Essays on Stock Market Volatility

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ABSTRACT

Essays on Stock Market Volatility

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Essay one investigates the dynamic relationships between volatility and various microstructure measures of both trade activity and quoted liquidity for each component stock in the TSE 35 Index, and for the Toronto 35 Index Participations (TIPs). These microstructure variables provide economic explanations for the documented regularities in volatility. The number of trades plays a more significant role in explaining intraday volatility than volume. Further investigation into partitioned volume reveals that the volatility impact of unexpected volume exceeds that of expected volume. Consistent with the lack of information signal of Easley and O'Hara (1992), no trade outcomes are significantly negatively related to volatility. Measures of quoted liquidity (quoted spreads and quote depth) are significantly positively and negatively related to volatility, respectively. Although trade and quote variables help explain the dynamic behavior of volatility, the addition of microstructure effects does not eliminate the GARCH effect.

Essay two examines sources of variation in volatility. Variance ratio tests are used to determine the impacts of public or private information or pricing errors on short-term stock volatility. The relative importance of public and private information is evaluated using the volatilities of medium-size trades and non-trading intervals. Public information has a significant impact on volatility, and on average accounts for 14% of volatility during trading periods. Medium-size trades convey more information than other trade categories, which

suggests that private information is a major source of volatility. The impact from various trading noises is investigated on intraday quote- and transaction-based returns Negative autocorrelation in transaction returns are caused by bid-ask errors, which on average range from 8 9% to 35% of the variance of transaction returns. In sharp contrast to a positive autocorrelation for an index portfolio replicating TIPs, returns on TIPs are negatively autocorrelated. This is consistent with pricing errors caused by a concentration of liquidity trading on TIPs and cross-autocorrelations among the component stocks that form the index portfolio.

Essay three investigates the abnormal returns, volatility and residual risk premium behavior of screen-sorted portfolios during the Canadian stock market Crash of 1987. The screens include beta, P/E ratio, size, dividend yield and the leverage ratio. The "news" effect of the volatility shock is assessed directly by examining the abnormal returns and indirectly by examining changes in the ex ante risk premia. The CAR's of the beta-sorted portfolios exhibit an inverse relationship to their pre-Crash betas. This can be explained by changes in systematic risk as well as a larger relative increase in the residual risk premium associated with the volatility shock for the smaller beta-sorted portfolios. A GARCH model is used to check the robustness of the CAR results for the beta-sorted portfolios.

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Chapter 1: Introduction

The behavior of market volatility and its impact have been the subject of extensive theoretical and empirical research for at least three reasons First, volatility is an important factor in asset pricing, as witnessed by the development of stochastic volatility option pricing models such as that of Hull and White (1987). Second, events such as the stock market crash of 1987 focus increased attention on the effects of volatility shocks. Since institutional investors dominate the market, some market observers believe that this dominance may lead to an increase in market volatility. Thus, volatility estimation and prediction become more important in implementing investment strategies. Third, an understanding of the behavior of volatility is necessary for conducting hypothesis tests. Studies such as Connolly (1989), Morgan and Morgan (1987) and Kryzanowski and Zhang (1993) find that neglecting heteroscedasticity can result in invalid inferences.

Each essay in this dissertation addresses certain specific issues related to volatility The first essay extends the existing literature on the intertemporal relationship between volatility and microstructure variables that measure trading activity and quoted liquidity Empirical regularities in volatility are well recognized in the finance literature. Volatility tends to "cluster" or to be serially correlated over time. This explains the popularity of ARCH or GARCH models proposed by Engle (1982) and Bollerslev (1986) to describe volatility behavior. Volatility is contemporaneously correlated with trading volumes (Karpoff, 1987) and quoted spreads (Lee, Mucklow and Ready, 1993). Clustering suggests that volatility has a predictable component, and that microstructure variables describing trade activity and

quoted liquidity may be relevant for modelling volatility. For example, Lamoureux and Lastrapes (1990) use volume in the GARCH variance equations of individual stocks, and find that the GARCH effect may be explained by trading volume.

Ross (1989), Kyle (1985), and Glosten and Milgrom (1985) show that both information flow and market liquidity play a central role in determining volatility. Measures of trade activity and quoted liquidity may help to explain how information is incorporated into security prices, and provide economic explanations for the observed regularities in volatility behavior. While a number of empirical studies examine the link between volume and volatility, little attention has been given to the impact of quoted liquidity on volatility in addition to volume. The Limit Order Trading System on the Toronto Stock Exchange (TSE) displays the quote prices with associated sizes which are good indicators of market liquidity.

Since studies by Jain and Joh (1990) and Gallant, Rossi and Tauchen (1992) only use a market index, they lack the quoted liquidity measures available with the use of individual stocks. Furthermore, since the market index itself may not be traded and index prices are affected by the stale price effect or non-synchronous trading of component stocks, individual stocks behave differently from the market index. Thus, the dynamic relationships between volatility and a comprehensive set of trade and quote variables for individual stocks remain uninvestigated. An index participation product, called TIPs, which is actively traded on the TSE provides a unique opportunity to investigate the market-wide relationship, since TIPs has its own quote spread and depth that may reflect the overall market liquidity.

The second essay deals with research on sources of variation in volatility, and specifically with whether public or private information or pricing errors are the main sources

for volatility. French and Roll (1986) show that private information is the principal source for high trading time volatility. Kaul and Nimalendran (1990) show that a significant portion of transaction return volatility is caused by bid-ask errors. Since information flows or pricing errors are unobservable, the interpretation of test results in these studies is based largely on proxies and assumptions about information flow Alternative ways of classifying returns to contrast them in terms of private information would provide new evidence on the sources for volatility patterns.

Medium-size orders appear to be associated with private information flow. Using a sample of tender offer targets, Barclay and Warner (1993) find that medium-size trades are responsible for a majority of cumulative price changes during the preannouncement period and informed traders are concentrated in the medium-size category. Non-trading outcomes are associated with a lack of private information flow (Easley and O'Hara, 1992). Thus, the effect of public information flow can be isolated for non-trading periods. Jones, Kaul and Lipson (1994) find that volatility for non-trading periods is a substantial portion of that for trading periods. Their study can be improved by using intraday observations, since non-trading occurs less frequently for the daily interval.

Many of the previous studies such as Kaul and Nimalendran (1990) are conducted on daily transaction returns or returns on daily closing bid quotes, the availability of intraday data allows for a determination of the impact of bid-ask errors on volatility over the short time horizon. Since pricing errors may be caused by delays in either bid or ask price adjustments (Mech, 1993), an examination of various quote-based returns may suggest the relative importance of certain pricing errors such as the monopolistic power of market makers

The existence of TIPs on the TSE provides an opportunity to investigate sources of volatility for the composite security, and for a comparison of these results with the results for individual component stocks. Gorton and Pennacchi (1993) and Subrahmanyam (1991) show that liquidity traders tend to concentrate on index instruments and individual component stocks are more exposed to adverse information trading. Since TIPs is a preferred instrument for liquidity trading, it may be less subject to firm-specific information trading and more affected by trading noises. As a single traded security, TIPs can also be compared with an index portfolio of the underlying component stocks.

The third essay examines the impact of volatility on the risk premium. The impact of a volatility shock on the risk premium is called a volatility feedback effect in the literature (Campbell and Hentschel, 1992). French, Schwert and Stambaugh (1987) find that the expected market risk premium is positively related to the predictable volatility of stock returns, and that unexpected stock market returns are negatively related to the unexpected change in the volatility of stock returns.

Fama and French (1992) show that stock risk is multidimensional, and that the systematic risk is an incomplete measure of risk. Firm-specific factors such as dividend yield, P/E ratio, market capitalization, and leverage may form a fundamental priced factor. While a substantial amount of evidence has accumulated on market anomalies associated with these factors in the long run, the impact of these firm-specific factors on stock performance during the relatively short period around the crash of October 1987 remains to be studied.

Thus, the primary purpose of this thesis is three-fold: first, to investigate the relationship between volatility and microstructure variables that measure information flow and

market liquidity; second, to provide economic explanations for the empirical regularities found for volatility; and third, to examine the impact of a major volatility shock on equity performance. The first two essays are most closely related due to their focus on the relationship between volatility and microstructure variables. While the first uses a regression-based approach to identify the significant explanatory variables, the second uses variance ratio tests to examine hypotheses about private or public information sources of volatility and to assess the impact of various pricing errors. The third essay uses a standard event study methodology to investigate the impact of the crash for various screen-sorted portfolios.

The remainder of the thesis is organized as follows:

In Chapter Two, a time series analysis of the dynamic relationship between volatility and microstructure variables is performed to determine the impact of measures of trade activity and quoted liquidity on the behavior of conditional volatility. Lead lag relations are examined using both Granger-causality tests and time series regressions. Information flow and market liquidity are proxied by volume and its components, number of trades, a non-trading indicator, quote spreads, and quote depth. Hypotheses based on the theoretical models are tested. Specific issues tested include whether the GARCH effect can be accounted for by microstructure variables, whether volume decomposition is useful in capturing information shocks, and what effect quoted liquidity has on volatility.

In Chapter Three, the sources of volatility are the focus Hypotheses proposed by French and Roll (1986) regarding public and private information and pricing errors are revisited. The conjecture that medium-size trades may convey more private information is exploited to assess the relative importance of private information. Non-trading periods are

used to evaluate the relative importance of public information. The impact of pricing errors due to bid-ask errors, overreaction and monopolistic market makers on volatility is examined by using the variance ratio test on quote- and transaction-based returns. Results of variance ratio tests on TIPs are compared with those of individual stocks and of an index portfolio of the TSE 35 stocks.

In Chapter Four, the impact of a volatility shock or the volatility feedback effect is examined around the crash of 1987. Studying this event allows for an investigation of short-horizon market anomalies based on screen-sorted portfolio returns. Changes in the risk premium are also examined.

In Chapter Five, the main findings and implications of the thesis are detailed. This is followed by a discussion of several avenues for future research.

Chapter 2: Trading Activity, Quoted Liquidity and Stock Volatility

2.1 Introduction

The behavior of volatility is important for the pricing of assets, since priced risk is related to volatility. The stochastic volatility option pricing models of Hull and White (1987), Scott (1987) and Wiggins (1987) illustrate that empirical regularities in volatility behavior are critical for pricing options. Schwert and Seguin (1990) show that a common "market" factor exists in the heteroscedasticity of stock returns.

Various empirical studies [e.g. Engle and Bollerslev (1986), Akgiray (1989), Schwert (1990)] find that stock volatility is serially correlated and exhibits excess kurtosis. This suggests that a predictable component can be extracted from past volatilities, which should be relevant in determining the risk premia of securities. The predictable component may be related to microstructure variables that account for trading activity and market liquidity. This conjecture is supported by the evidence that volatility is contemporaneously correlated with microstructure variables such as volume. The intertemporal dependence of volatility on these variables is valuable for prediction purposes.

Volatility models tend to be more statistical than economic in nature. Studies find that changes in stock volatility over time exhibit certain regularities, the most significant one being the clustering of volatility. Engle (1982) and Bollerslev (1986) propose the use of ARCH or GARCH estimators to capture such behavior. Although these models are a parsimonious representation of volatility, they lack an economic basis for their relationships. Microstructure variables may provide an economic grounding for the volatility prediction models. Lamoureux

and Lastrapes (1990) introduce volume into the GARCH model and find that volume plays a role as a proxy for information flow.

Recent empirical studies, such as Jain and Joh (1990) and Gallant, Rossi and Tauchen (1992) on the relationship between volatility and volume examine a market index. However, the relationship between volatility and volume at the individual stock level may be obscured in the process of aggregation into an index. While their results capture the impact of market-wide news on both volatility and volume, firm-specific news effects may be neglected. Thus, to capture both types of effects, the analysis should be conducted on a sample of individual stocks.

Examining individual stocks also allows for a determination of the impact of quoted liquidity on volatility. Theoretical models such as Kyle (1985), Glosten and Milgrom (1985), and Admati and Pfleiderer (1988) indicate that market liquidity and information flow are two fundamental factors affecting volatility. Volatility and trade or quote variables are jointly determined by information flow and supply of market liquidity. Since neither factor is directly observable, microstructure variables can be used to test the predictions of these theoretical models on volatility. Number of trades, unexpected volume and spread are used as proxies for information flow. The electronic system at the Toronto Stock Exchange (TSE) provides traders with an easy access to the limit order book, thus spread and quote depth are readily available for assessing market liquidity.

The purpose of this chapter is to investigate the dynamic relationship between volatility and various microstructure variables. A comprehensive examination of the determination of volatility is conducted. Normal variations in intraday trading activity and

quote behavior are accounted for when the link between volatility and a particular trade/quote variable is assessed. Attention is given to the effect of both trade activity and quoted liquidity on volatility.

The remainder of this chapter is organized as follows. Section 2.2 briefly reviews the literature on microstructure and volatility. In section 2.3, the null hypotheses are formulated. In section 2.4, methodological issues dealing with estimating volatility and partitioning volume are discussed. In section 2.5, the data are described and summary statistics for various microstructure variables are provided. In section 2.6, Granger-causality tests are performed on volatility and microstructure variables that measure information flow and market liquidity, and the results are analyzed. In section 2.7, results of multiple regressions are reported and interpretations are discussed. In the final section, concluding remarks are offered.

2.2 Literature Review

Various studies focus on the contemporaneous relationship between volatility and volume. Schwert (1989) relates stock market volatility to a number of economic variables, including financial leverage and stock market trading activities. He finds that financial leverage explains a small proportion of changes in volatility over time and trading volume is positively related to stock volatility. The finding is consistent with the survey by Karpoff (1987) on the relationship between volatility and volume.

Lamoureux and Lastrapes (1990) propose that volume can be viewed as a mixing variable related to the rate of information flow. They find that the GARCH effect is explained by incorporating volume into the conditional volatility function.

Gallant, Rossi and Tauchen (1992) use a seminonparametric approach to investigate the contemporaneous and intertemporal relationships among prices, volatility, and volume. Their study is based on the S&P composite stock index and the daily volume of shares traded on the NYSE. Their findings are that trading volume is positively and nonlinearly related to both unconditional and conditional volatility, that price changes lead volume movements, and that the effect is symmetric.

