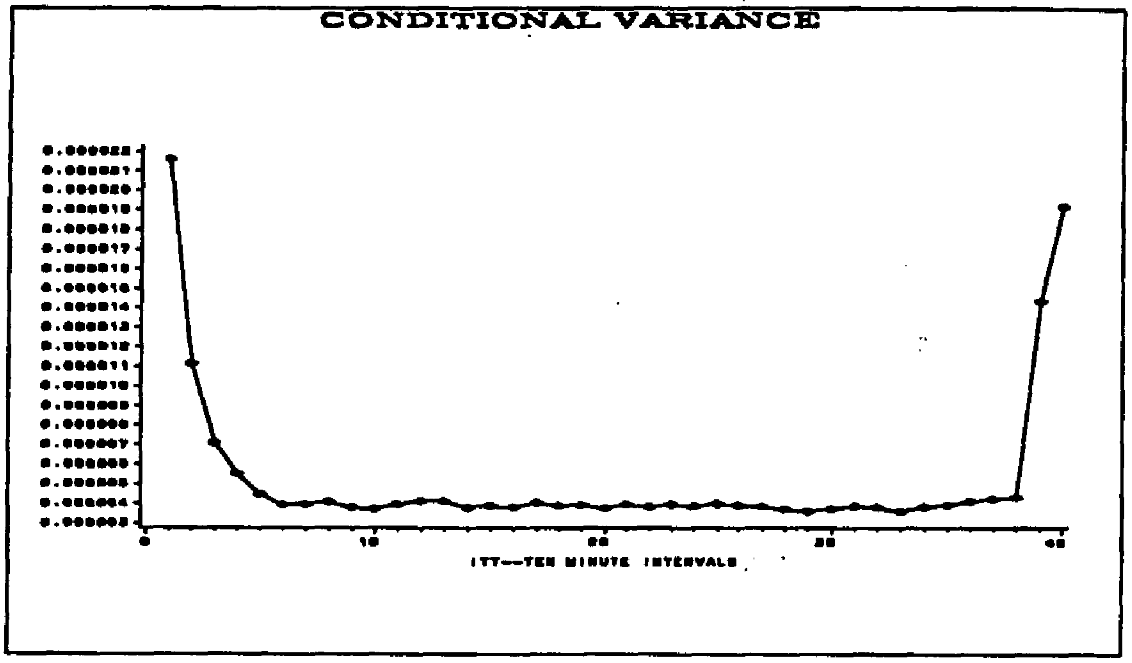



FIGURE 5-11
INTERNATIONAL TELEPHONE AND TELEGRAPH
CONDITIONAL VARIANCE AND VOLUME



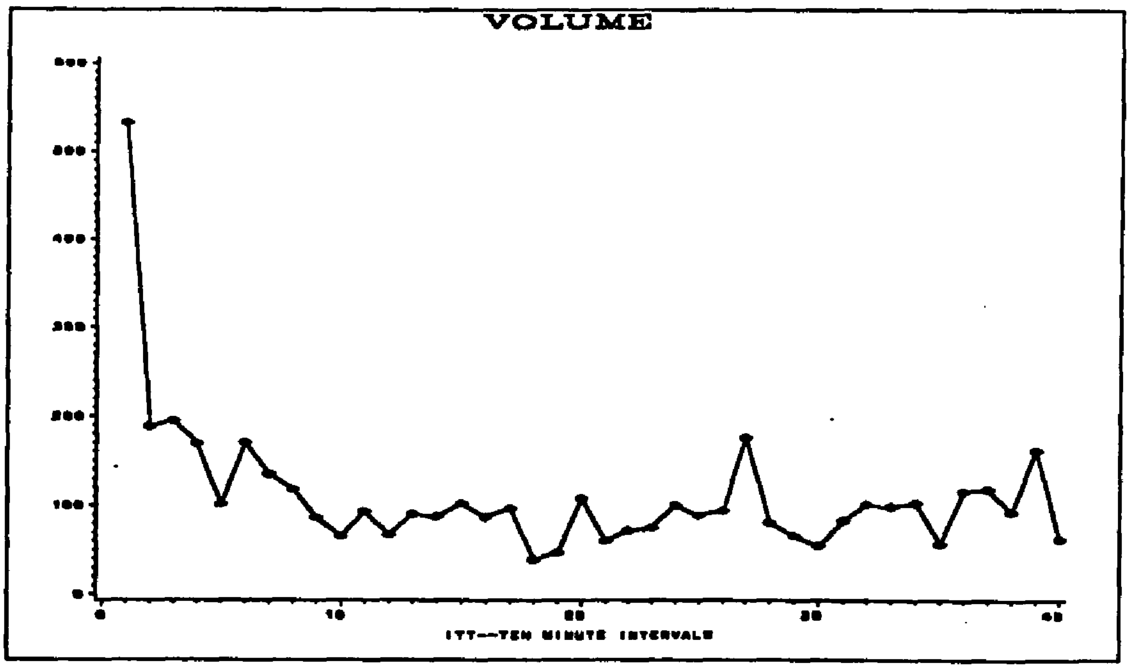
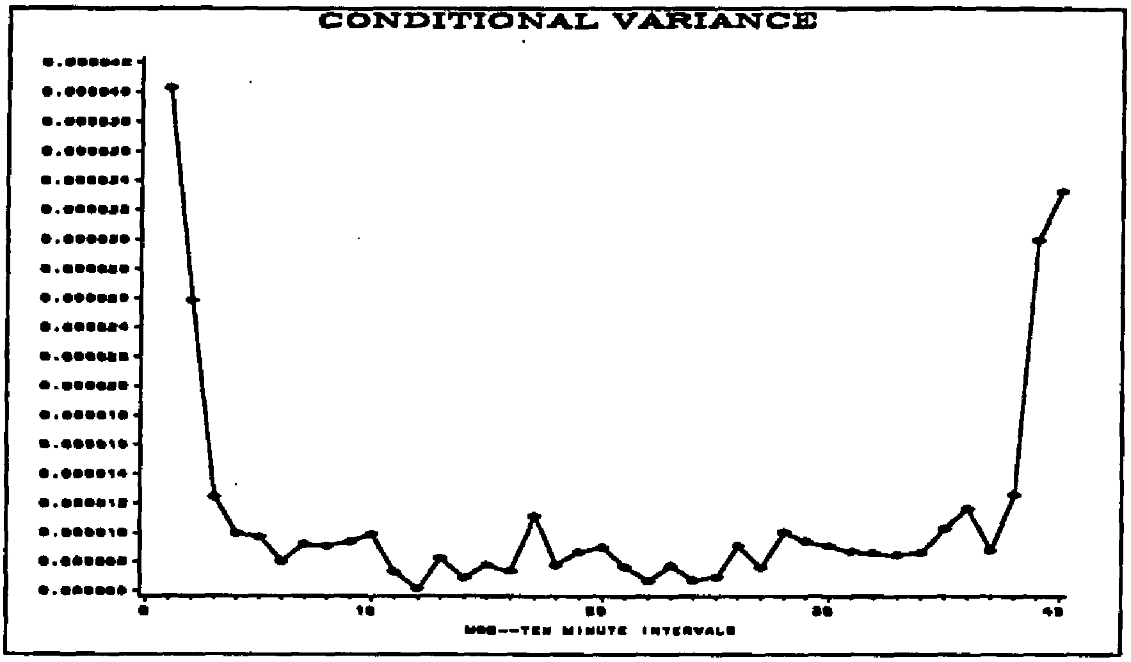