Jain and Joh (1988) investigate the joint generating process for hourly equity volumes and returns, based on the hourly S&P 500 index. They find a positive correlation between the contemporaneous trading volume and the absolute value of returns. They find different volume-return relations for positive and nonpositive returns, and that average volumes and average returns show significant differences across trading hours and days of the week.

Jones, Kaul and Lipson (1994b) show that the positive volatility-volume relation disappears when the relation between volatility and number of trades is controlled. They conclude that the occurrence of transactions per se generates volatility and the size of trades has no information content beyond that contained in the number of trades.

Bessembinder and Seguin (1992) examine the relationship between volatility, volume and open interest in eight futures markets. They partition volume into expected and unexpected components, and find that unexpected volume shocks have a relatively larger effect on volatility. Their findings are consistent with the hypothesis that volatility is affected inversely by market depth.

2.3 Data

Data are obtained from the time-stamped transaction data files of the Toronto Stock Exchange for the 12 month period from July 1990 to June 1991. The tape provides detailed trade and quote information for companies listed on the TSE. Each trading day is partitioned into 13 half-hour intervals that commences at 9:30 a.m. and ends at 4:30 p.m. Conversion of transaction prices into returns over a fixed time interval is necessary since transactions are not uniformly spaced in time. The half-hour sampling interval is largely a compromise between relatively few daily observations and the potential biases associated with aggregating transaction data and nontrading.

Since intraday observations are separated by overnight and weekend periods, time-series data are not uniform in the length of intervals. Volatilities estimated for opening intervals and Mondays may be affected by the closure of the market. At the market opening, information accumulates over a longer period of time and opening prices are usually determined by a call auction. Indicator variables for open and Monday are used to capture such effects. Foster and Viswanathan (1990) examine the implications of the assumption that informed traders have more information on Monday than on other days, and argue that volatility is the highest on Monday.

Since most public or private information is firm specific in nature (Mitchell and Mulherin, 1992), the impact of firm-specific information may be diversified away in the process of aggregation to a market index. The focus on individual stocks instead of an index allows for the detection of the relationship between volatility and microstructure variables caused by changes in firm-specific information flow. The use of individual stocks is also motivated by the availability of quote data for individual stocks. In this study, component

stocks in the TSE 35 index and TIPs (Toronto 35 Index Participations) are selected. The TSE 35 index represents the largest and most actively traded Canadian companies (see Appendix), so that the infrequent trading problem is less serious. Since its inception in March 1990, TIPs has become an actively traded market index instrument. Because it is a traded market index, the results for TIPs have implications for the overall market.

The Toronto Stock Exchange trades stocks in two different ways: on a trading floor and through the Computer Assisted Trading System (CATS). Trading in the more active stocks generally occurs through an integration of the traditional floor trading with an electronic system. Each of these active stocks has a designated market maker who is responsible for maintaining an orderly market. Trading in less active stocks generally takes place through the CATS, which provides access to the Market Order System of Trading (MOST) and to the Limit Order Trading System (LOTS). A few active issues are included in CATS, such as TIPs. The trend is towards closing floor trading and relying on the electronic system

The electronic open book system, which was implemented in 1990, allows brokers off the floor to enter orders. Members of the exchange have open access to the book of limit orders as well as the identity of the brokerage house submitting each limit order. Information on spreads and quote depth are readily available for investors. A large order trader in the electronic system or CATS has the option of not disclosing the part of an order that is in excess of 5,000 shares. However, the TSE gives priority to disclosed orders at the same price.

Returns are calculated using the average of bid and ask quotes. Prices are adjusted for quarterly dividends. While volatility is estimated using closing bid and ask quotes, volume is

measured for the interval up to the close. Volume is no longer contemporaneous with volatility. Since VOL_t is already in the information set of investors at the end of interval t, the simultaneity problems in determining volatility are avoided. Quoted spread is the difference between ask and bid quotes, and the percentage quoted spread (SPD_t) is given by (Ask_t - Bid_t)/m_t, where m_t is the bid-ask midpoint at time t. Quote depth (QD_t) is the sum of bid and ask sizes. In the research subsequently reported, all of the variables for quoted liquidity are measured at the end of each interval.

Correlations between the estimated volatilities and various trade and quote variables for each stock are presented in Table 2.1. As expected, the estimated volatility is positively correlated with volume, expected and unexpected volumes, number of trades, and the quoted spread, and is negatively correlated with quote depth. Dickey-Fuller tests for presence of unit roots are conducted for volume, number of trades and quote depths. The null hypothesis of a unit root is rejected for all of these series.

2.4 Methodology

2.4.1 Estimation of Volatility

Since volatility is not directly observable, the iterated weighted least squares (IWLS) procedure introduced by Schwert (1990) is used to give unbiased estimates of standard deviations conditional on observable variables. The procedure involves iterating three times between two equations. Pagan and Schwert (1990) show that weighted least squares provide consistent estimators of parameters. Equation (1) below is estimated first without the lagged volatility estimates. A weighted least squares procedure, based on Davidian and Carroll

(1987), uses the fitted values from equation (2) as weights for the estimation of (1). The two equations are:

$$R_t = \sum_{i=1}^{13} \gamma_i R_{t-i} + \sum_{i=1}^{13} \eta_i \sigma_{t-i} + \sum_{j=1}^{5} \alpha_j D_{jt} + \pi OP_t + u_t \tag{2.1}$$

$$\hat{\sigma}_t = \sum_{i=1}^{13} \omega_i \hat{u}_{t-i} + \sum_{i=1}^{13} \beta_i \hat{\sigma}_{t-i} + \sum_{j=1}^{5} \mu_j D_{jt} + \tau OP_t + e_t \tag{2.2}$$

where R_t is returns based on the average of bid and ask quotes at interval t, $\hat{\sigma}_t$ is the estimated volatility at t, D_{jt} are five dummy variables for days of the week at t, and OP_t is a dummy variable for the opening of the market. Lagged volatilities ($\hat{\sigma}_{t-i}$) and lagged unexpected returns ($\hat{u}_{t-i}$) are included in equations (1) and (2), because they capture persistence in volatility. The day-of-the-week dummy variables are perfectly predictable for interval t, and are used to capture normal differences in means of returns and volatilities by day of the week.

Returns for the opening period are treated differently by including the dummy variable (OP), because closing stock prices are used to compute returns and closing prices are inaccurate reflections of opening values. The dummy variable (OP) is used to remove the effects of stale price information.

Following Schwert and Seguin (1990), the estimated conditional volatility is given by:

$$\hat{\sigma}_t = |\hat{u}_t| \sqrt{\frac{\pi}{2}}$$

The relationship holds when residuals follow a conditional normal distribution, and σ_t will remain non-negative since it is based on the absolute deviation.

Returns based on bid-ask midpoints instead of transaction-based returns are used to

estimate volatility. Harris (1990a) and Kaul and Nimalendran (1990) demonstrate that bid-ask bounce leads to an overestimate of true volatility. Quote-based returns may mitigate the stale price problem, since quotes adjust to new information more frequently than transaction prices However, quote revision may still be sticky to some extent (Jones, Kaul and Lipson, 1994a) Therefore, the use of quote-based returns may underestimate the true volatility. Similar to an ARMA model in Stoll and Whaley (1990a) to purge the non-synchronous trading effects, the autoregressive terms in the IWLS estimator are used to reduce the stickiness problem In absence of trading, public announcements or information revealed in the trading of other related securities may still have an impact on the underlying value. Thus, quote-based returns will capture such changes.

2.4.2 Volume Decomposition

The Box-Jenkins procedure is used to estimate ARMA models for partitioning volume into expected and unexpected components. Since volume exhibits a consistent daily cycle based on the partial autocorrelations, temporal adjustment at the 13th lag succeeds in removing the temporal component. An examination of the volume series indicates that it can be represented as ARIMA(0,(1,2,3)(13), 3):

$$(1-\varphi_1 L - \varphi_2 L^2 - \varphi_3 L^3)(1-\varphi_{13} L^{13}) VOL_t = (1 - \theta_1 L - \theta_2 L^2 - \theta_3 L^3)\epsilon_t$$

where L is the lag operator. The well-documented patterns of trading volume imply that it is necessary to adjust for the day of the week and the opening and close of the market, since these regularities are part of all investors' knowledge. Since the same ARMA model is used

for all sample stocks, the MA(3) terms and a relatively long AR term are applied to each stock.

Diagnostic checks on the overall acceptability of residual autocorrelations are carried out by using the portmanteau Q-statistic (Ljung and Box, 1978). Q is approximately χ^2 distributed. The null hypothesis that the ARMA disturbances are serially independent is tested. Results show that the ARMA model is adequate to fit the volume series.

2.5 Hypotheses

Several hypotheses are proposed to investigate the dynamic relationship between volatility and microstructure variables. The first hypothesis , H_1, states that volume is positively related to volatility. Clark (1973) and Tauchen and Pitts (1983) show that volume and volatility are jointly endogenous variables that move together in response to information shocks. Easley and O'Hara (1987) demonstrate that trade size, as a proxy for information flow, affects volatility.

Failure to reject the first null hypothesis may imply that adverse information-based trading with increased volume is offset by an improved supply of market liquidity. Easley and O'Hara (1992) define "normal" volume as trading volumes due to expected liquidity trading. The greater the normal volume, the lower the volatility since informed traders effectively can hide their identity. Abnormal volumes convey information to the market and increase volatility. A variation of hypothesis H_1 is that unexpected volume is positively related to volatility, since unexpected volume is an effective proxy for information flow.

The second hypothesis, H_2, states that the number of trades is positively related to

volatility. Some disagreement exists as to the impact of number of trades. Easley and O'Hara (1987) argue that trade size is an indicator of information flow. Madhavan (1992) suggests that trading frequency, given trading volumes, may have a negative relation with spreads. His conclusion extends to volatility. Based on the assumption that transactions take place at a uniform rate in event time, Harris (1987) argues that the number of trades reflects the rate of information flow, and thus has a positive relation with volatility. The finding by Jones, Kaul and Lipson (1994b) can be viewed as a direct test of the Mixture of Distribution Hypothesis and it confirms that number of trades generates volatility. Barclay and Warner (1993) find consistent evidence that medium-size orders are more likely to be used by informed traders

The third hypothesis, H_3, states that non-trading outcomes are accompanied by lower volatility. Easley and O'Hara (1992) argue that a non-trading outcome serves as a signal for the existence of new information. Thus, volatility is reduced over time if such outcomes are believed to be a result of non-information. However, they may also be due to a lack of liquidity. The fourth hypothesis, H_4, states that volatility is symmetrically related to trading volume. The relationship between volatility and volume may be asymmetric for positive and negative price changes. Black (1976) refers to this as the leverage effect Asymmetry is investigated by examining the dynamic relationships for positive and negative returns. The fourth null hypothesis is tested using an indicator variable that differentiates the case of buyer-initiated volumes from that of seller-initiated volumes.

The fifth hypothesis, H_5, states that quoted spread is positively related to volatility. Glosten and Milgrom (1985), Madhavan (1992) and others discuss the adverse selection problem facing the market maker. The quote spread allows the market maker to recover

losses to informed traders from profits from liquidity traders. Thus, the quote spread is inversely related to the supply of liquidity and positively related to information flow.

The sixth hypothesis, H_6, states that quote depth is negatively related to volatility. Lee, Mucklow and Ready (1993) argue that quote depth is another dimension of market liquidity. They find that spreads and quote depths are two negatively related measures of market liquidity. On the TSE, member firms have options not to display large limit orders in excess of 5,000 shares. However, the publicized limit order has a similar effect to the "sunshine" trading strategy (Admati and Pfleiderer, 1990) that liquidity traders signal their motives of trading. Thus, quote size is a positive indicator for market liquidity.

Quote depths play a more significant role as discreteness problems get more severe. When the minimum trading tick is relatively large (as for low-priced stocks), the market maker and limit order submitters queue to supply liquidity to the market. The market maker may choose not to compete with other liquidity suppliers, given an increasing possibility of information arrival. This is reflected in a reduced quote depth.

2.6 Results of the Causality Tests

Correlation results show that several variables, such as volume, quoted spreads and quote depths, are correlated with estimated volatility. However, correlation does not imply causation. Since volatility is highly autocorrelated, the question of whether one affects the other can be framed in terms of possible lead-lag relations. Certain trade or quote variables "Granger-cause" market volatility if they lead volatility (Granger and Morgenstern, 1972). The results of the causality tests are of interest for at least three reasons: First, the tests help

determine whether measures of market liquidity are a quantitatively important predictor of volatility. Second, the test results allow for a direct comparison of the explanatory power of volume, quoted spread, and quote depth for volatility. Third, the tests can be applied to both the contemporaneous and lagged relationships.

The interrelationships among volatility, number of trades, volume, quoted spread and quote depth are investigated through a series of "causality" tests. For each of the five variables, whether lagged values of the other variables provide significant explanatory power in addition to that contained in the dependent variable's own past values is tested. The following canonical representations proposed by Geweke (1982) are used to test for causality:

$$\sigma_t = a + \sum_{i=1}^{n} \beta_i \sigma_{t-i} + u_{1t} \qquad Var(u_{1t}) = \sigma^2_{u1} \tag{2.4}$$

$$\sigma_t = a + \sum_{i=1}^{n} \beta_i \sigma_{t-i} + \sum_{j=1}^{m} \gamma_j X_{t-j} + u_{2t} \qquad Var(u_{2t}) = \sigma^2_{u2} \tag{2.5}$$

$$\sigma_t = a + \sum_{i=1}^{n} \beta_i \sigma_{t-i} + \sum_{j=0}^{m} \gamma_j X_{t-j} + u_{3t} \qquad Var(u_{3t}) = \sigma^2_{u3} \tag{2.6}$$

$$\sigma_t = a + \sum_{i=1}^{n} \beta_i \sigma_{t-i} + \sum_{j=-p}^{m} \gamma_j X_{t-j} + u_{4t} \qquad Var(u_{4t}) = \sigma^2_{u4} \tag{2.7}$$

where X_t are candidate causal variables such as volume, number of trades, quoted spread and quote depth at interval t. The lag length n for σ_t is particularly important, since omitting relevant lagged volatilities may inflate the significance of the lagged X's. n is selected such that the residuals (u's) are white noise.