**FIGURE 5-12**
**MOBIL**
**CONDITIONAL VARIANCE AND VOLUME**



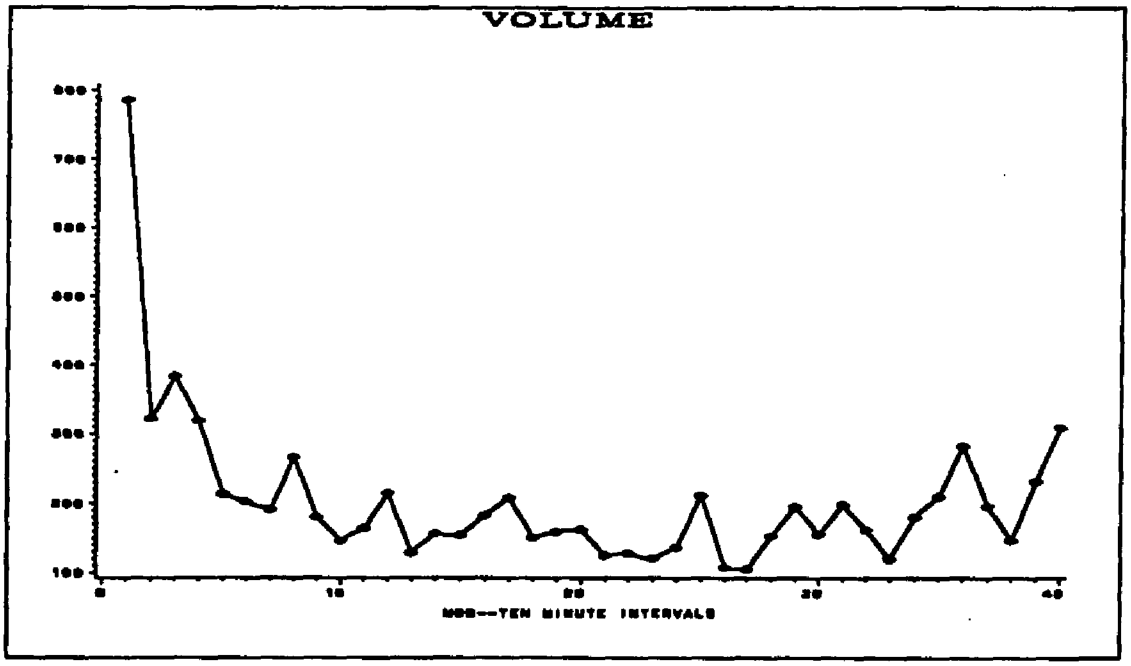
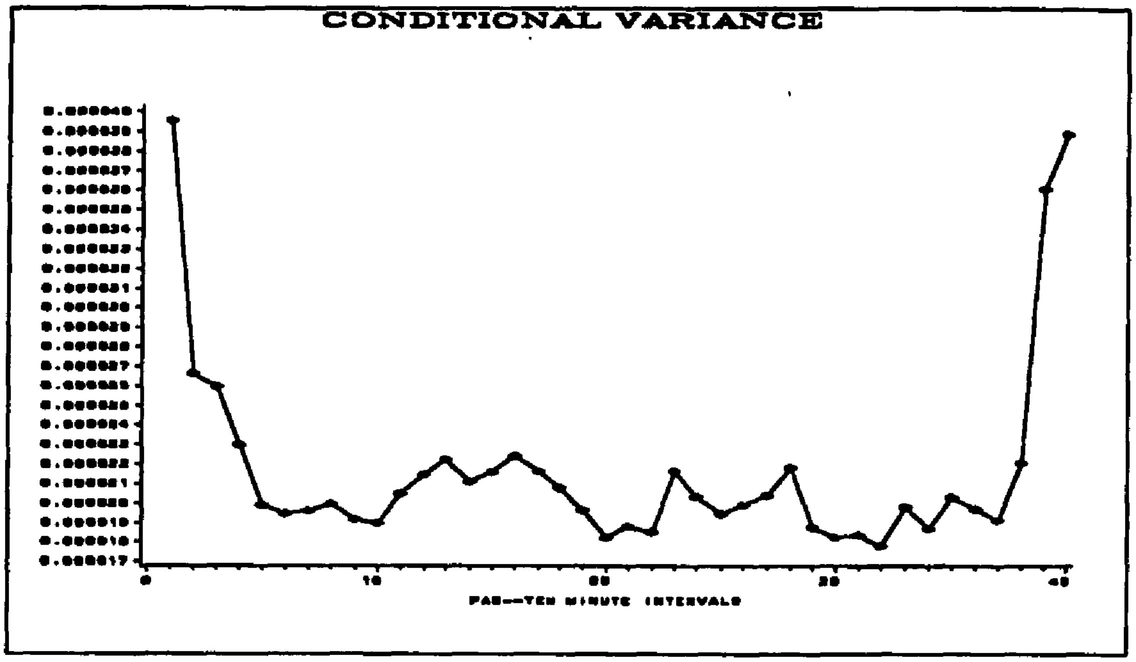



FIGURE 5-13
PACIFIC GAS AND ELECTRIC
CONDITIONAL VARIANCE AND VOLUME



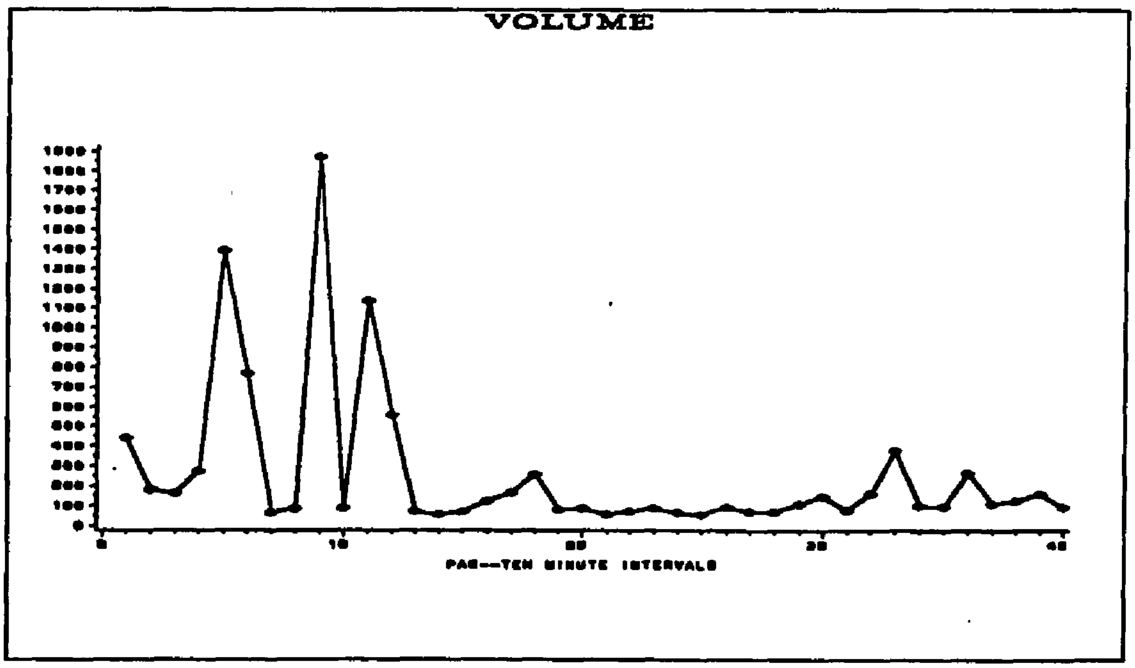
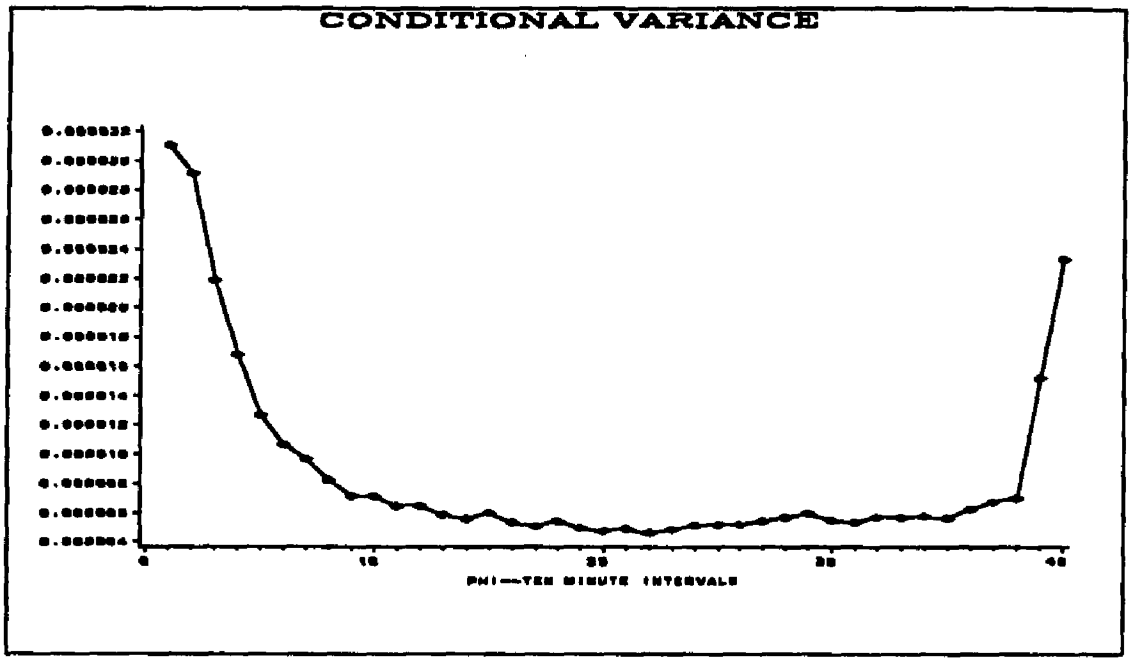



**FIGURE 5-14**
**PHILLIPS PETROLEUM**
**CONDITIONAL VARIANCE AND VOLUME**



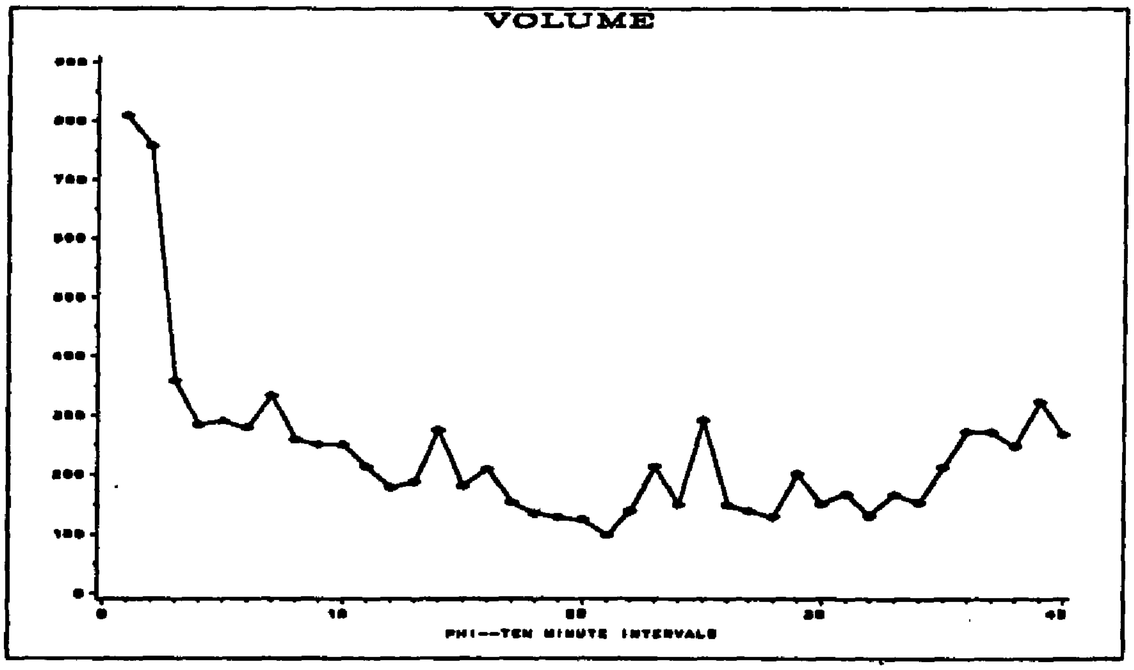
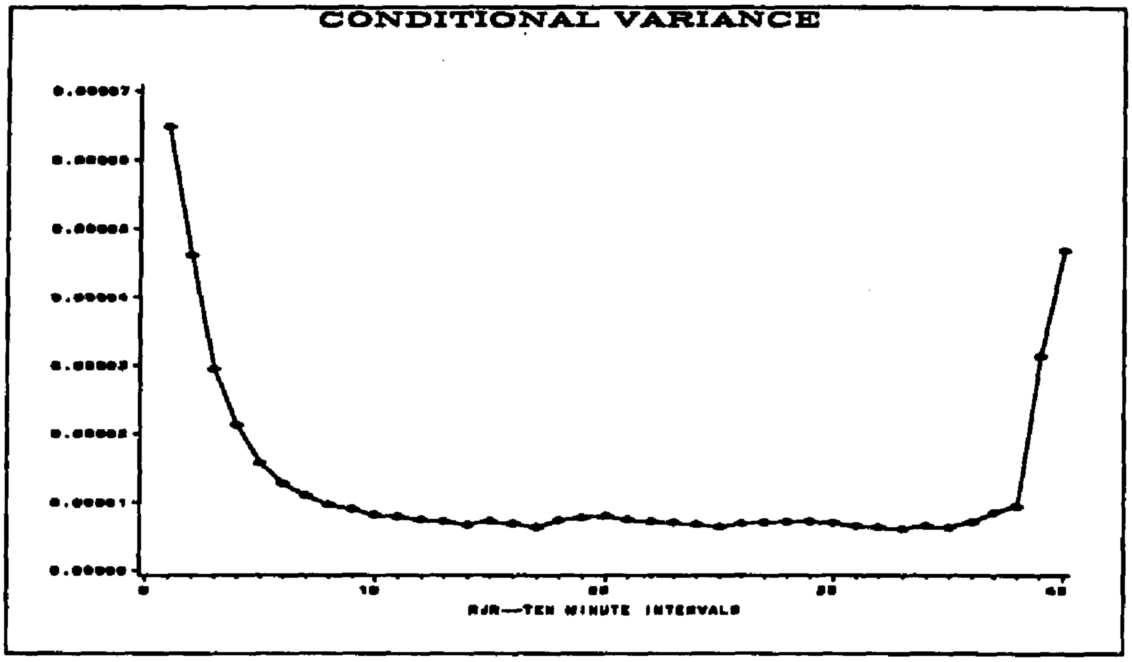



**FIGURE 5-15**
**RJR NABISCO**
**CONDITIONAL VARIANCE AND VOLUME**



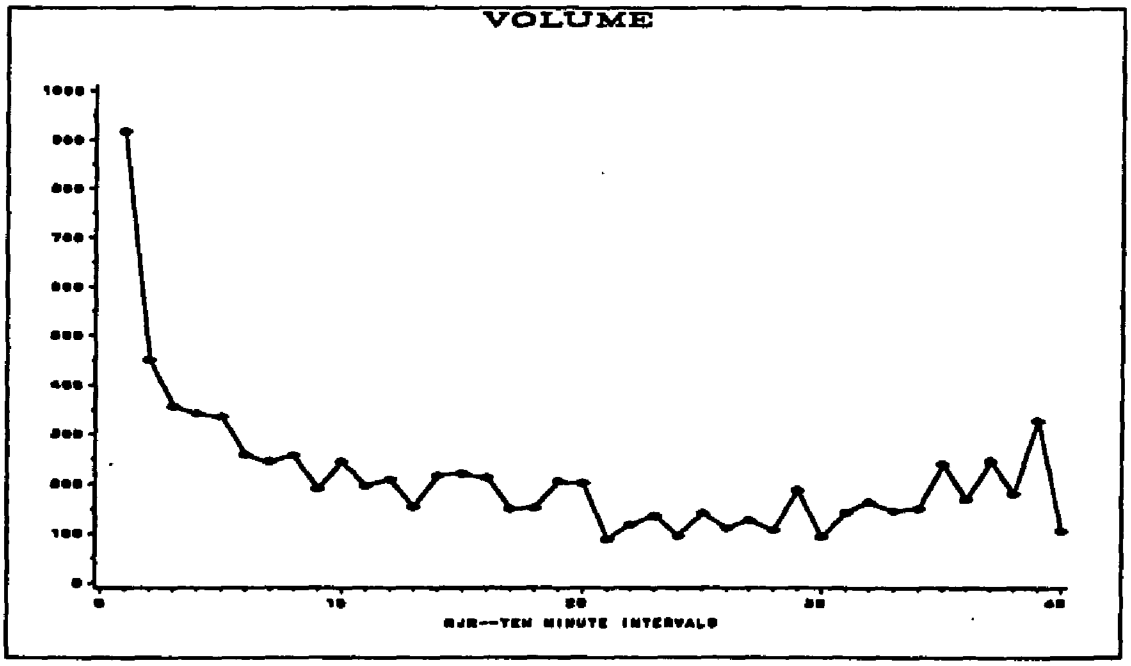



**TABLE 5-1**
**LOG LIKELIHOODS AND DEGREES OF FREEDOM**

| | VOLUME | | TRANSACTIONS | |
|---|---|---|---|---|
| | Log-likelihood | 1/df | Log-likelihood | 1/df |
| AME | 3771.96 | .04 | 3780.79 | .04 |
| ATL | 4394.23 | .67 | 4405.42 | .79 |
| ATT | 3929.41 | .03 | 3965.08 | .11 |
| BAX | 3813.09 | .83 | 3823.09 | .99 |
| BOE | 4159.69 | .03 | 4179.00 | .03 |
| CHE | 4036.31 | .79 | 4039.66 | .85 |
| DIG | 4263.51 | .98 | 4282.79 | .74 |
| DOW | 4133.87 | .58 | <u>4169.34</u> | .84 |
| GE | 3993.20 | .79 | 4025.17 | .74 |
| GM | <u>4349.68</u> | 1.00 | <u>4353.80</u> | .80 |
| ITT | 4333.87 | .17 | 4344.10 | .20 |
| MOB | 3963.52 | .03 | 4007.36 | .03 |
| PAC | 3605.51 | -- | 3612.67 | -- |
| PHI | 4131.54 | .85 | 4154.01 | .66 |
| RJR | 3993.69 | .77 | 3986.59 | .95 |

The underlined figures denote those models with a higher log-likelihood than the results of Chapter 4 based on the Likelihood Ratio test.

**TABLE 5-2**
**ESTIMATION RESULTS - VOLUME EFFECTS**

| | Mean equation | | | | Variance equation | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $a_0$ | $a_1$ | $a_2$ | $a_3$ | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ |
| | 00 | 00 | 00 | | 00000 | | | | 0000 | 00000 | 00000 |
| $AME_T$ | -.083 | .231 | .091 | -.208 | .789 | .000 | --- | .179 | .348 | .648 | .000 |
| | (-6.09) | (2.99) | (3.97) | (-6.45) | (5.53) | (0.02) | | ( 2.14) | (3.74) | (4.33) | (0.00) |
| $ATL_P$ | -.016 | .072 | .041 | -.092 | .039 | .138 | --- | .644 | .023 | .106 | .000 |
| | (-1.72) | (2.08) | (3.08) | (-2.28) | (0.90) | (4.18) | | (10.62) | (2.06) | (2.50) | (0.00) |
| $ATT_T$ | -.041 | .053 | .080 | -.254 | .177 | .019 | --- | .207 | .017 | .024 | .001 |
| | (-3.17) | (1.85) | (5.02) | (-8.31) | (2.33) | (0.77) | | ( 3.87) | (1.58) | (0.38) | (0.62) |
| $BAX_P$ | -.085 | .233 | .151 | -.224 | .136 | .054 | --- | .748 | .179 | .206 | .000 |
| | (-6.39) | (3.88) | (7.77) | (-7.14) | (1.37) | (1.52) | | (11.54) | (3.08) | (1.86) | (0.00) |
| $BOE_T$ | -.050 | -.011 | .068 | -.270 | .465 | .151 | .006 | --- | .052 | .131 | .000 |
| | (-4.52) | (-.39) | (4.64) | (-7.17) | (8.23) | (2.39) | ( 0.34) | | (3.70) | (1.95) | (0.00) |
| $CHE_P$ | -.036 | .015 | .062 | -.243 | .326 | .206 | --- | .462 | .058 | .000 | .000 |
| | (-3.24) | (0.40) | (4.06) | (-6.79) | (2.03) | (3.05) | | ( 3.20) | (1.75) | (0.00) | (0.00) |
| $DIG_P$ | -.056 | .280 | .067 | -.130 | .049 | .298 | --- | .699 | .000 | .006 | .000 |
| | (-7.22) | (12.4) | (6.62) | (-4.12) | (0.69) | (3.29) | | ( 9.24) | (0.02) | (0.09) | (0.00) |
| $DOW_P$ | -.012 | .135 | .042 | -.085 | .243 | .229 | --- | .222 | .034 | .325 | .000 |
| | (-1.29) | (4.01) | (2.51) | (-1.97) | (3.29) | (3.98) | | ( 2.54) | (2.01) | (4.69) | (0.00) |
| $GE_P$ | -.023 | .196 | .047 | -.190 | .404 | .060 | --- | .491 | .001 | .077 | .000 |
| | (-1.95) | (6.77) | (2.79) | (-6.31) | (1.65) | (3.02) | | ( 2.36) | (0.09) | (0.81) | (0.00) |
| $GM_P$ | -.007 | .047 | .057 | -.091 | .054 | .147 | --- | .654 | .036 | .119 | .000 |
| | (-1.27) | (1.68) | (5.65) | (-2.97) | (1.02) | (2.95) | | ( 7.39) | (1.88) | (2.00) | (0.00) |
| $ITT_T$ | -.024 | .091 | .042 | -.234 | .221 | .058 | --- | .274 | .021 | .171 | .000 |
| | (-3.10) | (3.61) | (3.56) | (-7.21) | (2.22) | (1.37) | | ( 1.46) | (1.79) | (2.70) | (0.00) |
| $MOB_T$ | -.054 | .040 | .081 | -.205 | .182 | .076 | --- | --- | .030 | .224 | .002 |
| | (-6.23) | (1.79) | (6.35) | (-7.13) | (6.78) | (3.28) | | | (3.18) | (5.62) | (0.73) |
| $PAC_N$ | -.064 | .090 | .080 | -.567 | 1.54 | .040 | .220 | --- | .174 | .021 | .000 |
| | (-3.88) | (1.80) | (3.62) | (-21.6) | (3.16) | (1.64) | ( 1.12) | | (2.70) | (0.10) | (0.00) |
| $PHI_P$ | -.017 | .093 | .043 | -.040 | .352 | .000 | --- | .189 | .242 | .381 | .000 |
| | (-1.71) | (1.45) | (2.92) | (-1.42) | (3.69) | (0.01) | | ( 1.56) | (3.02) | (3.61) | (0.00) |
| $RJR_P$ | -.023 | .164 | .039 | -.077 | .176 | .097 | --- | .460 | .187 | .455 | .000 |
| | (-2.25) | (2.65) | (2.16) | (-2.32) | (2.67) | (2.14) | | ( 7.37) | (4.24) | (4.18) | (0.00) |