The null hypotheses for H_1, H_2, H_5, and H_6 presented earlier are tested in terms of Granger causality. These canonical representations provide a unifying framework to test the null hypothesis that X_t does not Granger-cause volatility. The maximum likelihood (ML) measures of linear causality from X_t to σ_t and from σ_t to X_t are:

$$F_{x \to \sigma} = T\ln(\sigma_{u1}^2/\sigma_{u2}^2) \sim \chi^2(d)$$

$$F_{\sigma \to x} = T\ln(\sigma_{u3}^2/\sigma_{u4}^2) \sim \chi^2(d)$$

where d is the difference in degrees of freedom between the paired models, and T is the sample size. The likelihood ratio test statistic F has an asymptotic χ^2 distribution. In the tests reported herein, 13 lags are specified for each of the dependent and causal candidate variables, i.e., n=m=p=13.

The results of the Granger-causality tests for one candidate causal variable to volatility are summarized in Table 2.2. The first null hypothesis that volume does not Granger-cause volatility is rejected at the 1% significance level for only 5 of the 35 stocks. The evidence is not as strong as that in Jain and Joh (1988). In contrast, the results are stronger for number of trades. For 23 of the 35 stocks, the second null hypothesis that number of trades does not Granger-cause volatility is rejected at the 1% significance level.

The results for the two measures of quoted liquidity are also reported in Table 2.2. For 26 and 7 of the 35 stocks, the null hypotheses that quoted spreads and quote depth, respectively, do not Granger-cause volatility is rejected at the 1% significance level.

Except for four stocks, at least one microstructure variable Granger-causes volatility.

Number of trades and quoted spread appear to be significant causal variables across the sample. However, the evidence is not conclusive across the sample, since the Granger-causal relationships may change as other conditioning variables are included. The results suggest that incorporating these four variables into a model for volatility prediction warrants further investigation.

Granger-causality tests are also performed to determine whether the four trade and quote variables respond to volatility. The likelihood ratio test results are reported in Table 2.4. Volatility seems to Granger-cause number of trades for 18 of the 35 stocks, and Granger-cause volume for 16 of the 35 stocks. Taken together, the results indicate that volatility Granger-causes one of the trade activity variables for 22 of the 35 stocks at the 1% significance level. This is consistent with the findings of Gallant, Rossi and Tauchen (1992) that trading volume rises after large price movements. For the two quoted liquidity measures, the null hypothesis is rejected for only six stocks. This indicates that causality is unidirectional from the two quoted liquidity measures to volatility.

Since TIPs is an actively traded market index, its trade and quote variables may reflect the market-wide information flow and market liquidity. The results for TIPs confirm that number of trades is a significant causal variable for volatility while volume is not, since the null hypothesis is rejected for number of trades at the 1% significance level. Both quoted spreads and quote depth are significant causal variables for volatility for TIPs. The fact that none of the test statistics in Table 2.4 for TIPs are significant may suggest that causal relationships are unidirectional from trade and quote variables to volatility.

Since the information set for investors may include both trade and quote variables, the

basic causality tests can be extended to a "conditional" form that controls for these variables in order to test whether one candidate explains the volatility conditional on the other variables. For example, the conditional Granger-causality tests may determine whether quote depth (QD) is a significant causal variable for volatility even after controlling for the impact of the information content of lagged number of trades (NT). Specifically:

$$\sigma_t = a + \sum_{i=1}^{n} \beta_i \sigma_{t-i} + \sum_{j=1}^{m} \gamma_j Y_{t-j} + \sum_{k=1}^{l} \delta_k Y_{t-k} + u_{2t} \qquad Var(u_{2t}) = \sigma_{u2}^2 \tag{2.8}$$

where Y_t is the conditioning trade or quote variable at time t. When X_t is one of the trade variables, quoted spread is used as Y_t; otherwise, the number of trades is used as Y_t.

The results in Table 2.3 reveal a pattern of rejections identical to those in Table 2.2. The number of trades is a significant causal variable in determining volatility for 25 of the 35 stocks, while volume is significant for only 6 of the 35 stocks. For the two measures of quoted liquidity, the null hypothesis for the quoted spread is rejected at the 1% significance level for 28 of the 35 stocks, while the null hypothesis for quote depth is rejected less frequently (for 10 of the 35 stocks). The conditional form of the Granger-causality tests confirm that the previous causality results are robust to the assumption of causal variable. In most cases, stocks have similar significant results for the two types of Granger-causality tests.

2.7 Results of the Multiple Regressions

The results of the Granger-causality tests identify relevant potential variables for determining volatility behavior, though the regressions discussed in the previous section do not have specific structural interpretations. In this section, the contemporaneous and

intertemporal relationships between volatility and various trade and quote variables are examined. Instead of using portfolios, regressions are performed on individual stocks and TIPs to avoid aggregation problems. The hypotheses are specified as restrictions on the coefficients of the regressions. Robust regression with White (1980) heteroscedasticity-consistent standard errors are used. The form of a typical regression that provides a comprehensive examination is given by:

$$\sigma_t = a + b_1 VOL_t + b_2 VOLR_t + b_3 NT_t + b_4 DUM_t + b_5 SPD_t + b_6 QD_{t-1} + b_7 OP_t + b_8 MON_t + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t \tag{2.9}$$

where,

VOL_t	is volume for interval t;
$VOLR_t$	is volume when the trades during the interval are classified as a seller-initiated order (i.e., $VOLR_t = VOL_t$ if $p_t < m_{t-1}$; otherwise $VOLR_t = 0$);
p_t	is closing transaction price for interval t;
m_{t-1}	is the average of bid and ask quotes at the end of interval t-1;
NT_t	is number of trades for interval t;
DUM_t	is a dummy variable, which has a value of one for non-trading outcome at time t and zero otherwise;
SPD_t	is the percent quoted spread measured at the end of interval t; and
QD_t	is quote depth at the end of interval t.

Since all quote variables are measured at (t-1), they are included in the current information set of investors. Dummy variables for the opening (OP_t) and Monday (MON_t) are included to control for temporal regularities of the volatility series. The lagged volatilities are added to account for volatility clustering over time, and to remove autocorrelation in residuals. In the following section, results of multiple regressions are used to show the partial contributions of various trade and quote variables to volatility. Indicator variables for opening (OP) and Monday (MON) are used to control for the normal variation in volatility over time.

OP is significant for most of the 35 stocks.

2.7.1 Effects of Trading Activity Variables

The results of the first regression are reported in Tables 2.5. The effects of trade variables including volume, number of trades, no-trade indicator and the trade direction indicator are analyzed in this section. Several of the explanatory variables are correlated. Coefficient estimates are of partial effects on volatility, given the levels of other trade and quote variables.

Based on the second column of Table 2.5, the first null hypothesis on the relation between volume and volatility is not overwhelmingly rejected. In the first regression [Equation (2.9)], coefficients for volume are statistically significant and positive for only 15 of the 35 stocks at the 1% level. This is consistent with the results of the earlier Granger-causality tests. Volume has no marginal explanatory power when volatility is conditioned on number of trades.

Volume may lack significance because it measures the net effect of the two competing influences of information flow and supply of liquidity. The results for volume are consistent with a model of transaction-cost-elastic liquidity trading by George, Kaul and Nimalendran (1994). They show that the common belief that volume is positively related to asymmetric information may not hold when transaction costs are considered. Volume of liquidity trading is affected by transaction costs and negatively related to the degree of asymmetric information. Their model implies that the relationship between volume and informational asymmetry (or volatility) is ambiguous.

The results for volume may be contaminated by the inclusion in the regression of number of trades (NT), which is highly correlated with volume. As a sensitivity check, the regression is rerun without number of trades. This only increases the significance of volume marginally.

The second null hypothesis for the relation between number of trades and volatility is strongly rejected. Based on the fourth column of Table 2.5, the coefficients for number of trades (NT) are significantly positive for all 35 stocks at the 1% significance level (and at the 5% significance level for TIPs). The positive relation between number of trades and volatility is not sensitive to whether volume is included. This suggests that number of trades is more closely related to volatility. These results are consistent with the finding of Jones, Kaul and Lipson (1994b) that volatility is primarily determined by number of trades rather than volume.

Differences in the predictions on the role of the number of trades is attributed largely to the underlying assumption on what trade size moves prices. Easley and O'Hara (1987) argue that the larger the trade size the more likely traders are to view such a trade as being initiated by an informed trader. The implication is that the number of trades is likely to have an effect opposite to that of trade size, given a certain level of trading volume. However, empirical evidence indicates that information content is not monotonically related to trade size. Jones, Kaul and Lipson (1994b) show that trade size on average has no incremental information content beyond that contained in number of trades. The study by Barclay and Warner (1993) finds that medium-size orders actually move prices the most in their sample of tender offer targets. Our findings strongly supports that number of trades is associated with the rate of information flow.

The third null hypothesis on the relation between non-trading outcomes and volatility is rejected for 24 of the 35 stocks. Based on the fifth column of Table 2.5, the estimated coefficient of the dummy variable for non-trading interval (DUM) is statistically negative across most stocks at the 1% level. The negative sign is consistent with the prediction of Easley and O'Hara (1992). Thus, non-trading outcomes convey information about a lack of information arrival to the market. The coefficient of DUM for TIPs is significantly negative at the 1% level, suggesting that the negative relationship is likely to be market-wide.

The fourth hypothesis investigates the leverage effect on volatility. One cause for time-varying volatility is that leverage changes as stock prices change. If the volatility of the assets of a firm is relatively stable, a change in leverage causes a change in stock volatility. The estimated coefficient for VOLR is significant (and positive) for only 4 of the 35 stocks. This suggests that volatility is symmetrically related to volume, and that the direction of trading has almost no impact on volatility. The results are consistent with those of Gallant, Rossi and Tauchen (1992).

The leverage effect may be cancelled out by stronger information effects for purchases than for sales. Chan and Lakonishok (1993) argue that while institutional investors have many liquidity reasons to dispose of a stock, the choice of a particular stock to purchase conveys favorable firm-specific information.

2.7.2 Further Investigation of Volume

One possible explanation for the lack of significance for volume is that both information flow and liquidity supply are reflected by volume. To disentangle the two

offsetting effects, volume is partitioned into expected and unexpected components. The second regression investigates whether unexpected volume or volume shocks are more closely related to volatility. The regression is given by:

$$\sigma_t = a + b_1 UVOL_t + b_2 DUM_t + b_3 SPD_{t-1} + b_4 QD_{t-1} + b_5 OP_t + b_6 MON_t + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t \tag{2.10}$$

where $UVOL_t$ is unexpected volume generated by the ARMA models for interval t, and all the other variables are as defined previously.

Since the decomposed volume components are generated from the first stage regression and used in the second stage regression as independent variables, generated regressor problems need to be considered. In the second regression, unexpected volume is the residuals from the ARMA model. As shown in Pagan (1984), if only residuals from a supplementary regression are used in a second stage regression, valid inferences can still be made with the standard errors from the second stage regression.

The third regression includes both expected and unexpected volumes as independent variables, and is used to examine the impact of expected and unexpected volumes. Bessembinder and Seguin (1992) run a similar regression on futures markets, and find unexpected volume shocks have a larger impact on volatility. The regression is given as:

$$\sigma_t = a + b_1 EVOL_t + b_2 UVOL_t + b_3 DUM_t + b_4 SPD_{t-1} + b_5 QD_{t-1} + b_6 OP_t + b_7 MON_t + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t \tag{2.11}$$

where $EVOL_t$ is expected volume generated by the ARMA model for interval t, and all the

other variables are as defined previously. When both expected and unexpected volumes are used, the t-statistics of the OLS estimates for expected volume are overstated due to the incorrect estimation of standard errors. Thus, the results of the regressions that involve both expected and unexpected volumes are interpreted herein with caution.

Table 2.6 presents estimates of the second regression [Equation (2.10)] to investigate whether unexpected volume or volume shocks have a significant impact on volatility. Volatility is strongly related to unexpected volume for 24 of the 35 stocks at the 1% significance level, though the coefficient of unexpected volume for TIPs is not statistically significant. The results extend a similar finding for index futures by Bessembinder and Seguin (1992) to individual equities. A higher than expected volume may signal to the market that new information is arriving (Easley and O'Hara, 1987). Coefficients for unexpected volume are positive for all 35 stocks, which is consistent with the belief that unexpected volume captures information flow. However, the average adjusted R^2s vary between 0.121 and 0.258, which are in a lower range than those of the regressions which include number of trades. Thus, our evidence suggests that unexpected volume is only marginally better than volume as a measure of information flow.

The third regression [Equation (2.11)] includes both expected and unexpected volumes. Based on the results reported in Table 2.7, the coefficients for unexpected volume are statistically significant and positive for 24 of the 35 stocks at the 1% level. In contrast, the coefficients for expected volume are significant for only 8 of the 35 stocks. Since expected and unexpected volumes are generated from first stage regressions, "generated regressor" problems (Pagan, 1984) may be relevant. Because t-statistics in the second stage regression

tend to be overstated for the estimated coefficients of expected volume, the results may be inconclusive for those stocks with significant expected volume.

The ambiguous role for expected volume may be due to the two competing forces that affect its relationship with volatility. On the one hand, expected volume includes "normal" volume arising from liquidity trading. According to Admati and Pfleiderer (1988), discretionary uninformed traders tend to concentrate their trading to reduce adverse information costs. Thus, part of expected volume is likely to reduce volatility. On the other hand, expected volume incorporates the volume of expected informed trading based on recent trading activities. According to Hasbrouck and Ho (1987), order types tend to depend positively on previous orders, partly due to the process of "working an order" by traders over time. Thus, the estimated coefficient of expected volume tends to capture the net (and ambiguous) effect.

2.7.3 Effects of Quoted Liquidity

The two measures of quoted liquidity are included in all three regressions. The fifth null hypothesis on the relation between quoted spreads and volatility is rejected for 29 of the 35 stocks and for TIPs at the 1% level, based on the sixth column in Table 2.5. The estimated coefficients for percentage quoted spreads are positive for most of the 35 stocks This suggests that a significant portion of quoted spread is due to information flow.