The t-statistics are in parentheses.

**TABLE 5-3**
**ESTIMATION RESULTS - TRANSACTION EFFECTS**

| | Mean equation | | | | Variance equation | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $a_0$ | $a_1$ | $a_2$ | $a_3$ | $\alpha_0$ | $\alpha_1$ | $\alpha_2$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ |
| | 00 | 00 | 00 | | 00000 | | | | 0000 | 00000 | 00000 |
| $AME_T$ | -.092 | .189 | .118 | -.156 | .336 | .020 | --- | .344 | .211 | .003 | .047 |
| | (-5.69) | (3.00) | (5.37) | (-4.69) | (2.17) | (0.77) | | ( 3.64) | (4.17) | (0.03) | (2.03) |
| $ATL_P$ | -.023 | .070 | .034 | -.124 | .052 | .065 | --- | .719 | .019 | .036 | .000 |
| | (-2.77) | (2.59) | (2.97) | (-3.99) | (0.91) | (3.28) | | (11.66) | (2.21) | (0.86) | (0.00) |
| $ATT_T$ | -.060 | .023 | .102 | -.160 | .093 | .017 | --- | .347 | .084 | .063 | .029 |
| | (-3.99) | (0.54) | (5.46) | (-5.02) | (0.54) | (0.49) | | ( 2.25) | (2.71) | (0.67) | (2.00) |
| $BAX_P$ | -.071 | .160 | .130 | -.200 | .465 | .031 | --- | .455 | .196 | .611 | .000 |
| | (-6.57) | (3.15) | (7.66) | (-7.44) | (1.57) | (0.67) | | ( 2.83) | (2.02) | (2.56) | (0.00) |
| $BOE_T$ | -.050 | -.030 | .069 | -.281 | .335 | .025 | .029 | --- | .132 | .121 | .028 |
| | (-4.56) | (-.77) | (4.65) | (-8.34) | (4.01) | (0.82) | ( 1.14) | | (5.40) | (1.79) | (1.20) |
| $CHE_P$ | -.034 | .012 | .060 | -.254 | .050 | .163 | --- | .548 | .045 | .002 | .038 |
| | (-3.42) | (0.37) | (4.46) | (-7.91) | (0.42) | (2.43) | | ( 5.24) | (1.78) | (0.02) | (1.29) |
| $DIG_P$ | -.056 | .236 | .069 | -.114 | .007 | .043 | --- | .839 | .049 | .052 | .000 |
| | (-7.97) | (7.85) | (7.21) | (-4.40) | (0.09) | (1.97) | | (13.18) | (3.04) | (0.92) | (0.00) |
| $DOW_P$ | -.013 | .112 | .053 | -.080 | .029 | .145 | --- | .419 | .060 | .159 | .019 |
| | (-1.34) | (2.80) | (3.77) | (-2.25) | (0.41) | (2.64) | | ( 4.20) | (2.12) | (2.49) | (1.09) |
| $GE_P$ | -.030 | .166 | .069 | -.186 | .138 | .229 | --- | .237 | .122 | .254 | .014 |
| | (-3.26) | (3.50) | (4.56) | (-5.19) | (1.34) | (3.61) | | ( 2.44) | (2.42) | (2.83) | (0.83) |
| $GM_P$ | -.010 | .042 | .058 | -.084 | .058 | .167 | --- | .678 | .025 | .032 | .000 |
| | (-1.36) | (1.47) | (5.39) | (-2.52) | (1.06) | (3.71) | | ( 9.28) | (1.98) | (0.75) | (0.00) |
| $ITT_T$ | -.025 | .075 | .030 | -.181 | .051 | .000 | --- | .414 | .063 | .082 | .026 |
| | (-3.25) | (2.25) | (2.78) | (-6.19) | (0.81) | (0.01) | | ( 3.12) | (3.01) | (1.66) | (1.60) |
| $MOB_T$ | -.059 | .043 | .076 | -.169 | .316 | .203 | --- | --- | .308 | .288 | .028 |
| | (-4.74) | (0.63) | (4.35) | (-4.49) | (3.50) | (3.50) | | | (4.32) | (3.69) | (1.25) |
| $PAC_N$ | -.072 | .027 | .100 | -.431 | .953 | .147 | .274 | --- | .184 | .434 | .000 |
| | (-4.37) | (0.45) | (4.35) | (-12.4) | (2.16) | (2.63) | ( 1.75) | | (2.65) | (2.27) | (0.00) |
| $PHI_P$ | -.014 | .107 | .041 | -.050 | .021 | .000 | --- | .419 | .221 | .085 | .027 |
| | (-1.30) | (1.31) | (2.70) | (-1.53) | (0.39) | (0.01) | | ( 5.10) | (4.16) | (1.82) | (1.95) |
| $RJR_P$ | -.026 | .144 | .049 | -.054 | .084 | .003 | --- | .294 | .387 | .017 | .053 |
| | (-2.55) | (2.16) | (3.47) | (-2.17) | (0.83) | (0.15) | | ( 2.81) | (3.09) | (0.19) | (2.20) |

The t-statistics are in parentheses.

**TABLE 5-4**
**DISTRIBUTIONAL TESTS ON VOLUME RESIDUALS**

| | skew | kurt | *S* stat | $\chi^2$ Total | $\chi^2$ Tail region | $\chi^2$ Midpoint region |
|---|---|---|---|---|---|---|
| AME | -.043 | 0.771 | 0.28 | 160.79 | 2.68# | 20.15 |
| ATL | -.032 | 2.586 | 0.15 | 281.89 | 3.50# | 43.85 |
| ATT | -.190 | 0.620 | 5.49* | 240.54 | 3.48# | 1.18# |
| BAX | -.004 | 0.693 | 0.00 | 228.14 | 5.91# | 6.48 |
| BOE | -.149 | 1.831 | 3.38 | 208.41 | 1.72# | 2.79# |
| CHE | .070 | 0.839 | 0.75 | 104.53 | 5.71# | 0.65# |
| DIG | -.018 | 2.202 | 0.05 | 43.89 | 2.69# | 5.14# |
| DOW | -.029 | 1.686 | 0.13 | 268.62 | 0.06# | 22.83 |
| GE | -.290 | 2.275 | 12.74* | 111.53 | 2.76# | 17.51 |
| GM | .038 | 1.982 | 0.21 | 240.68 | 15.90 | 27.31 |
| ITT | -.275 | 1.799 | 11.43* | 332.01 | 22.64 | 42.16 |
| MOB | -.283 | 2.444 | 12.11* | 90.40 | 7.64 | 17.11 |
| PAC | -.262 | 0.067 | 10.42* | 132.81 | 3.88# | 11.72 |
| PHI | -.359 | 2.922 | 19.49* | 439.19 | 6.59 | 41.29 |
| RJR | .122 | 2.161 | 2.25 | 228.43 | 0.62# | 42.74 |

The $\chi^2(1)$ value for the *S* statistic at the 0.05 significance level is 3.84. An '*' represents significance at the .05 level. A '#' indicates that the null hypothesis cannot be rejected using the $\chi^2$ goodness of fit tests.

TABLE 5-5
DISTRIBUTIONAL TESTS ON TRANSACTION RESIDUALS

| | skew | kurt | $S$ stat | $\chi^2$ Total | $\chi^2$ Tail region | $\chi^2$ Midpoint region |
|---|---|---|---|---|---|---|
| AME | -.102 | 0.641 | 1.59 | 104.39 | 0.59# | 12.53 |
| ATL | .049 | 2.555 | 0.37 | 237.11 | 0.20# | 33.03 |
| ATT | -.097 | 0.247 | 1.44 | 351.17 | 17.34 | 57.36 |
| BAX | .026 | 0.894 | 0.10 | 485.97 | 8.26 | 3.57# |
| BOE | -.065 | 0.730 | 0.63 | 143.37 | 9.41 | 4.90# |
| CHE | .031 | 0.658 | 0.14 | 84.03 | 4.46# | 3.45# |
| DIG | -.049 | 1.799 | 0.37 | 24.59* | 0.53# | 10.33 |
| DOW | -.059 | 1.438 | 0.53 | 98.99 | 0.50# | 5.11# |
| GE | -.063 | 1.005 | 0.60 | 132.13 | 3.22# | 14.26 |
| GM | -.083 | 1.670 | 1.04 | 175.07 | 7.49 | 42.74 |
| ITT | -.226 | 0.871 | 7.76* | 439.41 | 32.80 | 31.38 |
| MOB | -.212 | 1.706 | 6.83* | 283.33 | 3.75# | 39.99 |
| PAC | -.235 | -0.017 | 8.35* | 203.10 | 2.01# | 8.26 |
| PHI | -.149 | 2.088 | 3.38 | 87.02 | 3.66# | 24.27 |
| RJR | .044 | 1.759 | 0.29 | 218.88 | 0.06# | 1.38# |

The $\chi^2(1)$ value for the $S$ statistic at the 0.05 significance level is 3.84. An '*' represents significance at the .05 level. A '#' indicates that the null hypothesis cannot be rejected using the $\chi^2$ goodness of fit tests.

TABLE 5-6
TESTS FOR NONLINEAR DEPENDENCE ON VOLUME RESIDUALS

| | LB(6) $r$ | LB(6) $r^2$ | LB(6) $\|r\|$ | AUTOCORRELATION FOR LAG-1 $r$ | $r^2$ | $\|r\|$ |
|---|---|---|---|---|---|---|
| AME | 7.04 | 39.95* | 35.69* | .020 | .043 | .058 |
| ATL | 7.36 | 7.43 | 11.24 | .003 | .057 | .075 |
| ATT | 10.69 | 4.88 | 8.40 | -.033 | .001 | .038 |
| BAX | 10.61 | 6.03 | 5.19 | -.010 | .054 | .058 |
| BOE | 0.80 | 38.49* | 34.44* | -.010 | -.037 | -.042 |
| CHE | 6.27 | 7.56 | 7.56 | .057 | -.008 | -.024 |
| DIG | 19.94* | 3.88 | 3.34 | .076* | .009 | .018 |
| DOW | 11.15 | 4.31 | 10.16 | .067 | -.011 | .021 |
| GE | 15.65* | 66.12* | 62.73* | .087* | .206* | .174* |
| GM | 3.99 | 16.43* | 17.34* | -.004 | .066* | .037 |
| ITT | 8.49 | 1.23 | 3.65 | .070 | .016 | .030 |
| MOB | 6.15 | 32.75* | 19.84* | .033 | .016 | .033 |
| PAC | 6.63 | 24.45* | 27.73* | .032 | .089* | .079* |
| PHI | 6.29 | 34.16* | 41.86* | -.016 | .098* | .120* |
| RJR | 4.43 | 7.43 | 12.31 | .048 | -.013 | -.005 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. An '*' represents significance at the .05 level.

TABLE 5-7
TESTS FOR NONLINEAR DEPENDENCE ON TRANSACTION RESIDUALS

| | LB(6) $r$ | LB(6) $r^2$ | LB(6) $\lvert r \rvert$ | AUTOCORRELATION FOR LAG-1 $r$ | $r^2$ | $\lvert r \rvert$ |
|---|---|---|---|---|---|---|
| AME | 6.58 | 31.24* | 24.48* | -.051 | .030 | .020 |
| ATL | 7.45 | 18.91* | 24.42* | .029 | .095* | .110* |
| ATT | 14.62* | 4.93 | 6.56 | -.067* | .058 | .050 |
| BAX | 6.00 | 15.23* | 13.44* | .088* | .054 | .092* |
| BOE | 2.83 | 29.74* | 21.17* | -.002 | .029 | .025 |
| CHE | 7.17 | 6.80 | 6.54 | .058 | -.020 | -.037 |
| DIG | 30.01* | 32.93* | 35.31* | .076* | .086* | .115* |
| DOW | 12.87* | 2.15 | 4.45 | .063* | .019 | .035 |
| GE | 13.99* | 10.71 | 12.58 | .078* | -.003 | -.004 |
| GM | 3.55 | 13.03* | 11.61 | -.019 | .059* | .022 |
| ITT | 4.50 | 3.92 | 4.60 | -.011 | .020 | .026 |
| MOB | 6.08 | 37.03* | 23.46* | .033 | .026 | -.018 |
| PAC | 12.06 | 10.69 | 11.01 | -.091* | .065 | -.038 |
| PHI | 4.74 | 17.08* | 22.84* | -.011 | .087* | .105* |
| RJR | 3.95 | 8.10 | 13.79* | -.002 | .075 | .055 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. An '*' represents significance at the .05 level.

# CHAPTER 6

## VARIANCE RATIO TESTS AND ARCH EFFECTS

In a recent work, Lo and MacKinlay (1989) suggest that a variant of the variance-ratio statistic can be used to test for the presence of nonlinear dependence. In their paper, they specifically point out its relevance for ARCH processes. They argue that the standard variance ratio test can be adjusted by a weighted combination of the variances of the autocorrelations, thereby taking account of the presence of second order dependence. They conclude their work by providing a number of simulations that favorably compare the power of this adjusted variance ratio test to that of the Box-Pierce $Q$ statistic and the Dickey-Fuller $t$ tests.

In this chapter we wish to further examine the properties of this unconditional, variance-ratio statistic when the underlying return generating process contains a specific type of second order dependence. In particular, we generate random series from a GARCH(1,1) process with different degrees of persistence and then apply the standard and variance, adjusted statistic to each model. In this way, we can directly verify Lo and MacKinlay's proposition with a finite sample taken from a population with known moments.

In the first section of this chapter, we discuss the theory behind the standard variance ratio test and the variant developed by Lo and MacKinlay (1989). We critique their hypothesis concerning the ability of the adjusted test to account for ARCH type dependence. The second section provides a description of our simulation and the Monte Carlo

study, along with a description of the actual return series used in the subsequent analysis. In the last section, we present our results and a discussion of their implications for our intradaily findings.

## A. STATISTICAL THEORY

The concept of using the ratio of the unconditional variances from different sampling intervals to test the null hypothesis of a random walk is not new. This time-variance relationship enjoys a long history with particular reference to the works of Working (1949), Osborne (1959), and the previously noted contributions of Young (1971), Schwartz and Whitcomb (1977), and Perry (1982) [see footnote 1]. Its application to the detection of second-order dependence, in particular ARCH effects, is the reason for the resurgence of interest in the topic.

Given a times series of log prices, $\{_1p_t\}_{t=0}^{n}$, sampled at some interval denoted by the unit subscript, '$_1$', we can express the random walk hypothesis as $_1p_t = {_1p_{t-1}} + {_1e_t}$, where the $_1e_t \sim N(0,\sigma_1^2)$. Hence the change in the series, $\{\Delta_1 p_t\}_{t=1}^{n}$, is white noise with a variance of $\sigma_1^2$ (We have referred to this series throughout this paper as $r_t$). If we now sample the data by using every other observation from the original series, we obtain a series of first-differences denoted as $\{\Delta_2 p_\tau\}_{\tau=1}^{n}$. In this case, every element of $\{\Delta_2 p_\tau\}$ is the sum of two adjacent elements of $\{\Delta_1 p_t\}$ or $\Delta_2 p_1 = \Delta_1 p_1 + \Delta_1 p_2$, $\Delta_2 p_2 = \Delta_1 p_3 + \Delta_1 p_4$, etc.. Diebold (1988) refers to this series as '2-aggregated' with higher order aggregates denoted as q-aggregated for q > 2.

The unconditional variances of $\{\Delta_1 p.\}$, $\{\Delta_2 p.\}$, and $\{\Delta_k p.\}$ are $\sigma_1^2$, $\sigma_2^2$, and $\sigma_k^2$, respectively. Under the null hypothesis of a random walk the following relationship holds:

$$\sigma_q^2 = q\sigma_1^2,\ q = 1,\ldots,n/k$$

or

$$2\sigma_1^2/\sigma_2^2 = 3\sigma_1^2/\sigma_3^2 = \ldots = (n/k)\sigma_1^2/\sigma_{n/k}^2 = 1.$$

In order to improve the power of this test, the q differences can be based on overlapping intervals. This provides n-q+1 terms in the calculation of the aggregated series rather than only n/q terms as defined above. We call these overlapping-interval variance ratios after subtracting one, $M_r(q)$, with q denoting the degree of aggregation. If the two series forming the ratio were independent the statistics would have central F-distributions. Since the aggregated series are not independent of the original series, the relationship holds only at the limit and the asymptotic distribution of $(n^{½})M_r(q)$ is $N(0,2[2q-1][q-1]/3q)$.

Diebold (1988) provides fractiles of $M_r(q)$ for some finite sample sizes and aggregation values. Lo and MacKinlay (1988) use unbiased estimates of the variances in the ratio.[30] They also provide a variant

[30] The unbiased estimate of the unconditional variance of the first differences of the original series is:

$$\sigma_1^2=\frac{1}{(n-1)}\sum_{t=1}^{n}(p_t-p_{t-1}-\mu)^2,$$

where $\mu$ is the mean of the first differences. The unbiased estimate for the aggregated series is:

$$\sigma_q^2=\frac{1}{m}\sum_{t=q}^{n}(p_t-p_{t-q}-q\mu)^2,$$

of the statistic that purportedly adjusts for the effects of heteroskedasticity. This variant is based on the approximation of the variance ratio statistic by a linear combination of autocorrelations. Or in notational form:

$$M_r(q) = \frac{2(q-1)}{q} r(1) + \frac{2(q-2)}{q} r(2) + \ldots + \frac{2}{q} r(q-1) + o_p(n^{-1/2})$$

where $r(.)$ is the autocorrelation coefficient of lag (.) and $o_p(n^{-1/2})$ refers to terms which are of order smaller than $n^{-1/2}$ in probability. Hence the statistic can be adjusted by the asymptotic variances of the autocorrelations, denoted $\delta(j)$. This leads to a $N[0,V(q)]$ limiting distribution for $M_r(q)$.[31] We can then standardize the statistic to yield $Z^*(q)$, which is equal to $M_r(q)/V^{½}$ and is distributed as $N(0,1)$ asymptotically. Lo and MacKinlay (1989) note that the $\delta(j)$'s are numerically equivalent to White's (1980) heteroskedasticity-consistent covariance estimator.