Based on the seventh column in Table 2.5, the estimated coefficients for quote depths are statistically significant and negative for all 35 stocks and TIPs at the 1% level The discreteness of spread changes implies that shifts in market liquidity may be more easily

detected in quote depths rather than spreads. The negative sign for quoted depth is consistent with the belief that most limit orders are used by non-informed traders.

Since limit orders can be "picked off" by other investors, limit order submitters provide the market with a free trading option whose value depends on the short run volatility of prices. In the regressions [Equations (2.9) to (2.11)], both quoted spread and quote depth are measured at the end of the previous interval, t-1. Thus, the results suggest that the measures of quote liquidity change in anticipation of changes in volatility or the rate of informational flow. This is consistent with the finding by Lee, Mucklow and Ready (1993) that the magnitude of the liquidity drop is positively related to the magnitude of the subsequent price reaction to earnings announcements.

Our measures of quote liquidity are not perfect since information on quoted liquidity is not limited to quote spread and quote depth associated with the best quote prices. The electronic system adopted at the TSE publicly discloses the next levels of bids and asks with their associated sizes and the identity of the brokerage house on each limit order. Reputations can be developed for providing superior liquidity and thus become an additional factor.

2.7.4 GARCH Effects

Since the residuals from a simple OLS regression without lagged volatilities were all highly autocorrelated, the regressions reported include 13 lagged volatilities. As an extension to the study by Lamoureux and Lastrapes (1990), whether including trade and quote variables can explain the GARCH effect is examined next. The F-statistics for the lagged volatilities (as well as the t-statistics for some of the individual lags) indicate that lagged values of volatility

are still significant in explaining volatility. In Tables 2.5 to 2.7, the joint hypothesis that all relevant coefficients of lagged volatility are zero is rejected for most of the stocks. Adding these microstructure variables does not eliminate the GARCH effect, and all volatility series still exhibit strong persistence. These findings are consistent with Bessembinder and Seguin (1992), while different from Lamoureux and Lastrapes (1990).

The difference may be explained by the fact that contemporaneous volume is used in their GARCH model as a determinant for volatility. Since contemporaneous volume is positively correlated with volatility (Karpoff, 1987) and may be an endogenous variable, a simultaneous equation problem may bias the results of Lamoureux and Lastrapes. Blume, Easley and O'Hara (1994) suggest that the informational role of volume is different from that of price, since volume provides information on information precision that cannot be deduced from price. Our results suggest that forecasts of volatility from past returns contain relevant information not contained in the historical values of trade and quote variables.

2.8 Concluding Remarks

In this chapter, the dynamic relationship of volatility with a number of trading activity and quote variables is investigated, using half-hour data obtained from the transaction database for the TSE. The tested hypotheses are based on previous theoretical models of asymmetric information. Both Granger-causality tests and multiple regression analysis indicate that the relation between volume and volatility is weak and ambiguous, when volatility is conditioned on number of trades and measures of quoted liquidity. Partitioning volume helps extract the volume component related to the rate of information flow, since unexpected

volume generated from an ARMA model has a significantly positive relationship with volatility.

Our findings show that the positive relation between number of trades and volatility are significant across the entire sample. The role of volume as a proxy for information flow is subsumed by number of trades. This suggests that number of trades may be a better measure fcr the rate of information flow. Non-trade outcomes are significantly negatively related to volatility. This is consistent with the theoretical model by Easley and O'Hara (1992) in which such outcomes serve as a signal for a lack of information. The leverage effect, or asymmetric response of volatility to price declines, is not evident..

Measures of quoted liquidity are associated significantly with volatility. The relationship is positive for quoted spreads, and negative for quote depth. Granger-causality tests reveal a weak lead-lag relation from the two quote variables to volatility. While the contribution from these variables in determining volatility is significant, lagged values of volatility are still useful in modelling volatility.

Chapter 3: Information Flow, Trading Noise and Stock Volatility

3.1 Introduction

Recent research examines the behavior of time-varying volatility and sources of volatility regularities using variance ratio tests. This intuitive and reliable tool for statistical inference is applied to the returns on periods classified by characteristics which reflect different information flows. French and Roll (1986) propose three hypotheses to explain the high volatility during trading hours; namely, the arrival of public information to the market, the revelation of private information through trading, and pricing errors or noise generated by the trading process. Since the components of information flow are unobservable, a common approach is to compare volatility of periods with contrasting characteristics, thereby isolating the impact of public and private information.

Private information can be proxied by number of trades, especially medium-size trades. Empirical studies on the role of trade size by Barclay and Warner (1993), among others, indicate that medium-size orders are more likely to be used by informed traders. By comparing periods dominated by medium-size orders with those dominated by other sizes, it is possible to assess the relative importance of private information flows in determining volatility. Similarly, non-trading outcomes, as shown in Easley and O'Hara (1992), indicate a lack of private information. Thus, non-trading periods can be used to capture the impact of public information on volatility. Jones, Kaul and Lipson (1994a) calculate variance ratios between non-trading and trading days, and conclude that public information is a major source of short-term volatility.

Pricing errors may result from various aspects of the market making process, such as bid-ask effects, overreactions, monopolistic rents, or delays in quote adjustment. Returns based on bids and asks, when examined separately and compared with transaction returns, help to isolate the pricing errors implied by certain market-making practices. The Toronto Stock Exchange (TSE) is a hybrid system of floor trading and an electronic open limit order book. The designated market maker (DMM) competes with member firms who have access to the limit order book and enter their orders electronically. Availability of intraday quote data allows for the evaluation of the monopolistic power of market makers in quote adjustment, and of the impact of bid-ask errors over very short time horizons. The latter allows for an extension of the study by Kaul and Nimalendran (1990).

The purpose of this chapter is two-fold: first, to investigate the relative importance of public and private information as sources of empirical volatility patterns; and second, to identify the significance of pricing errors in volatility behavior. To this end, return periods are classified according to the following criteria: non-trading, trading dominated by medium-size orders, and seasonal factors. Variance ratio tests are used to examine the two possible causes of volatility in different settings. First, medium-size trades and no-trading events are used to assess the relative importance of the flow of private and public information. Second, variance ratio tests based on quote and transaction returns are used to determine autocorrelation structures and to evaluate the impact of pricing errors on volatility behavior.

TIPs, an index participations product based on the Toronto 35 index, has been actively traded on the TSE since March 1989. Theoretical models by Subrahmanyam (1991), and Gorton and Pennacchi (1993) show that the introduction of basket instruments leads to

concentration of liquidity traders and affects the distribution of informed and liquidity traders on component stocks. Variance ratio tests are used herein to investigate whether TIPs and an index portfolio of component stocks exhibit different dynamics.

The remainder of this chapter is organized as follows. In the next section, a brief literature review is provided. In section 3.3, the methodology is discussed and hypotheses regarding sources of volatility are presented. In section 3.4, the data are described. In section 3.5, the results of various variance ratio tests are reported and analyzed. In the last section, some concluding remarks are offered.

3.2 Literature Review

Trade size is commonly believed to be positively related to the likelihood of information-driven trade. Because the value of private information tends to be short-lived, competition among informed traders may force them to choose a relatively large order size. Easley and O'Hara (1987) construct a theoretical model in which trade size serves as a signal for the arrival of private information. The larger the order size, the more likely it is to be initiated by informed traders. Seppi (1992) investigates the importance of information revelation in the pricing of block trades and examines the role of block trade size. He finds evidence that information content is increasing in block size.

On the other hand, real-world trading mechanisms put large-size orders under closer scrutiny, and may make them less appealing to informed traders. Barclay and Warner (1993) propose the Stealth Trading Hypothesis that informed traders concentrate in the medium-size category, and find supporting evidence that medium-size trades account for a larger

proportion of cumulative price movements. They attribute their finding to the existence of the upstairs market in which uninformed traders have incentives to reveal their identities, and informed traders face large price concessions. Cornell and Sirri (1992) find that insider trading concentrates on medium-size orders. Jones, Kaul and Lipson (1994b) find that trade size has no information content beyond that contained in the frequency of transactions. Benveniste, Marcus and Wilhelm (1992) show that specialists can improve on the terms of trade that result from pooling informed and uninformed traders by identifying and sanctioning informed traders. Thus, large-size trades are audited for their trading motives, as argued in Harris (1991). Harris (1987) uses the number of trades instead of trading volume as a mixing variable for the mixture of normal distributions.

Recent research shows that volatility is lower if no trading occurs, or markets are closed. Easley and O'Hara (1992) demonstrate that non-trading outcomes serve as a proxy for lack of information. The time between trades updates the market maker's belief about the likelihood of information arrival. French and Roll (1986) and Jones, Kaul and Lipson (1994a) employ variance ratio tests to investigate the sources of volatility. While the former compare the periods when the market is open to when it is closed, the latter compare trading to non-trading periods when the market is open. French and Roll show that private information is the main factor for determining high trading-time volatility. Jones, Kaul and Lipson find that a significant portion of volatility occurs without trading, and conclude that public information is the main determinant of volatility.

Admati and Pfleiderer (1988) assume a class of liquidity traders who have discretion over the timing of their trades to explain the concentration of trading at the open and the

close. The interacting strategic decisions of informed and liquidity traders leads to trading concentration, improved liquidity, and higher price volatility. Foster and Viswanathan (1990) assume the existence of strategic informed traders, and study the intertemporal behavior of trading volumes, trading costs and price volatility. Their model predicts that volatility and trading costs are highest on Monday, and that trading costs are low when trading volume is high and volatility is low. The model of Admati and Pfleiderer (1988) predicts that trading costs are low and prices are more volatile when trading volume is high.

Stoll and Whaley (1990a) find the ratio of the variance of open-to-open returns to close-to-close returns is consistently greater than one. The greater volatility at the open is attributed to private information revealed by trading and to temporary price deviations induced by the specialist. Harvey and Huang (1991) link weekly volatility patterns to the timing of the release of macroeconomic announcements, and conclude that public information is the main driving force for volatility. Mitchell and Mulherin (1994) find that, while the number of Dow Jones announcements are directly related to market activity, patterns in news announcements do not explain the day-of-the-week seasonalities in stock market activity.

French and Roll (1986) argue that pricing errors generate negative autocorrelation By comparing the variance of long period returns with the variance implied by daily returns, they are able to assess the variance of the relative pricing error. Their results indicate that 4% to 12% of the daily variance is caused by mispricing. Kaul and Nimalendran (1990) use the variance ratio test to evaluate the effect of bid-ask bounce on observed volatility, and find that it accounts for almost 50% of measured short-term volatility.

Amihud and Mendelson (1987) propose a simple model of price adjustment. They

show that partial price adjustments lead to positive autocorrelation and, overreaction and trading noise lead to negative autocorrelation. Harris (1990a) shows that price discreteness results in negative autocorrelation in transaction returns. Mech (1993) examines the autocorrelation structure and delays caused by various market-making strategies using two return series based on bid and on ask prices. He tests the implications from various market-making hypotheses (such as market maker monopoly, inventory effects and inefficiency in quote adjustment), and finds that the market-making hypotheses explain little of the observed autocorrelation in portfolio returns.

Harris (1990b) shows that cash market volatility due to index order imbalances should decrease if a cash index alternative such as index participations becomes widely accepted. The improvement in liquidity will result from a decrease in the costs of market-making in the cash index, since index-motivated demands for liquidity are different from firm-specific demands for liquidity.

Subrahmanyam (1991) shows that the adverse selection problem faced by market-makers is expected to be less severe in markets for baskets of securities than in markets for individual securities. The introduction of a basket is expected to increase the overall informativeness of the price of the underlying portfolio to market-wide information, and make individual security prices less informative in the security-specific component and more informative in the systematic component.

Gorton and Pennacchi (1993) argue that the creation of these security baskets improves the welfare of uninformed investors by reducing their trading losses. Such a basket instrument is not redundant and is a superior trading vehicle in that it minimizes the liquidity

traders' losses to insiders; that is, it reduces the information advantage of insiders over liquidity traders.

3.3 Methodology and Hypotheses

3.3.1 Estimation of Volatility

The iterated weighted least square (IWLS) estimator which is previously described in section 2.4.1 is applied to estimate volatility. Quote-based returns are used to lessen the stale price problem, since quotes may adjust to new information more frequently than transaction prices. Only when the impact from bid-ask errors is investigated, both quote- and transaction-based returns are used. Stoll and Whaley (1990a) use an ARMA model to adjust for non-synchronous trading. The IWLS estimator includes autoregressive terms for returns, thereby reducing non-synchronous trading effects.

To assess the relative importance of public information, volatility should be measured even in the absence of trading. Public announcements or information revealed in the trading of other stocks may still have an impact on quote-based returns. Returns are based on quote midpoints instead of transaction prices. This not only avoids the spurious volatility generated by bid-ask bounce, but also allows for the calculation of volatility for non-trading periods. However, quote revision may be sticky or delayed. Thus, the use of quote-based returns may underestimate the true volatility. Autoregressive terms in the IWLS estimator are used to adjust for such delays in quote revisions.

The unconditional variances used in the variance ratio tests are based on the estimated conditional volatility. The volatility of various categories of returns are determined by

regressing the estimated volatility on the indicator variables. The variance ratios herein are calculated for the following scenarios: (1) periods dominated by medium size trades versus other trade sizes; (2) periods of no trading versus trading; and (3) different days or intraday intervals. To illustrate,

$$\hat{\sigma}_t^2 = \sigma_M^2 D_{Mt} + \sigma_{SL}^2 (1 - D_{Mt}) + \tilde{u}_t \tag{3.1}$$

gives the mean volatility for periods dominated by medium and small/large trades (σ^2_M and σ^2_{SL}). D_{Mt} is the indicator variable for periods dominated by medium size trades. The estimated coefficients on the dummy variables can be used to calculate the variance ratios of the medium trade size category to other trade size categories as follows:

$$VR = \frac{\sigma^2_M}{\sigma^2_{SL}} \tag{3.2}$$

3.3.2 Relative Importance of Volatility Sources

The relative importance of certain components of information flow for different periods is examined by variance ratio tests. Variances are compared for the same length of measurement intervals, and the following hypotheses are tested. The first hypothesis, H_1: Public information is a significant source of volatility, is examined by comparing volatility of non-trading to trading intervals. Since private information is revealed only when trading occurs, the ratio of non-trading to trading volatility shows whether volatility due to public information is a significant fraction of total volatility. The critical assumption is that the arrival

of public information is not related to the likelihood of non-trading outcomes. The first null hypothesis, H_{01}, states that the ratio of variance for non-trading periods to trading periods is zero.