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where $m = q(n-q+1)(1-q/n)$.

[31] The variance $V(q)$ is denoted by:

$$V(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q}\right] \delta(j),$$

where

$$\delta(j) = \frac{\sum_{t=j+1}^{n} (p_t - p_{t-1} - \mu)^2 (p_{t-j} - p_{t-j-1} - \mu)^2}{\left[\sum_{t=1}^{n} (p_t - p_{t-1} - \mu)^2\right]^2}.$$

The $\delta(j)$ refers to the asymptotic variance of the autocorrelations of the return series and the $\mu$ is the mean of same series.

However, all of the above results are based on the unconditional variances. In fact the actual simulation results reported by Lo and MacKinlay (1989) are based on series that contain heteroscedasticity but not in the conditional variances. They point out that a reparametrization of the variance they use would correspond to Engle's (1982) ARCH process, but they do not explicitly examine this possibility. In this chapter, we provide results that do in fact account for ARCH behavior in the return series.

## B. DATA AND SIMULATION DESCRIPTION

In order to carry out the Monte Carlo simulation, we create a return series, $r_t$, with the following form:

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

where $\mu$ is the mean return and the conditional distribution of the $e_t$ is N(0,1). To create this series we first generate a series of normally distributed pseudo-random variables, $e_t$, with a zero mean and unit variance. We then use these $e_t$'s to create a return series of the form:

$$r_1 = \mu + h_1^{1/2}e_1,\ r_2 = \mu + h_2^{1/2}e_2, \ldots,\ r_t = \mu + h_t^{1/2}e_t,$$

where the starting values for $h_0$ and $e_0$ are zero and the value of $h_1$ is equal to $\alpha_0$. The remaining conditional variances are defined as:

$$h_2 = \alpha_0 + \alpha_1 e_1^2 + \beta_1 h_1,\ h_3 = \alpha_0 + \alpha_1 e^2 + \beta_2 h_2, \ldots$$

and so forth, where the $\epsilon_t$'s equal $h_t^{1/2} e_t$. Hence, we create a return series that incorporates GARCH effects in the innovations. We look at different degrees of persistence by varying the values of $\alpha_1$ and $\beta_1$ from zero to one in the case of $\alpha_1$ and from zero to nine in the case of $\beta_1$.[32] Note that the combination of .1 and .9 creates an I-GARCH series or a series with an infinite unconditional variance.

Because Lo and MacKinlay (1988) provide results of their test for both an equally-weighted and value-weighted index of weekly returns, we attempt to replicate the same series and re-evaluate their results in the presence of GARCH. The weekly returns are calculated from the Center for Research on Security Prices daily return file. They consist of the Wednesday close to close price from May 2, 1974 to December 26, 1985. We further include ten equally-weighted sized based portfolios over the same period in the analysis. These portfolios consist of the same stocks as the indices except they are divided into deciles based on their capitalization value at the end of each preceding year. Hence, we have 12 returns series of 608 weeks with aggregation values, q, of 2, 4, 8, and 16. As a final comparison, we include the estimates of the ten and thirty minute return series for our 15 companies.

[32] The actual Monte Carlo simulation consists of 5,000 replications for each of the values of $\alpha_1$ and $\beta_1$.

## C. SIMULATION RESULTS AND DISCUSSION

Tables 6-1 through 6-4 provide the 1%, 5%, and 10% critical values for the 2, 4, 8, and 16-aggregated data respectively. The first two columns in each table give the corresponding GARCH values for $\alpha_1$ and $\beta_1$. The upper portion of each table provides the critical values for the standard variance ratio test with no adjustment for heteroskedasticity. These ratios, after adding one, have (approximately) a central F-distribution under the assumption that the ratio is composed of independent variables. The lower portion contains the values for the adjusted statistic, which have a standard normal distribution. Both statistics are used to test the null hypothesis that the variance ratio is equal to zero since the $M_r(q)$ statistic has a one subtracted from it. The first row of each table corresponds to data that is distributed N(0,1) since the GARCH parameters are set to zero in the simulation.

We first look at the results for the standard statistic for each of the aggregation values. As the persistence in the conditional variance is increased, the results for the standard statistic approach zero with the right tail decreasing faster than the left. As the aggregation value increases the values for the tails move farther from zero indicating that the statistic is sensitive to the level of aggregation or sample size. This is consistent with the properties of the F-distribution with different degrees of freedom.

The adjusted variance ratio statistic, in the bottom half, is easier to interpret since it should correspond to the normal distribution aymptotically. Hence, the critical values for the 1%, 5%,

and 10% levels should be around 2.576, 1.96, and 1.645 respectively. As can be seen from the results, the empirical distribution for our sample size initially exhibits negative skewness in the 2-aggregated data with the right tail being consistently smaller than the theoretical values and the left larger. However, this pattern is reversed in the higher aggregations. There seems to be no general pattern in this behavior as we vary the level of persistence using the $\beta_1$ parameter. Interestingly, the adjusted statistic does not seem to take account of the GARCH effects. This can be seen by the fact that the results show little variation with or without the presence of GARCH and across any persistence level. However, we wish to examine the behavior of this statistic when actual data are used.

Table 6-5 provides some preliminary statistics for the ten equally weighted portfolios and the two indices. The portfolios with the smaller size companies exhibit greater mean returns than the portfolios with the larger companies. They also have greater degrees of autocorrelation, with the relevant coefficients moving from two to zero as we go from portfolio one to portfolio ten. Particularly noteworthy is the presence of second order dependence in portfolio ten and the value weighted index, since neither exhibit first order dependence.

In table 6-6, we present the variance equation results of estimating a GARCH(1,1) model with a normal conditional distribution on each of the original return series. We also provide the corresponding variance ratio test for each aggregation level. The GARCH results indicate a high degree of persistence with all the models exhibiting a stationary variance process since the sum of $\alpha_1$ and $\beta_1$ is less than one.

No pattern of persistence is exhibited, although there is a gradual drop in the $\alpha_1$ estimate as we move down the table. We next look at the variance ratio results.

All the ratios except two are positive, confirming the results of the autocorrelation coefficients in table 6-5. Since a number of the return series exhibit $\alpha_1$ estimates of around one and $\beta_1$ estimates of about eight, we use our previous simulation results for these values to determine the 5% significance levels. We are particularly interested in the ratios for portfolio ten and the value-weighted index, since they exhibit only second order dependence. We find that for the equally-weighted index and the first nine portfolios the null hypothesis of a random walk is rejected. This finding is expected since all these series exhibit significant autocorrelation.

However, the results for portfolio ten and the value-weighted index indicate that the ability of the adjusted variance ratio test to detect ARCH dependence is questionable. For every aggregation level of portfolio ten and the value-weighted index, the adjusted statistic is unable to reject the random walk hypothesis. Yet, both series exhibit evidence of strong GARCH effects. Thus, we must question the proposed robustness of the test in detecting nonlinear dependence.

In the final table, table 6-7, we present the result of applying the variance ratio tests to our intradaily data. We provide these figures simply for comparative purposes since we do not have either the appropriate aggregation value in our tables or the corrected ARCH estimates. However, the results again suggest that the adjusted statistic is not accounting for the presence of ARCH effects. Our

reasoning is again based on the fact that if a series exhibits only second order dependence, the variance ratio test does not seem reject the null hypothesis. This seems to be the case for the DIG and DOW series when we compare the results of table 6-7 with those of table 3-5. We note in passing that the positive lag-1 autocorrelation coefficient for RJR is dominated by a large lag-2 negative coefficient, thereby leading to a negative value for the variance ratio in table 6-7.

We conclude this chapter on a negative note. Our results indicate that Lo and MacKinlay's proposition concerning the robustness of the adjusted variance ratio test to ARCH effects is questionable. The failure of our Monte Carlo simulation to find any discernible difference in the value of the test with or without GARCH effects is our first piece of contrary evidence. Our contention is confirmed when we find that the test is unable to detect the presence of nonlinear dependence in both the value-weighted index and the last decile equally-weighted portfolio over the time period examined. Further support for our view is provided by the results of the ten minute return data. Hence, we are led to conclude that their contention is incorrect and simply adjusting the statistic by the unconditional variances of the autocorrelation coefficients does not improve its capacity to detect ARCH effects.