The second hypothesis, H_2: Private information is a significant source of volatility, is examined by comparing medium trade to small/large trade volatility. Since private information is more likely to be revealed by medium size orders, the ratio of medium-size to other trade size volatility shows whether private information (or more precisely, that related to medium size trades) contributes significantly to volatility. The second null hypothesis, H_{02}, states that private information revealed by medium trades as compared to other trade sizes is the same, that is, that the ratios of variances for medium size trades to large/small trades equal one.

If the variance ratio is greater than one, it implies that medium trades convey more information. Under the assumption that the likelihood of public information arrival is independent of trade size, the difference in volatility reflects the incremental amount of private information revealed by medium-size trades. This provides indirect evidence on whether private information is an important factor in determining volatility.

The third hypothesis, H_3: Bid-ask bounce explains a significant portion of transaction price volatility is examined by the following variance ratio test used in Kaul and Nimalendran (1990). The relative importance of the effect of bid-ask errors on volatility is assessed by:

$$VR = \frac{Var(RD_t)}{Var(R_{Tt})} \tag{3.3}$$

where R_{Tt} is transaction returns, and RD_t is the difference between quote- and transaction-

based returns. Measurement intervals of one, two, and three days, and one week are examined herein. The variance ratio VR that is significantly different from zero implies that the impact of bid-ask errors is a significant factor in the estimated volatility based on transaction prices.

3.3.3 Variance Ratio Tests for Autocorrelation Structure

Pricing errors due to trading noise lead to serially correlated returns, especially when measured over the short run. Since neither public nor private information should cause autocorrelation in returns, an examination of autocorrelation structure helps reveal the impact of pricing errors on volatility. The variance ratio test is conducted over a longer period of time, as in French and Roll (1986). The variance ratio, VR(k), for k intervals, is given by:

$$VR(k) = \left(\frac{1}{k}\right)\left(\frac{VAR(R_t^k)}{VAR(R_t)}\right) \tag{3.4}$$

where R_t^k is a k-period return, and R_t is a one-period return. Under the null hypothesis of the random walk, the variance of the k-period return must be linear in any of the observation intervals. The variance ratio of a k-period return is equal to k times the variance of a one-period return. It can be written as the weighted average of the first k-1 autocorrelation coefficients as follows:

$$VR(k) = 1 + \sum_{i=1}^{k-1} \frac{2(k-i)}{k}\rho_i \tag{3.5}$$

where ρ_i is the estimate of the ith-order autocorrelation coefficient of returns. The variance ratios need to be corrected for small-sample biases (Kaul and Nimalendran , 1990). Effects on volatility from noise trading or delays in quote revisions tend to disappear as the length of

the measurement interval increases. Comparisons of short- and long-term variance ratios reveal the relative contribution of pricing errors to short-term volatility.

The fourth hypothesis, H_4: Pricing errors other than bid-ask errors contribute significantly to volatility is tested by examining the autocorrelation structure of quote-based returns. The null hypothesis, H_{04}, states that variance ratios using quote-based returns equal one. As shown by Amihud and Mendelson (1987), delays in quote adjustment or partial adjustment lead to positive autocorrelation, while overreaction leads to negative autocorrelation. Noise and price discreteness also result in negative autocorrelation. Since bid-ask bounce leads to negative first-order autocorrelation, the analysis is conducted herein on quote-based returns to avoid bid-ask errors.

The fifth hypothesis, H_5: Monopolistic power of market maker exists through a delay in quote adjustment is tested using quote-based returns. The designated market maker can be viewed as a monopolist, since each stock has only one DMM whose power includes setting an opening price and discretion over temporary halts so that a floor transaction can be completed. However, member firms have an open access to the limit order book as well as to the identity of the brokerage house submitting each limit order. Their electronically entered orders are transmitted with a 30 second delay to the floor.

The availability of quote returns makes it possible to infer the impact of pricing errors due to the market-making process. Different aspects of the market-making process imply that bid and ask prices may exhibit different speeds of adjustment to new information. If the market maker is able to charge a monopolistic rent, ask prices rise faster and fall more slowly than bid prices. On the other hand, if inventory rebalancing is a major concern to the market

maker, bid prices rise faster and fall more slowly than ask prices. As in Mech (1993), two return series based on quotes are defined. R_1 is a series of returns calculated from ask prices when the bid-ask midpoint rises, and from bid prices when the average falls. R_2 is calculated in the opposite way. Specifically:

$$\begin{aligned} R_{1t} &= (Ask_t - Ask_{t-1})/m_{t-1} && if \quad m_t > m_{t-1}, \\ &= (Bid_t - Bid_{t-1})/m_{t-1} && if \quad m_t < m_{t-1}, \\ &= 0 && otherwise \end{aligned} \tag{3.6}$$

where m_t is the average of the bid and ask quotes. The autocorrelation of these series is examined using variance ratio tests. If R_1 is closer to reflecting the true quote adjustment process, R_1 is less autocorrelated than if returns are calculated from bid-ask midpoints. The null hypothesis, H_{05}, states that variance ratios based on R_1 equal one. The test result indicates whether the monopolistic power of the DMM is important in explaining the observed autocorrelation in returns.

3.4 Data

Data are obtained from the time-stamped transaction data files of the Toronto Stock Exchange over the 13 month period from June 1, 1990 to June 30, 1991. The database provides detailed trade and quote information for companies listed on the TSE. The stocks contained in the TSE 35 index are selected for study, since stocks in this index represent the largest and most actively traded Canadian companies. This makes the infrequent trading problem less serious. Prices are adjusted for quarterly dividends and share recapitalization. The Toronto 35 index is a market value weighted index. The market value weights are

expressed as numbers of shares, and these predetermined number of shares are used in the index calculation (see Appendix).

An instrument representing a basket of the TSE 35 stocks, called TIPs (Toronto 35 Index Participations), is also studied. Since this unique market index is traded as a single instrument on the TSE, it has its own trading volume and quotes. This differs from the market indices used in other studies. An index portfolio of TSE 35 stocks is formed using the predetermined weights to replicate TIPs. This is an alternative way to hold the same position as holding TIPs.

Trading in these active stocks occurs through an integration of traditional floor trading with an electronic system. The electronic open book system, which was implemented in 1990, allows brokers off the floor to enter orders. Members of the exchange have open access to the book of limit orders as well as to the identity of the brokerage house submitting each limit order. A trader with a large order has the option of not disclosing the part of order in excess of 5,000 shares. However, the TSE gives priority to disclosed orders at the same price.

The TSE is open from 9:30 a.m. to 4:00 p.m., providing 13 half-hour intervals per day. Half-hour return data impose a structure of a fixed length interval, and all trades within an interval are assumed to occur at the close of the interval. The choice of the half-hour interval is based on two conflicting factors. A longer return interval may bias the results towards finding no role for certain trade-size orders, while a shorter interval may result in a larger number of no transaction observations.

Compared with the previous studies based on daily data, the data sample is broadened

by using half-hour data summarized from the transaction data files for individual assets. This avoids the potential aggregation problem of using daily data for a portfolio of stocks as in earlier studies. By using intraday data to construct a half-hour return series, the very short-term behavior of quote and transaction returns can be examined to detect any pricing errors. Returns are computed as the natural logarithm of average bid and ask prices for trading and nontrading periods.

The trade size categories are determined as follows. Small-size trades are those under 400 shares; medium-size trades are those between 400 and 10,000 shares; and large-size trades are above 10,000 shares. If the total *number* and *volume* of medium trades over an interval exceeds that of small or large trades, the interval is defined as being dominated by medium size trades.

Descriptive statistics for interday and intraday volatility patterns are reported in Table 3.1. Since intertemporal volatility patterns are common to individual stocks, an equally weighted portfolio of TSE35 stocks is formed and its variance ratios across the week are examined. The half-hour volatility for each weekday, shown in Figure 1, follow a U-shape. To test the equality of these volatilities formally, variance ratios are calculated for weekdays and adjacent intraday periods. In Panel A, the volatility for both Thursdays and Fridays are significantly greater than those of Mondays. This evidence is not consistent with the conjecture of Foster and Viswanathan (1990). They argue that the longer the market is closed, the more significant is the advantage of informed traders at the opening.

Lakonishok and Maberly (1990) document that individuals tend to trade more on Mondays, while institutions are less active. In Panel A of Table 3.2, relative frequency of

small trades is marginally larger and number of large trades is smaller on Monday than on any other day. A reduction in institutional large trades appears to be an explanation for the relative low volatility of Mondays. In Panel B of Table 3.1, variance ratios for the first four periods and the last period of each trading day are significantly greater than one. Volatilities peak at the opening and reach their lowest point in the middle of the day. The U shaped pattern of volatility is asymmetric, since volatility at the open is higher than that at the close.

3.5 Empirical Findings

3.5.1 Evidence on Non-trading versus Trading Volatilities

When the market is open but no trading occurs, this observable "event" may serve as a signal for a lack of information. Since private information can only be revealed through trading, the variance ratios of nontrading to trading periods help to explain the role of private information in determining stock volatility. If public information is assumed to arrive in the market at a constant rate, the ratio of the variances of nontrading to trading periods reveals the importance of public information relative to private information in determining return volatility. Alternatively, under the assumption that private information accounts for a smaller fraction of volatility than public information (as in Jones, Kaul and Lipson, 1994a), the variance ratio indicates the pattern of public information flow to the market .

The ratios of the variances of nontrading periods to trading periods are presented in Table 3.3. All of the variance ratios are well below one. For 26 of the 35 stocks, variance ratios are statistically significant at the 1% level, and the null hypothesis H_{01} that variance ratios of non-trading to trading periods are zero is rejected for all 35 stocks at the 1% level.

The variance ratios range from 5% to 21%, and the median variance ratio for the TSE35 stocks is 14%. This indicates that volatility due to public information (or other non-trading factors) accounts for a significant proportion of trading volatility. This is consistent with Easley and O'Hara (1992) who show that volatility is reduced when non-trading outcomes are observed.

The variance ratio for TIPs is even higher at 29.3%. If market-wide information is more likely to be public announcements (such as macroeconomic news releases), this suggests that TIPs is affected more by public information since it is a trading vehicle for market-wide information. Alternatively, firm-specific information for component stocks may affect TIPs with a lag. Private information is revealed through the trading of component stocks and their impact becomes public information which in turn may affect the volatility during non-trading periods.

However, even without trading, volatility represents a substantial proportion of normal trading volatility. Interpretation of this result depends on the assumption invoked for the process governing information flow. Under the assumption that public information arrives at a constant rate, this result implies that private information is a dominant factor in determining volatility. Our evidence on TIPs also confirms that the basket of securities is less affected by the adverse selection problem, as trade-related information accounts for a smaller fraction of the volatility for TIPs. By trading TIPs rather than its component stocks, liquidity traders can reduce their expected losses to informed traders (as conjectured by Gorton and Pennacchi (1993)).

3.5.2 Results for Medium-size Trades

The variance ratio of medium-size orders to other order sizes (small/large) is used to investigate whether private information, conveyed by medium-size orders, is a significant determinant of volatility (i.e., H_2). In Table 3.4, the ratios of the variances of medium-size trades to both small- and large-size trades are reported. For 33 of the 35 stocks, the variance ratios are greater than one at the 1% significance level. They vary between 3.07 and 11.91 and the median variance ratio is 8.01. The mean variance ratio of 1.59 for medium- to large-size trades indicates that volatility is higher during the periods dominated by medium-size orders. This rejection of the second null hypothesis is consistent with the finding of Barclay and Warner (1993) that informed trades are concentrated in the medium-size category.

Because the existence of TIPs provides an opportunity to reduce trading costs (especially for liquidity traders), lesser informed traders will optimally migrate to trading TIPs. The Kyle model (1985) suggests that the higher the stock's variance, the greater is the value of the insider's superior information. The variance ratio for TIPs is 1.89, which is less that the median variance ratio for the TSE 35 stocks. In contrast to the case for the component stocks that constitute TIPs, medium-size orders are used less for information trading and have less price impacts on TIPs.

Interpretation of the variance ratio results depends on the assumption invoked about public information flow. If public information arrives at a constant rate, our variance ratios measure the incremental impact from the differential private information conveyed by various types of orders. Alternatively, increases in medium-size trades may be caused by public information release. Wang (1994) and Foster and Viswanathan (1993) show that volume

follows the public release of information. Assuming differential analytical abilities for various market participants, Kim and Verrecchia (1994) show that public information disclosures stimulate trading based on informed judgements. Thus, the results of the variance ratio tests may be due to the possibility that medium-size trades tend to coincide with the release of public information. For the purpose of predicting volatility, the above results help in identifying the number of medium-size trades as a proxy for the rate of information flow.

3.5.3 Effects of Bid-Ask Bounces

The results of the variance ratio tests on the differences between transaction returns and returns using the average of bid and ask prices are reported in Table 3.5. For the average of the TSE35 stocks, bid-ask errors contribute from 8.9% to 35.2% to the variance of transaction returns. As the measurement interval increases, the relative importance of bid-ask errors becomes smaller. The variance ratios for TIPs are comparatively smaller for the shorter intervals, ranging from 9.5% to 18.7%. This is consistent with lower transaction costs for TIPs. For example, TIPs has a minimum guaranteed fill (MGF) of 1,500 shares, which is larger than for most individual stocks. Thus, the results support the third hypothesis that bid-ask bounces explain a significant portion of transaction price volatility in the short time intervals.

The results of the variance ratio tests on transaction returns are reported in Table 3.7. The mean variance ratio for the TSE35 stocks is significantly smaller than one for a one-day interval at the 1% level. In comparison with the results based on quote midpoint returns, the negative autocorrelation in transaction returns over the shorter interval is mainly caused by

bid-ask bounce effects. As the measurement interval increases, the variance ratios approach one.

3.5.4 Effects of Pricing Errors

Since returns based on quote midpoints contain no bid-ask effect, variance ratio tests based on such returns reveal the impact of pricing errors (other than the effect of bid-ask bounce) on volatility. The results of variance ratio tests based on quote midpoint returns are reported in Table 3.6 for measurement intervals of 1 day to 1 week. The variance ratios are calculated between k-period variances and a one-period variance. This extends the findings of Kaul and Nimalendran (1990) in two ways: first, the availability of intraday quotes allows for an investigation of very short term return behavior; and second, the traded index TIPs provides a means of conducting such a test for a traded market proxy.

The mean variance ratios for the TSE35 stocks are not significantly different from one, ranging from 0.86 to 1.19 for measurement intervals of one day and one week, respectively. These results are similar to those in Kaul and Nimalendran (1990) in that the variance ratios increase with the length of the measurement interval. When k goes to one week, the variance ratio is greater than one, indicating positive autocorrelation in returns over longer intervals. The variance ratios for individual stocks vary considerably from significantly smaller than one (0.65 for TRP over a one-day measurement interval) to significantly greater than one (1.33 for VO over a one-day interval). The results show that returns can be either negatively or positively autocorrelated.

The variance ratios for TIPs are significantly less than one, and range from 0.44 to

0.65 for measurement intervals of one day to one week, respectively. This differs from the mean variance ratio for the same 35 stocks. The fact that returns for TIPs are negatively autocorrelated suggests that TIPs behaves more like an individual security than a portfolio of securities. Since only liquidity trading leads to pricing error that is corrected over time, as manifested as negative autocorrelation in returns, the results for the variance ratio for TIPs is consistent with the concentration of liquidity traders on TIPs, as predicted by the theoretical model of Subrahmanyam (1991).

The existence of TIPs provides liquidity traders with a superior alternative trading vehicle that minimizes the adverse selection problem. As a result, informed trading for individual component stocks is proportionally higher. The index portfolio of TSE35 stocks exhibits drastically different results from that of TIPs. The variance ratios are significantly greater than one, ranging from 1.31 to 2.65. This implies that the returns of the non-traded index portfolio are positively autocorrelated. Lo and MacKinlay (1990) suggest that unaccounted-for cross-autocorrelation is one possible reason for such calculated positive autocorrelations. If overreaction behavior exists for TIPs to the trading of component stocks, its returns may exhibit a negative autocorrelation. In contrast, forming the index portfolio diversifies away the overreaction behavior of component stocks (if overreactions are not highly correlated across stocks).

The results for the variance ratio tests using quote-based returns are reported in Table 3.8. The mean variance ratio for the TSE35 stocks is similar to the variance ratio for TIPs. Both are significantly less than one for different measurement intervals. Compared with the variance ratios for quote midpoint returns and transaction returns, R_1 is more negatively

autocorrelated. This suggests that delays in quote revision are not a dominant factor, since partial quote adjustment leads to a positive autocorrelation. The negative autocorrelation in R_1 may be caused by overreaction in bid or ask quotes. No evidence exists to support the monopolistic power of DMM (i.e., for H_5). This is understandable given that the open limit order book allows for member firms to compete with market makers.

3.6 Concluding Remarks

The three hypotheses proposed by French and Roll serve as the benchmarks for interpreting the results of the variance ratio tests, although reality is more complex than is embodied in these hypotheses. For example, since trading is more likely after the release of public information (Foster and Viswanathan, 1993), disentangling the effects of public information from private information is difficult. The strategy herein is to use various proxies for private information, and to arrive at conclusions based on the robustness of the overall results.

The results for the variance ratio tests for the medium-size trades and for non-trading intervals improve our understanding about information flow and the behavior of volatility. Public information has a significant impact on volatility, and on average accounts for 16% of volatility during trading periods. Results of variance ratio tests on medium-size trades indicate that medium-size trades convey more information than other trade size categories. This implies that the exercise of private information appears to have a significant impact on volatility.

While the index portfolio formed by the underlying TSE35 stocks has positively

autocorrelated returns, TIPs exhibits a negative return autocorrelation. This may be explained by overreaction due to the concentration of liquidity trading on TIPs, and to a lead-lag relationship caused by different reaction speeds of component stocks to market-wide news.

The study by Kaul and Nimalendran (1990) is extended to the very short time horizon and to quote-based returns. The results for the autocorrelation structure are similar to their findings that the most negative autocorrelation in transaction returns may be caused by bid-ask errors, which on average range from 8.9% to 35% of the variance of transaction returns. In contrast to the variance ratios on the average of the TSE35 stocks, the variance ratios for TIPs are consistently below one. Little evidence exists that TSE market makers possess any monopolistic power in adjusting quotes.

Chapter 4: Stock Market Crash Behavior of Screen-Sorted Portfolios

4.1 Introduction

The stock market crash of October 1987 ("Crash") was a significant international event during which equity prices fell dramatically on an international scope. The existing literature focuses primarily on the possible causes of the Crash. Roll (1988, 1989) argues that the Crash can be ascribed to the normal response of each country's stock market to a worldwide market movement. He finds beta to be the most significant explanatory variable of the Crash, and that various institutional characteristics had no significant influence on the extent of the Crash. Mitchell and Netter (1989) claim that the proposed American tax bill with an anti-takeover provision was the triggering event for the Crash. However, even if most of the negative news (such as the proposed tax bill) reached the market before October 19, minor events may still have caused the large price movements associated with the Crash.

A number of authors argue that a sudden, market-wide shift in the risk premium is a possible cause of the Crash. Since portfolio insurance, given asymmetric information, implies an underestimation of future price volatility, Grossman (1988) concludes that a volatility shock can increase the risk premium significantly. Fama (1989) concludes that the Crash appears to be an adjustment to changes in fundamental values; especially, to changes in expectations about growth after an extended bull market, and to increased discount rates caused by increased expected returns. Miller (1989) suggests that fundamental-based explanations for the Crash are possible. These include a revision in risk attitudes and a major trigger that induced a major shift in the anticipated growth rate. Amihud, Mendelson and

Wood (1990) argue that the main news was the Crash itself, which caused investors to re-evaluate their liquidity risk perceptions upwards. Leland and Rubinstein (1988, p.45) argue that "one piece of news, the prior behavior of the market itself, was news".

Consideration of factors in addition to systematic risk to explain expected returns has theoretical, empirical and practitioner support. According to Fama and French (1992), stock risk is multidimensional, and beta appears to be an incomplete measure of risk. Keim (1988) argues that firm-specific factors (characteristics or screens) may be imperfect surrogates for an underlying and more fundamental priced 'factor' that is missing from the CAPM. Thus, these factors can be used to aid in the extraction of information about risk and expected returns. The existing literature on market anomalies, which is reviewed somewhat in the next section, provides empirical justification for the use of firm-specific factors to extract information about risk and risk premium. Also, according to Bannister (1990), Jones (1990), amongst others, active individual investors and portfolio managers use various firm-specific characteristics or screens to attempt to outperform the market.

A number of authors examine the performance of screen-sorted portfolios during the Crash. Arbel, Carvell and Postnieks (1988) study the Crash behavior of portfolios screened by industry, beta, P/E ratio, company size, dividend yield and price-to-book ratio. While they find that high beta stocks had larger price declines, they do not determine if these high beta stocks declined more or less than they should have declined since they do not examine market- and/or risk-adjusted returns. Like Roll (1988), Limmack and Ward (1990) find that systematic risk is the only consistently significant determinant of stock price movements during the Crash. However, they find that the importance of unsystematic risk increased

immediately after the Crash. Noise could be a significant factor since overreaction appears to be an important aspect of the Crash based on the market behavior of insiders [Seyhun (1990)]. Other studies dealing with other aspects of the market Crash include Bennett and Kelleher (1988), Gammill and Marsh (1988), Greenwald and Stein (1988) and Harris (1989).

This chapter has two primary objectives. The first is to investigate the behavior of the market- and risk-adjusted returns (CAR's) around the Crash of various portfolios of stocks listed on the Toronto Stock Exchange (TSE), which are formed using firm-specific characteristics or screens. The behavior of TSE-listed stocks may differ from that of stocks listed on the New York and American Stock Exchanges in that resource-based stocks account for a much higher proportion of the stocks on the TSE.

The second objective is to investigate the role that changes in systematic risk and nonsystematic risk (or noise) played in return determination during the Crash period. The risk premia associated with such volatility shifts may help to determine if the risk aversion of the consensus investor changed after the Crash. Since the most striking characteristic of the Crash appears to be the unanticipated magnitude of the volatility shock, the "news" effect of this "abnormal" volatility shock will be examined using an event study methodology. Schwert (1990) finds that the daily return volatility increased sharply during and after the Crash in the United States, and returned to a lower level more quickly than experience predicted. Similarly, Hatch and White (1988) find that the moving standard deviation of daily returns for the TSE 300 Index did not increase (permanently) after the Crash based on its behavior over the period, 1977-88.

The remainder of this chapter is organized as follows. In the next section, the firm-

specific screens are discussed, the hypotheses are formulated, and the methodology is described. In section 4.3, the data are described. In section 4.4, the results are presented and analyzed. In the fifth and final section, some concluding remarks are offered.

4.2 Firm-Specific Screens, Null Hypotheses and Methodology

Five firm-specific screens are used to extract information about risk or its relationship with expected returns; namely:

(1) Stock Beta - Stock betas are relevant for market-timing decisions in anticipation of a market movement (such as a downward "correction"). Roll (1988) and Limmack and Ward (1990) find beta to be the most significant explanatory variable during the Crash both internationally and in the United States.

(2) Price/Earnings (P/E) Ratio - Ball (1978) argues that earnings proxy for omitted variables that affect expected returns. Basu (1983) finds that E/P is likely to be higher for stocks with higher risks and expected returns. Jaffe, Keim and Westerfield (1989) find significant E/P effects using the CAPM and U.S. data for 1951-1986. Mei (1993) confirms that E/P contains some information for asset pricing not conveyed by exposure to systematic risk.

(3) Market Capitalization or Size - Banz (1981) finds that smaller firms tend to have higher risk-adjusted returns than larger firms. Jaffe, Keim and Westerfield (1989) and Fama and French (1992) provide more recent evidence of a size effect in expected returns.

(4) Dividend Yield - Brennan's (1970) tax-based model predicts that dividend payout is

an additional explanatory variable for stock returns. Numerous empirical studies [such as Litzenberger and Ramaswamy (1982) and Keim (1985)] find that dividend yield helps in the prediction of share returns.

(5) Leverage or Debt/Equity (D/EQ) Ratio - Christie (1982) shows that leverage changes due to unequal changes in stock and bond prices over time cause variation in stock volatilities. Bhandari (1988) finds a positive relation between average returns and leverage, and suggests that D/EQ may be used as a proxy for risk in addition to beta. Ball and Kothari (1989) argue that equity returns cause changes in market-valued leverage, and consequently in risk.

Risk-adjusted returns should not be related to systematic risk if beta is an adequate measure of priced risk and beta is relatively stable over time. As discussed above, the empirical evidence suggests otherwise. French, Schwert and Stambaugh (1987) find that unexpected returns are negatively related to unexpected changes in the volatility of stock returns. If firm-specific factors other than beta are related to an ex ante risk premium in addition to that captured by the CAPM, then an unexpected volatility shock (e.g., a market crash) could lead to a larger negative impact measured using ex post returns for those stocks that have a true ex ante risk premium that is relatively higher than that implied by the CAPM. Thus, based on beta-risk-adjusted ex post returns given the size, P/E and leverage anomalies, smaller cap stocks are expected to underperform larger cap stocks, lower P/E stocks are expected to underperform higher P/E stocks, and higher leveraged stocks are expected to underperform lower leveraged stocks over the Crash. Since the dividend yield effect may be primarily tax motivated, higher dividend yield stocks are expected to outperform lower

dividend yield stocks. Of course, changes in systematic risk or noise may confound the discovery of the expected relationships.

One set of ten equally-weighted portfolios is formed from the individual firm rankings for each of the five firm-specific screens. Two dummy-variable, single-factor models are used to calculate cumulative average residuals (CAR's) for the event window [-20, +20] for each of the screen-sorted portfolios [for greater details, see Thompson (1985) and Karafiath (1988)]. [-20, +20] represents the 41-day period which starts from the 20th day prior to the event day [0] and runs up to and includes the 20th day after the event day (October 19, 1987). Unlike the first model, the second model allows for a permanent change in beta on the date of the Crash (October 19, 1987 or [t=0]). Specifically:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \sum_{t=-20}^{20} T_{jt} D_t + \varepsilon_{jt}, \text{ and} \tag{4.1}$$

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \Delta\beta_j R_{mt} D_{[0,170]} + \sum_{t=-20}^{20} T_{jt} D_t + \varepsilon_{jt} \tag{4.2}$$

where R_{jt} is the return on the j-th screen-sorted portfolio for [-170, 170];
α_j is the intercept;
β_j is the systematic risk for the j-th screen-sorted portfolio;
$\Delta\beta_j$ is the change in beta on and after the Crash;
R_{mt} is the return on the TSE 300 composite index for [-170, 170];
T_{jt} is the abnormal return (AR) of the j-th screen-sorted portfolio on date t;
D_t is a dummy variable with a value of 1 for date t in the event window [-20, 20] and zero otherwise;
$D_{[t1, t2]}$ is a dummy variable with a value of one in the interval [t1, t2] and zero elsewhere, where t1 and t2 represents the starting and ending days, respectively; and
ε_{jt} is the random error term with standard properties.

The portfolio approach is used to deal with the contemporaneous covariance caused

by having the same event date for every security. The use of simultaneous equations for individual stocks is not feasible herein since it requires a large number of observations relative to the number of companies. The null hypothesis that the mean abnormal return (AR) is equal to zero is tested using a t-test, which accounts for any contemporaneous correlation among the individual stocks in each screen-sorted portfolio. Since statistically significant autocorrelation may exist in the residuals using daily data, an Estimated Generalized Least Squares (EGLS) procedure is used to construct the auto-regressive process for the residuals and then to estimate the regression parameters in equations (4.1) and (4.2) Unless stated otherwise, all statistical significance discussed subsequently in the text is evaluated at the 5% level.