**TABLE 6-1**
**SIMULATION RESULTS**
**2-AGGREGATED DATA**

| GARCH | | Standard Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -0.147 | 0.148 | -0.117 | 0.112 | -0.099 | 0.094 |
| 1 | 0 | -0.270 | 0.256 | -0.200 | 0.197 | -0.169 | 0.161 |
| 1 | 1 | -0.251 | 0.234 | -0.195 | 0.184 | -0.166 | 0.154 |
| 1 | 2 | -0.248 | 0.242 | -0.195 | 0.184 | -0.165 | 0.154 |
| 1 | 3 | -0.243 | 0.232 | -0.191 | 0.177 | -0.162 | 0.151 |
| 1 | 4 | -0.238 | 0.224 | -0.179 | 0.171 | -0.152 | 0.143 |
| 1 | 5 | -0.222 | 0.217 | -0.176 | 0.166 | -0.148 | 0.140 |
| 1 | 6 | -0.218 | 0.213 | -0.169 | 0.164 | -0.145 | 0.137 |
| 1 | 7 | -0.191 | 0.187 | -0.154 | 0.152 | -0.132 | 0.125 |
| 1 | 8 | -0.187 | 0.181 | -0.147 | 0.141 | -0.122 | 0.117 |
| 1 | 9 | -0.173 | 0.162 | -0.134 | 0.125 | -0.112 | 0.106 |

| GARCH | | Adjusted Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -2.605 | 2.469 | -2.018 | 1.922 | -1.717 | 1.622 |
| 1 | 0 | -2.599 | 2.479 | -2.038 | 1.899 | -1.774 | 1.608 |
| 1 | 1 | -2.598 | 2.433 | -2.072 | 1.934 | -1.778 | 1.638 |
| 1 | 2 | -2.587 | 2.437 | -2.030 | 1.910 | -1.761 | 1.579 |
| 1 | 3 | -2.567 | 2.466 | -2.071 | 1.977 | -1.808 | 1.633 |
| 1 | 4 | -2.601 | 2.469 | -2.061 | 1.949 | -1.789 | 1.622 |
| 1 | 5 | -2.604 | 2.499 | -2.047 | 1.908 | -1.724 | 1.580 |
| 1 | 6 | -2.640 | 2.522 | -2.096 | 1.936 | -1.783 | 1.631 |
| 1 | 7 | -2.594 | 2.460 | -2.043 | 1.931 | -1.736 | 1.628 |
| 1 | 8 | -2.671 | 2.494 | -1.995 | 1.873 | -1.714 | 1.607 |
| 1 | 9 | -2.643 | 2.457 | -2.063 | 1.927 | -1.753 | 1.640 |

**TABLE 6-2**
**SIMULATION RESULTS**
**4-AGGREGATED DATA**

| GARCH | | Standard Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -0.246 | 0.271 | -0.195 | 0.200 | -0.167 | 0.168 |
| 1 | 0 | -0.332 | 0.387 | -0.266 | 0.278 | -0.232 | 0.227 |
| 1 | 1 | -0.337 | 0.371 | -0.261 | 0.284 | -0.223 | 0.231 |
| 1 | 2 | -0.336 | 0.385 | -0.267 | 0.285 | -0.231 | 0.235 |
| 1 | 3 | -0.324 | 0.396 | -0.269 | 0.298 | -0.228 | 0.237 |
| 1 | 4 | -0.317 | 0.392 | -0.259 | 0.286 | -0.223 | 0.232 |
| 1 | 5 | -0.323 | 0.378 | -0.255 | 0.283 | -0.223 | 0.226 |
| 1 | 6 | -0.320 | 0.388 | -0.256 | 0.282 | -0.220 | 0.228 |
| 1 | 7 | -0.301 | 0.350 | -0.240 | 0.261 | -0.206 | 0.212 |
| 1 | 8 | -0.293 | 0.330 | -0.227 | 0.251 | -0.195 | 0.208 |
| 1 | 9 | -0.270 | 0.296 | -0.213 | 0.219 | -0.181 | 0.182 |

| GARCH | | Adjusted Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -2.416 | 2.722 | -1.953 | 2.034 | -1.689 | 1.729 |
| 1 | 0 | -2.473 | 2.786 | -1.944 | 2.028 | -1.663 | 1.669 |
| 1 | 1 | -2.449 | 2.643 | -1.914 | 2.029 | -1.641 | 1.682 |
| 1 | 2 | -2.385 | 2.754 | -1.890 | 2.035 | -1.660 | 1.692 |
| 1 | 3 | -2.409 | 2.839 | -1.900 | 2.126 | -1.645 | 1.715 |
| 1 | 4 | -2.448 | 2.752 | -1.932 | 2.068 | -1.655 | 1.747 |
| 1 | 5 | -2.368 | 2.642 | -1.886 | 2.009 | -1.664 | 1.687 |
| 1 | 6 | -2.427 | 2.819 | -1.920 | 2.116 | -1.661 | 1.726 |
| 1 | 7 | -2.433 | 2.688 | -1.937 | 2.020 | -1.654 | 1.677 |
| 1 | 8 | -2.403 | 2.801 | -1.910 | 2.048 | -1.634 | 1.739 |
| 1 | 9 | -2.491 | 2.805 | -1.951 | 2.070 | -1.668 | 1.693 |

TABLE 6-3
SIMULATION RESULTS
8-AGGREGATED DATA

| GARCH | | Standard Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -0.354 | 0.432 | -0.283 | 0.316 | -0.243 | 0.254 |
| 1 | 0 | -0.423 | 0.523 | -0.316 | 0.389 | -0.286 | 0.319 |
| 1 | 1 | -0.426 | 0.515 | -0.333 | 0.384 | -0.291 | 0.316 |
| 1 | 2 | -0.414 | 0.544 | -0.346 | 0.405 | -0.303 | 0.320 |
| 1 | 3 | -0.430 | 0.589 | -0.338 | 0.406 | -0.292 | 0.315 |
| 1 | 4 | -0.420 | 0.552 | -0.338 | 0.409 | -0.295 | 0.325 |
| 1 | 5 | -0.412 | 0.551 | -0.329 | 0.399 | -0.285 | 0.318 |
| 1 | 6 | -0.421 | 0.580 | -0.341 | 0.402 | -0.292 | 0.324 |
| 1 | 7 | -0.414 | 0.531 | -0.324 | 0.391 | -0.284 | 0.318 |
| 1 | 8 | -0.393 | 0.540 | -0.325 | 0.378 | -0.284 | 0.311 |
| 1 | 9 | -0.382 | 0.504 | -0.309 | 0.353 | -0.265 | 0.288 |

| GARCH | | Adjusted Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -2.351 | 2.849 | -1.835 | 2.068 | -1.591 | 1.715 |
| 1 | 0 | -2.289 | 2.967 | -1.864 | 2.070 | -1.615 | 1.696 |
| 1 | 1 | -2.212 | 2.948 | -1.827 | 2.039 | -1.593 | 1.672 |
| 1 | 2 | -2.269 | 2.834 | -1.816 | 2.092 | -1.585 | 1.747 |
| 1 | 3 | -2.229 | 3.075 | -1.832 | 2.107 | -1.583 | 1.747 |
| 1 | 4 | -2.296 | 3.043 | -1.852 | 2.105 | -1.621 | 1.751 |
| 1 | 5 | -2.183 | 2.770 | -1.822 | 2.116 | -1.585 | 1.757 |
| 1 | 6 | -2.263 | 2.988 | -1.860 | 2.159 | -1.598 | 1.739 |
| 1 | 7 | -2.258 | 2.834 | -1.808 | 2.128 | -1.575 | 1.726 |
| 1 | 8 | -2.276 | 2.938 | -1.832 | 2.112 | -1.585 | 1.727 |
| 1 | 9 | -2.345 | 2.919 | -1.852 | 2.152 | -1.605 | 1.728 |

**TABLE 6-4**
**SIMULATION RESULTS**
**16-AGGREGATED DATA**

| GARCH | | Standard Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -0.499 | 0.628 | -0.397 | 0.486 | -0.343 | 0.399 |
| 1 | 0 | -0.513 | 0.746 | -0.418 | 0.540 | -0.374 | 0.429 |
| 1 | 1 | -0.543 | 0.778 | -0.429 | 0.557 | -0.374 | 0.441 |
| 1 | 2 | -0.538 | 0.805 | -0.443 | 0.541 | -0.382 | 0.446 |
| 1 | 3 | -0.531 | 0.817 | -0.427 | 0.566 | -0.375 | 0.452 |
| 1 | 4 | -0.531 | 0.762 | -0.429 | 0.562 | -0.380 | 0.460 |
| 1 | 5 | -0.532 | 0.774 | -0.431 | 0.548 | -0.378 | 0.445 |
| 1 | 6 | -0.530 | 0.800 | -0.437 | 0.552 | -0.388 | 0.434 |
| 1 | 7 | -0.528 | 0.763 | -0.439 | 0.539 | -0.374 | 0.445 |
| 1 | 8 | -0.545 | 0.779 | -0.438 | 0.564 | -0.376 | 0.443 |
| 1 | 9 | -0.521 | 0.739 | -0.434 | 0.538 | -0.382 | 0.423 |

| GARCH | | Adjusted Variance Ratio | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1% level | | 5% level | | 10% level | |
| $\alpha_1$ | $\beta_1$ | LT | RT | LT | RT | LT | RT |
| 0 | 0 | -2.250 | 3.052 | -1.811 | 2.167 | -1.544 | 1.742 |
| 1 | 0 | -2.138 | 3.130 | -1.793 | 2.219 | -1.566 | 1.741 |
| 1 | 1 | -2.170 | 3.210 | -1.772 | 2.168 | -1.565 | 1.734 |
| 1 | 2 | -2.218 | 3.115 | -1.796 | 2.196 | -1.531 | 1.748 |
| 1 | 3 | -2.216 | 3.176 | -1.770 | 2.180 | -1.539 | 1.772 |
| 1 | 4 | -2.162 | 3.268 | -1.768 | 2.247 | -1.557 | 1.770 |
| 1 | 5 | -2.157 | 2.955 | -1.776 | 2.193 | -1.542 | 1.763 |
| 1 | 6 | -2.185 | 3.154 | -1.792 | 2.225 | -1.562 | 1.807 |
| 1 | 7 | -2.187 | 3.028 | -1.730 | 2.223 | -1.543 | 1.854 |
| 1 | 8 | -2.207 | 3.108 | -1.753 | 2.247 | -1.518 | 1.811 |
| 1 | 9 | -2.242 | 3.053 | -1.774 | 2.194 | -1.548 | 1.777 |