The first null hypothesis, H_0^1, is that the market-risk-adjusted cumulative abnormal returns (CAR's) of screen-sorted portfolios should not be statistically different cross-sectionally in an efficient capital market. H_0^1 can be expressed in terms of the CAR for the j-th screen-sorted portfolio over the interval [t1, t2] as follows. H_0^1: $CAR_{j[t1,t2]} = 0$. This is equivalent to the following linear hypothesis of the regression coefficients:

$$H_0^1 \quad \sum_{t=t1}^{t2} \gamma_{jt} = 0$$

Seemingly Unrelated Regressions (SUR) are also used to estimate equations (4.1) [and (4.2)] jointly across the ten screen-sorted portfolios for the same screen. Use of the GLS estimator does not lead to a gain in efficiency since each equation contains the same explanatory variable. The following joint tests of the first hypothesis are performed

$$H_0^{1'}: \; CAR_{1,[t1,t2]} = \cdot \; = CAR_{10,[t1,t2]} = 0$$

$$H_0^{1''}: \; CAR_{1,[t1,t2]} = CAR_{10,[t1,t2]} = 0$$

These tests jointly test the differences in CAR's between the ten portfolios, and the two extreme portfolios, respectively. These tests are conducted for the following intervals: [t=0] (i.e., October 19, 1987), [5, -1], [0, 5], [1, 5], [-20, -1], [1, 20], and [-20, 20].

The estimation of the standard deviation of the prediction error (T_{jt}) assumes that the variability of the market is the same during the event window and the estimation period. Since the market was more volatile around Black Monday [Schwert (1990)], this could result in too many rejections of the null hypotheses. Although Brown and Warner (1985) find that the CAR methodology is robust to misspecification, Connolly (1989), Kryzanowski and Zhang (1993), among others, demonstrate that inferences can change with the consideration of the time-varying conditional residual variance. GARCH models are used herein to examine the robustness of the EGLS results for selective intervals within the event window.

The one-beta model (4.1) assumes that systematic risks are constant although the betas are likely to have shifted during the Crash period. Limmack and Ward (1990) find that noise played an increasingly important role around the Crash. Tests are conducted herein on the beta-sorted portfolios, using the pre-crash level betas as controls, to assess the impact of the Crash on systematic and unsystematic risks.

The second null hypothesis, H_0^2: $\Delta\beta_j = 0$, states that changes in systematic risk after the Crash are not significant It is tested by examining the statistical significance of $\Delta\beta_j$ in equation (4.2).

The third null hypothesis H_0^3, states that changes in the required risk premium for the residual risk of the beta-sorted portfolios are not significant. Longstaff (1989) suggests that, in the context of a continuous time CAPM, a multi-factor model of discrete-time returns includes a variance term. De Long, Shleifer, Summers and Waldmann (1990) present a model in which arbitrage may not eliminate the effects of noise traders on prices, and a risk results from the unpredictability of noise traders' beliefs. Engle (1990) recommends the use of a GARCH-M model to test the stability of the price of volatility over the Crash period.

H_0^3 can be tested using a variant of the following GARCH-M-type model:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \lambda_j h_{jt} D_{[0,170]} + \varepsilon_{jt} \tag{4.3}$$

$$h_{jt} = c_j + a_j \varepsilon_{jt-1}^2 + b_j h_{jt-1} \tag{4.4}$$

where R_{jt} is the return on the beta-sorted portfolio j, h_{jt} is the conditional residual variance, λ_{jt} is the risk premium for the conditional residual variance, and all the other terms are as defined earlier.

The third null hypotheses (H_0^3; $\lambda = 0$) is tested by examining the statistical significance of the λ_j estimate in equation (4.3). Since the GARCH-type model (4.3) does not provide estimates of contemporaneous volatility, only the effect on the ex ante risk premium and its changes can be examined. Thus, the "news" effect of contemporaneous changes in volatility is studied indirectly herein [as in French, Schwert and Stambaugh (1987)].

4.3 Description of the Data

Daily returns for 949 common stocks and the TSE300 composite index were obtained from the TSE/Western Data Base for the 341 trading days centered on October 19, 1987 [t=0]. The pre- and post-event estimation periods each consists of 150 days (-170, -21] and [21, 170], respectively).

Size is measured by the market value of a stock's equity using the monthly stock price and the number of shares outstanding as of September 1987, as obtained from the TSE/Western Data Base. The P/E ratios and dividend yields are obtained from the September 1987 issue of the TSE Review and the Financial Post of September 26, 1987. The debt-to-equity ratios are obtained from the Report on Business: Canada Company Handbook and the Financial Post Company Cards for only 504 stocks. Data unavailability for this screen primarily occurred for small cap stocks.

The correlations between the various screens are reported in Table 4.1. The correlation coefficients are statistically significant from zero for only two cases; namely, between dividend yield and P/E ratio, and between size and D/EQ ratio. Even for these two cases, the correlation coefficients are small in magnitude. Interestingly, the correlation between dividend and beta is not statistically significant probably due to the large number of junior resource companies in the sample who have little or no debt and pay no dividends, the senior resource firms with depleting assets that pay high liquidating dividends, and the marginally healthy firms that pay artificially high dividends. The correlation between P/E and size is also not significant because the P/E portfolios contain many negative P/E ratios for mainly resource-based companies.

4.4 Empirical Findings

The abnormal return performance of two types of screen-sorted portfolios are not significantly different around the Crash, the empirical findings for the P/E-ratio- and leverage-ratio-sorted portfolios are only referred to in the footnotes.

4.4.1 Behavior of the Beta-sorted Portfolios

4.4.1.1 Abnormal Returns

The abnormal returns (AR's) for the ten beta-sorted portfolios for the event day (October 19, 1987) for the one- and two-beta models are reported in panel A of Table 4.2 Based on the t-values for the AR's for the one-beta model, the portfolio AR's are inversely related to their level of systematic risk (β). The highest (lowest) beta-sorted portfolio exhibits a statistically significant and positive (negative) AR. Based on the t-values for the AR's of the two-beta model, all of the portfolios exhibit statistically significant negative AR's.

The multi-day, one-beta model CAR's are reported in panel A of Table 4.3. The CAR's for time intervals that are not longer than five days from the event day (namely, [0, 5] and [1, 5]) exhibit a similar pattern to that for the AR's on the event day. The robustness of this relationship is examined using the GARCH one-beta model estimates for the period [0, 5]. Based on unreported results, the GARCH-model CAR's exhibit a similar pattern to the one-beta model CAR's in that the higher beta-sorted portfolios have statistically significant and positive CAR's, and the lower beta-sorted portfolios have statistically significant and negative CAR's. The CAR's for portfolio 6 are the only exception to this monotonic inverse relationship. Over longer time intervals, the CAR's for the smaller beta-sorted portfolios are still significantly negative, and the CAR's for the highest beta-sorted portfolio are no longer

positive or statistically significant.

Based on the F-values in Table 4.3, the hypothesis ($H_0^{1'}$) of the joint equality of the one-beta model CAR's to zero across the ten portfolios is rejected for all but one of the time intervals (namely, [-20, -1]). Based on the F-values reported in table 4.4, the two-beta model CAR's are consistently not statistically significant for time intervals that end before the event day.

Since the inverse relationship between the CAR performances of the portfolios and their betas only existed for the event and subsequent days, changes in systematic risk together with residual risk could have played a significant role in their performances. The finding that securities with lower betas were more seriously affected by the volatility shock is consistent with the evidence supporting market overreaction behavior, and also with the evidence for U.S. markets that low systematic risk stocks exhibit abnormally positive returns in rising markets (the long-run experience) if return symmetry occurs in falling markets.

4.4.1.2 Systematic Risk Changes

The test results for changes in the betas of the beta-sorted portfolios are reported in Table 4.5. Based on the t-values for a test of H_0^2, the betas for the lower beta-sorted portfolios (1 and 2) increased, and those for the higher beta-sorted portfolios (7 through 10) decreased after the Crash. The F-value of 67.03 for a test of the second null hypotheses (H_0^2) that none of the beta changes are significantly different from zero across the set of ten beta-sorted portfolios is statistically significant. Thus, H_0^2 is not supported empirically for the beta-sorted portfolios.

An examination of the CAR's for the two-beta model reported in Table 4.4 suggests

that changes in systematic risk are one plausible explanation for the observed inverse relationship between the abnormal returns and the systematic risks. The first null hypothesis H_0^1 is rejected for all portfolios for most of the intervals that end after the Crash. Specifically, the CAR's are negative and significant for time intervals of [0, 5], [1, 5], [-1,1], [-5,5], [1, 20] and [-20, 20] for all ten beta-sorted portfolios. The differences in the two-beta CAR's for the two extreme portfolios are smaller than the corresponding differences for the one-beta model CAR's for most of the time intervals. For example, the differences in the one- and two-beta model CAR's for portfolios 1 and 10 over the event window [-20, 20] are 11.3 and 44.7 percent, respectively. However, based on the F-values, these CAR differences are statistically significant for the one-beta model but not for the two-beta model. The null hypothesis ($H_0^{1'}$) of the joint equality of the two-beta CAR's to zero is rejected for the shorter interval [1, 5] that follows the event day but not for the longer interval [1, 20].

4.4.1.3 Residual Risk Premium Changes

If during the volatile period of the Crash the risk due to trading noise increased, then an inverse relationship between abnormal returns and systematic risk may be explained by a possible change in the risk premium required to cope with the incremental risk due to trading noise changes. The evidence on the reversal in equity returns over short time intervals which has been documented by Lehmann (1990a,b), amongst others, suggests that such a risk premium is related to previous price changes. Thus, during the period immediately after the Crash, changes in the risk premium for trading noise might be inversely related to the level of systematic risk. Further, if the price drop on Black Monday was believed to be an overreaction, any inverse relationship observed between CAR and β might be due to an

increased willingness of investors to bet on the likelihood of a rebound. Seyhun (1990) provides supportive evidence that corporate insiders bought stocks in record numbers during and after the Crash. Shleifer and Summers (1990) argue that positive feedback trading makes it easier to understand the Crash.

The estimates of the change in the risk premium for residual volatility, λ_j, from the GARCH-M model (4.3) and (4.4) for the ten beta-sorted portfolios are reported in Table 4.6. Somewhat consistent with Limmack and Ward (1990), the pricing of residual risk plays a weak (but increasingly important) role after the Crash. Unlike the case for the other portfolios, the λ_j estimate for portfolio one (the portfolio with the lowest beta) is of the expected sign and is statistically significant. This rejection of H_0^3 indicates that the ex ante risk premium for this portfolio's volatility increased significantly immediately after the Crash. This helps to explain the previous findings that the portfolios with lower betas had more negative abnormal returns.

Although the GARCH-M model cannot capture the contemporaneous effect of the volatility shock, any significant change in the ex ante residual risk premium is indirect evidence for the impact of the unanticipated volatility during the Crash. Since collinearity between residual variances and betas tends to reduce the residual risk premium, the results suggest that the lower beta-sorted portfolios were affected more by the volatility shock associated with the Crash. In summary, changes in systematic risk and in own variance help to partially explain the return behavior of beta-sorted portfolios.

4.4.2 Behavior of the Size-sorted Portfolios

The one-and two beta model AR's for a test of H_0^1 for the size-sorted portfolios for the

event day are reported in panel B of Table 4.2. The AR estimates are significant and negative for all portfolios except portfolio 1 for the one-beta model. However, the magnitudes of the AR's are quite similar across each of the ten size-sorted portfolios for each model.

The one-beta model CAR's for the size-sorted portfolios for various time intervals are presented in panel B of Table 4.3. The CAR results subsequently discussed also apply to the CAR's from the two-beta model. Over long time intervals which include or follow the Crash (such as [1, 20] and [-20, 20]), portfolio 10 (the largest firms) has no statistically significant CAR's, unlike all the other portfolios. Thus, as expected due to a possible "flight-to-large-size", the largest firms performed relatively well during and after the Crash. Based on the CAR's for most time intervals for the one-beta model, the middle size-sorted portfolios (4, 5 and 6) exhibited the worst CAR performances. Therefore, the expectation that larger firms should perform better in a crisis is only supported for the largest firms. Based on the F-values in panel B of Table 4.3, the hypothesis (H_0^{II}) that the CAR's for the ten portfolios are jointly significantly different from zero is rejected for all time intervals except [-5, 1]. This suggests that no significant investor movement occurred towards large firms in the five days preceding the Crash.

4.4.3 Behavior of the Dividend-yield-sorted Portfolios

The one- and two-beta model AR's for a test of H_0^{II} for the dividend-yield-sorted portfolios for the event day are reported in panel C of Table 4.2. All of the AR's are negative and statistically significant. The F-values for a test of the differences in the AR's jointly for the ten portfolios is significant for both models.

The one-beta model CAR's for various time intervals are reported in panel C of Table

4.3. They weakly support the popular belief that high dividend yielding securities are more desirable in a crisis situation. The one-beta model CAR's for the highest dividend-yield-sorted portfolio are not significant over the intervals [0, 5] and [-20, 20] unlike the significantly negative CAR's for the other nine portfolios for these time intervals. Over the whole event window [-20, 20], the CAR's are inversely (though not monotonically) related to the mean dividend yield for the portfolios. For example, portfolio 1 exhibits the highest loss of 29.1 percent and portfolio 10 the lowest loss of 3.7 percent over this time interval. Based on the F-values, the test of the hypothesis ($H_0^{1'}$) of the joint equality of the CAR's to zero for the ten dividend-yield-sorted portfolios can not be rejected for the time intervals that precede the Crash, and can be rejected for the other time intervals. Based on the F-values, the test of the hypothesis ($H_0^{1''}$) of no difference in CAR's for the two extreme dividend-yield-sorted portfolios is rejected. This suggests that the differences in the performances of the dividend-yield-sorted portfolios can be attributed to the differences in their reactions to the Crash.