**TABLE 6-5**
**DESCRIPTIVE STATISTICS AND TESTS FOR NONLINEAR DEPENDENCE ON PORTOLIOS AND INDICES**

| | mean | std dev | LB(6) r | LB(6) $r^2$ | LB(6) $\|r\|$ | AUTOCORRELATION LAG-1 r | LAG-2 r |
|---|---|---|---|---|---|---|---|
| P1 | .00879 | .0279 | 227.77* | 49.80* | 203.13* | .468* | .285* |
| P2 | .00616 | .0253 | 154.26* | 48.43* | 115.05* | .397* | .229* |
| P3 | .00552 | .0242 | 111.08* | 75.59* | 102.25* | .331* | .190* |
| P4 | .00491 | .0238 | 86.49* | 63.11* | 90.31* | .304* | .161* |
| P5 | .00440 | .0241 | 68.52* | 76.66* | 87.47* | .280* | .143* |
| P6 | .00428 | .0240 | 54.55* | 62.23* | 63.86* | .248* | .120* |
| P7 | .00403 | .0227 | 43.97* | 49.93* | 61.60* | .223* | .109* |
| P8 | .00362 | .0221 | 30.33* | 43.81* | 50.65* | .183* | .075 |
| P9 | .00338 | .0222 | 21.91* | 56.09* | 65.73* | .142* | .053 |
| P10 | .00261 | .0222 | 7.19 | 57.46* | 67.05* | .041 | -.006 |
| EW | .00414 | .0224 | 74.41* | 67.73* | 80.60* | .281* | .146* |
| VW | .00177 | .0214 | 5.96 | 67.79* | 74.23* | .045 | .012 |

The critical values for the Ljung-Box, LB(6), statistic at the 0.10, 0.05, and 0.01 significance level are 10.64, 12.59, and 16.81 respectively. An '*' represents significance at the .05 level. The portfolio containing the companies with the smallest capitalizaton is P1.

TABLE 6-6
GARCH ESTIMATES AND VARIANCE RATIO STATISTICS
OF PORTOLIOS AND INDICES

| | GARCH VARIANCE EQUATION | | | STANDARD VARIANCE RATIO (ADJUSTED VARIANCE RATIO) | | | |
|---|---|---|---|---|---|---|---|
| | $\alpha_0$ | $\alpha_1$ | $\beta_1$ | 2 | 4 | 8 | 16 |
| P1 | .1470 | .5393 | .3152 | 0.440 | 1.082 | 1.792 | 2.883 |
| | (6.04) | (11.3) | (6.39) | (5.845) | (7.413) | (7.340) | (5.387) |
| P2 | .1517 | .4161 | .3608 | 0.407 | 0.905 | 1.419 | 2.197 |
| | (5.16) | (9.78) | (4.92) | (6.233) | (7.755) | (7.318) | (5.043) |
| P3 | .0476 | .1782 | .7373 | 0.373 | 0.800 | 1.265 | 1.890 |
| | (2.56) | (4.49) | (11.1) | (5.523) | (6.917) | (6.483) | (4.468) |
| P4 | .0376 | .1339 | .7944 | 0.351 | 0.701 | 1.058 | 1.629 |
| | (2.75) | (3.21) | (14.7) | (5.428) | (6.647) | (5.894) | (3.830) |
| P5 | .0498 | .1319 | .7732 | 0.337 | 0.684 | 0.942 | 1.373 |
| | (2.32) | (3.31) | (11.2) | (5.154) | (6.123) | (5.301) | (3.255) |
| P6 | .0398 | .1167 | .8071 | 0.314 | 0.624 | 0.800 | 1.059 |
| | (2.72) | (3.37) | (15.7) | (4.774) | (5.711) | (4.828) | (2.755) |
| P7 | .0441 | .1242 | .7835 | 0.294 | 0.595 | 0.694 | 0.880 |
| | (2.29) | (3.41) | (12.5) | (4.359) | (5.209) | (4.312) | (2.414) |
| P8 | .0426 | .1253 | .7825 | 0.267 | 0.523 | 0.582 | 0.777 |
| | (2.49) | (3.44) | (13.0) | (3.645) | (4.370) | (3.669) | (2.093) |
| P9 | .0149 | .0841 | .8819 | 0.239 | 0.482 | 0.431 | 0.466 |
| | (1.66) | (3.33) | (23.1) | (2.766) | (3.361) | (2.702) | (1.260) |
| P10 | .0188 | .0995 | .8588 | 0.145 | 0.271 | 0.107 | 0.028 |
| | (1.85) | (4.00) | (22.5) | (0.726) | (1.012) | (0.804) | (-.038) |
| EW | .0119 | .0878 | .8867 | 0.220 | 0.733 | 0.917 | 1.334 |
| | (1.87) | (3.89) | (29.7) | (5.248) | (6.378) | (5.709) | (3.755) |
| VW | .0158 | .1057 | .8585 | -0.050 | 0.079 | 0.127 | 0.160 |
| | (1.88) | (3.92) | (23.7) | (0.963) | (1.366) | (1.203) | (0.445) |

The figures in parentheses under the GARCH estimates are the corresponding t-statistics. Those in parentheses under the variance ratios are the adjusted variance ratio statistic. The numbers refer to the appropriate aggregation value, i.e. 2 is for 2-aggregated.

**TABLE 6-7**
**VARIANCE RATIO STATISTICS**
**FOR INDIVIDUAL STOCKS**

| | STANDARD VARIANCE RATIO | ADJUSTED VARIANCE RATIO |
|---|---|---|
| AME | -0.2348 | -4.0760 |
| ATL | -0.0914 | -2.1315 |
| ATT | -0.2515 | -4.8101 |
| BAX | -0.1930 | -3.9956 |
| BOE | -0.3655 | -5.3435 |
| CHE | -0.1880 | -3.1815 |
| DIG | -0.0162 | -0.1171 |
| DOW | 0.1540 | 0.4197 |
| GE | -0.1481 | -1.0930 |
| GM | -0.1656 | -0.5889 |
| ITT | -0.2495 | -4.1191 |
| MOB | -0.2998 | -2.3603 |
| PAC | -0.6064 | -9.3766 |
| PHI | -0.1623 | -1.4266 |
| RJR | -0.2080 | -1.5101 |

The ratios in this table are 3-aggregated since they represent the ten and thirty minute return series.

## CHAPTER 7

## SUMMARY AND DICUSSION OF FUTURE RESEARCH

In this dissertation, we examine (1) the time series behavior of intradaily stock prices with special emphasis on the presence of nonlinear dependence, (2) the effects of aggregation in attenuating the observed dependence in the conditional variance, (3) the role of volume and the number of transactions as possible proxies for the rate of information arrival to the market, and (4) the ability of the unconditional variance ratio test to detect the presence of ARCH effects.

We begin the dissertation with a discussion of the differences between the martingale model of asset prices and the random walk model. Since the former is less restrictive is allows for certain types of dependence to exist while still maintaining those probabilistic assumptions associated with an asset market in competitive equilibrium. We also touch on the role that asymmetric information among market participants plays in the realization of the actual price of each asset.

In Chapter 2, we review the literature on the distributional and market micostructure properties of both intradaily and longer intervals. Our discussion is generally restricted to those works that attempt to ascertain the best model capable of accounting for the observed empirical characteristics of the data. With Chapter 3, we begin our actual analysis with a number of descriptive statistics, tests of normality and white noise processes, and evidence on both the linear and nonlinear dependence found in the data.

In Chapter 4, we provide the actual estimation results of applying the generalized autoregressive conditonal heteroskedasticity model to the the ten and thirty minute return data. Based on these results and those from Chapter 3, we posit that a mixture of distributions may in fact describe the return generating process. The difference between this and previous models is that such a mixture must account for the observed nonlinear dependence, as well as the distributional characteristics. Our results suggest that the power-exponential provides a better fit to the data than either the normal or Student-t.

Chapter 5 looks at two proxies for the arrival of information to the market, volume and the number of transactions. Our intent is to determine if the observed GARCH effects can be explained by the information hypothesis discussed by previous authors. We find that our sample does not exhibit any such affects and in fact application of the proposed model raises a number of econometric problems with that particular type of anaylsis. With Chapter 6, we close out the result section of the dissertation. Here we look at the robustness of the unconditional, variance ratio test in detecting ARCH effects. We provide evidence using both Monte Carlo simulation and actual index return data that strongly rejects the hypothesis.[33]

Finally, in closing, we note a number of ideas that deserve further investigation. The first concerns the difference detected between the beginning/end of day price process and the rest of the day. The presence of the variance effect raises a number of interesting

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[33] We should point out that our results specifically address the null hypothesis of a random walk. If the null hypothesis is instead a martingale then Lo and MacKinlay's argument is still valid.

questions on how the market reacts to the closing of the market. Also of interest is how aggregation of the intradaily data to daily data over a longer time span would affect the observed dependence. If daily returns, as represented by the end of day price, are considered different from intradaily returns then the GARCH effects may still exist at that interval even though they do not exist in the thirty minute returns. The second concerns the actual estimation technique we use in our analysis. Since the Student-t and power-exponential distributions are encompassed within a more general family, a natural extension is to develop the estimation technique to accomplish this. This would allow a more direct comparison of the two distributions based on the likelihood ratio test. A further step would be to incorporate this extension within a mixture of distributions framework thereby achieving a quite general specification. Another possibility is the development of a variance ratio test that can not only account for the presence of ARCH effects but also provide some indication of the relationship among the conditional variances as the data are aggregated. Finally, the presence of ARCH in return data must still be explained in terms of the way the market prices risk. If the ARCH effects are being priced then we should find a corresponding effect on the mean or first moment. This leads to such models as the ARCH in mean and also to an examination of whether the risk can be considered systematic or individual to each company. If the latter holds then traditional models such as the CAPM should still be robust to the presence of ARCH.

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**Title of Dissertation:** The Time-Series Behavior of Intradaily Stock Prices

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