4.5 Concluding Remarks

In this chapter, the performance of five types of screen-sorted portfolios is investigated for the stock market Crash of 1987. The CAR method is used to obtain the risk- and market-adjusted returns for the portfolios. The four major findings are as follows. First, the performance of the beta-sorted portfolios over various time intervals around the Crash is inversely related to systematic risk (β). Second, significant changes in betas account for part of the performance differences, and an increased role for noise and its associated risk premium appear to explain another portion of this observed inverse relationship. Unlike the other nine

beta-sorted portfolios, the lowest beta-sorted portfolio had a statistically significant increase in its residual risk premium following the Crash. Further investigation is required to determine whether volatility shocks tend to have a more adverse impact on securities with lower betas, and whether or not residual risk tends to be priced during more volatile periods in the stock market. Third, the portfolios sorted on two screens (size and dividend yield) performed as expected. The largest size- and dividend-yield-sorted portfolios performed better during the Crash. Fourth, two types of screen-sorted portfolios (P/E ratios and leverage ratios) did not exhibit significantly different performance during the Crash.

Chapter 5: Main Findings and Future Research

This thesis has investigated issues related to stock market volatility; such as the relationship between volatility and trade and quote variables, the sources of variation in volatility, and the impact of a major volatility shock on the performance of screen-sorted portfolios. The main findings are summarized as follows: first, among the variables of trade activity, number of trades and unexpected volume are positively related to volatility, while the non-trading indicator is negatively related to volatility. The relation between volume and volatility is not consistently strong across the individual stocks. Quoted spread and quote depth are positively and negatively related to volatility, respectively. While the contribution from these variables to the determination of volatility is significant, lagged values of volatility are still useful in modelling volatility.

Second, based on the variance ratio tests for the medium-size trades and for non-trading intervals, public information has a significant impact on volatility (14% on average), and private information conveyed by medium-size trades accounts for the significant difference in volatility relative to other categories of trades. The fact that the likelihood of the arrival of private information is not monotonically related to trade size is also consistent with the finding that number of trades serves as a better proxy for information flow than volume.

Bid-ask errors induce on average 8.9% to 35% of the variance of the transaction returns for individual stocks. Quote-based returns for TIPs exhibit strong negative autocorrelation while returns for the index portfolio exhibit positive autocorrelation. This evidence supports the conjecture that liquidity traders concentrate on TIPs, and that

corrections of its pricing errors over time induce negative autocorrelation. Cross-autocorrelations among component stocks due to different adjustment speeds to market-wide news may explain the positive autocorrelation in returns of the non-traded index portfolio.

Third, the performance of the beta-sorted portfolios over various time intervals around the Crash is inversely related to systematic risk (β), and changes in betas as well as increases in the risk premium associated with volatility help to explain the observed inverse relationship. The portfolios sorted on size and dividend yield performed as expected; the largest size- and dividend-yield-sorted portfolios performed better during the Crash.

Future research in the area of stock volatility and microstructure can be carried out in the following directions: First, the investigation of the roles for trading activity and market liquidity variables in explaining stock volatility can be further extended to relationships that cross markets. For example, measurements of trading activities and market liquidity for index futures, such as volumes and open interests, can be used to explain market-wide volatility behavior. Stocks that are interlisted can also be used to examine whether different market trading mechanisms result in different price dynamics.

Second, TIPs and a planned index participations product on the TSE 100 index provide an opportunity to investigate whether the introduction of basket securities affect market liquidity and information trading on individual stocks. Information flow can be further divided into market-wide and firm-specific components in order to study systematic and unsystematic volatilities.

Third, the intraday lead-lag relation between returns of TIPs and returns of its component stocks can be investigated. Chan (1992) and Stoll and Whaley (1990) study the

lead-lag relation between index futures and a cash market index. Their study can be extended to index participations products, which are under the same trading mechanism as the component stocks.

Fourth, the electronic trading system on the TSE displays the identity of brokerage firms which submit limit orders, although firms may choose not to disclose the portion of large limit orders in excess of 5,000 shares. Such an open limit order book attracts "sunshine" traders who want to post their precommitted orders. The availability of the identity of traders makes it easy to negotiate large order trades in an upstairs market. It would be interesting to examine how different traders are affected by the open limit order book, and whether such publicized limit orders have lower price impacts.

References

Admati, A.R. and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Admati, A.R. and P. Pfleiderer, 1991, Sunshine trading and financial market equiliorium, *Review of Financial Studies* 4, 443-481.

Akgiray, V., 1989, Conditional heteroskedasticity in time series of stock returns: Evidence and forecasts, *Journal of Business* 62, 55-80.

Amihud, Yakov, and Haim Mendelson, 1987, Trading mechanisms and stock returns: An empirical investigation, *Journal of Finance* 42, 533-555.

Amihud, Yakov, Haim Mendelson and Robert A. Wood, 1990, Liquidity and the 1987 stock market crash, *Journal of Portfolio Management* (Spring), 65-69.

Arbel, Avner, Steven Carvell and Erik Postnieks, 1988, The smart crash of October 19th, *Harvard Business Review* (May-June), 124-136.

Ball, Ray, 1978, Anomalies in relationships between securities' yields and yield-surrogates, *Journal of Financial Economics* 6, 103-126.

Ball, Ray and S.P. Kothari, 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, *Journal of Financial Economics* 25, 51-74.

Bannister, Barry B., 1990, In search of excellence: A portfolio management perspective, *Financial Analysts Journal* (March-April), 68-71.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Barclay, Michael J., Robert H. Litzenberger, and Jerold B. Warner, 1990, Private information, trading volume, and stock-return variances, *Review of Financial Studies* 3, 233-253.

Barclay Michael J., and Jerold B. Warner, 1993, Stealth trading and volatility: which trades move prices, *Journal of Financial Economics* 34, 281-305.

Basu, Sanjoy, 1983, The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* 12, 129-156.

Bennett, P. and J Kelleher, 1988, The international transmission of stock price disruption in October 1987, *Federal Reserve Bank of New York Quarterly Review* 13, 17-33.

Benveniste, Lawrence M., Alan J. Marcus, and William J. Wilhelm, 1992, What's special about the specialist?, *Journal of Financial Economics* 32, 61-86.

Bessembinder, Hendrik, and Paul Seguin, 1992, Future-trading activity and stock price volatility, *Journal of Finance* 47, 2015-2034.

Bessembinder, Hendrik, and Paul Seguin, 1993, Price volatility, trading volume, and market depth: evidence from futures markets, *Journal of Financial and Quantitative Analysis* 28, 21-39.

Bhandari, Laxmi C., 1988, Debt/Equity ratio and expected common stock returns: Empirical evidence, *Journal of Finance* 43, 507-528.

Black, Fisher, 1976, Studies of stock price volatility changes, *Proceedings of the 1976 Meetings of the Business and Economics Statistics Section*, American Statistical Association, 177-181.

Blume, Lawrence, David Easley and Maureen O'Hara, 1994, Market statistics and technical analysis: The role of volume, *Journal of Finance* 49, 153-181.

Bollerslev, T., 1986, Generalized autoregressive conditional heteroscedasticity, *Journal of Econometrics* 31, 307-327.

Brennan, Michael C., 1970, Taxes, market valuation and corporate financial policy, *National Tax Journal* 23, 417-427.

Brown, Stephen J. and Jerold B. Warner, 1985, Using daily stock returns: The case of event studies, *Journal of Financial Economics* 14, 3-32.

Chan, Kalok, 1992, A further analysis of the lead-lag relationship between the cash market and stock index futures market, *Review of Financial Studies* 5, 123-152.

Chan, Louis K.C., and Josef Lakonishok, 1993, Institutional trades and intraday stock price behavior, *Journal of Financial Economics* 33, 173-199.

Chow, K. Victor, and Karen C. Denning, 1993, A simple multiple variance ratio test, *Journal of Econometrics* 58, 385-401.

Christie, Andrew, 1982, The stochastic behaviour of common stock variances: Value, leverage and interest rate effects, *Journal of Financial Economics* 10, 407-432.

Clark, P.K., 1973, A subordinated stochastic process model with finite variances for speculative prices, *Econometrica* 41, 135-155.

Cohen, Kalman J., Gabriel A. Hawawini, Steven F. Maier, Robert A. Schwartz, and David K. Whitcomb, 1980, Implications of microstructure theory for empirical research on stock price behavior, *Journal of Finance* 35, 249-257.

Connolly, Robert A., 1989, An examination of the robustness of the weekend effect, *Journal of Financial and Quantitative Analysis* 24, 133-169.

Cornell, Bradford, and Erik R. Sirri, 1992, The reaction of investors and stock prices to insider trading, *Journal of Finance* 47, 1031-1059.

Davidian, Marie, and Raymond J. Carroll, 1987, Variance function estimation, *Journal of the American Statistical Association* 82, 1079-1091.

De Long, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economics* 98, 703-738.

Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Easley, David, and Maureen O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance* 47, 577-605

Ederington, Louis, and Jae Ha Lee, 1993, How markets process information: News releases and volatility, *Journal of Finance* 48, 1161-1191.

Engle, Robert F., 1982, Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, *Econometrica* 50, 987-1007.

Engle, Robert F., 1990, Discussion, *Review of Financial Studies* 3, 103-106.

Engle, Robert F. and Tim Bollerslev, 1986, Modelling the persistence of conditional variances, *Econometric Reviews* 5, 1-50.

Epps, T.W., and M.L. Epps, 1976, The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis, *Econometrica* 44, 305-325.

Fama, Eugene F., 1989, Perspectives on October 1987 or what did we learn from the crash?, in: R. Kamphuis, R. Kormendi, and J. Watson, eds., *Black Monday and the future of financial markets* (Homewood, IL: Irwin), 71-82.

Fama, Eugene F. and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Ferguson, Robert, 1989, On crashes, *Financial Analysts Journal* (March-April), 42-51.

Foster, Douglas F. and S. Viswanathan, 1990, A theory of interday variations in volume, variance, and trading costs in securities markets, *Review of Financial Studies* 3, 593-624.

Foster, Douglas F. and S. Viswanathan, 1993, The effect of public information and competition on trading volume and price volatility, *Review of Financial Studies* 6, 23-56.

French, Kenneth R. and Richard Roll, 1986, Stock return variances: The arrival of information and the reactions of traders, *Journal of Financial Economics* 17, 5-26.

French, Kenneth R., G. William Schwert and Robert F. Stambaugh, 1987, Expected stock returns and volatility, *Journal of Financial Economics* 37, 1247-1257.

Gallant, A. Ronald, Peter E. Rossi, and George Tauchen, 1992, Stock prices and volume, *Review of Financial Studies* 5, 199-242.

Gammill, James F. and Terry A. Marsh, 1988, Trading activity and price behavior in the stock and stock index futures market in October 1987, *Journal of Economic Perspectives* 2, 25-44.

George, Thomas J., Gautam Kaul, and M. Nimalendran, 1994, Trading volume and transaction costs in specialist markets, *Journal of Finance* 49, 1489-1505.

Gerety, Mason S. and J. Harold Mulherin, 1994, Price formation on stock exchanges: the evolution of trading within the day, *Review of Financial Studies* 7, 609-629.

Geweke, J., 1982, Measurement of linear dependence and feedback between time series, *Journal of the American Statistical Association* 77, 304-324.

Glosten, Lawrence R., 1994, Is the electronic open limit order book inevitable?, *Journal of Finance* 49, 1127-1161.

Glosten, Lawrence R., and L.E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21, 123-142.

Glosten, Lawrence R. and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial*

Economics 14, 71-100.

Gorton, Gary B. and George G. Pennacchi, 1993, Security baskets and index-linked securities, *Journal of Business* 66, 1-27.

Granger, Clive W.J. and Oskar Morgenstern, 1970, *Predictability of Stock Market Prices* (Heath-Lexington, Lexington, MA).

Grant, James L., 1990, Stock return volatility during the Crash of 1987, *Journal of Portfolio Management* (Winter), 69-71.

Greenwald, Bruce and Jeremy Stein, 1988, The task force report: The reasoning behind the recommendations, *Journal of Economic Perspectives* 2, 3-23.

Grossman, Sanford J., 1988, An analysis of the implications for stock and futures price volatility of program trading and dynamic hedging strategies, *Journal of Business*, 275-298.

Harris, Lawrence, 1987, Transaction data tests of the mixture of distributions hypothesis, *Journal of Financial and Quantitative Analysis* 22, 127-141.

Harris, Lawrence, 1989, The October 1987 S&P 500 stock-futures basis, *Journal of Finance* 44, 77-99.

Harris, Lawrence, 1990a, Estimation of stock variances and serial covariances from discrete observations, *Journal of Financial and Quantitative Analysis* 25, 291-306.

Harris, Lawrence, 1990b, The economics of cash index alternatives, *Journal of Futures Markets* 10, 179-194.

Harris, Lawrence, 1991. Liquidity, trading rules, and electronic trading systems, *Monograph series in Finance and Economics* , New York University Salomon Center.

Harvey, Andrew, 1990, *The Econometrics Analysis of Time Series*, Cambridge: The MIT Press.

Harvey, Campbell R., and Roger D. Huang, 1991, Volatility in the foreign currency futures market, *Review of Financial Studies* 4, 543-569.

Hasbrouck, Joel, 1991, The summary informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571-595.

Hasbrouck, Joel and Thomas Ho, 1987, Order arrival, quote behavior, and return-generating

process, *Journal of Finance* 42, 1035-1048.

Hatch, James and Robert White, 1989, Anatomy of a stock market crash: The case of October 1987, *Canadian Investment Review*, 17-22.

Hull, John and Alan White, 1987, The pricing of options on assets with stochastic volatilities, *Journal of Finance*, 42, 281-340.

Jaffe, Jeffrey, Donald B. Keim and Randolph Westerfield, 1989, Earnings yields, market values, and stock returns, *Journal of Finance* 44, 135-148.

Jain, P.C. and Gun-Ho Joh, 1988, The dependence between hourly prices and trading volume, *Journal of Financial and Quantitative Analysis* 23, 269-283.

Jog, Vijay M., 1988, Stock pricing anomalies: Canadian experiences, *Canadian Investment review* 1, 55-62.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994a, Information, trading, and volatility, *Journal of Financial Economics* 36, 127-154.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994b, Transactions, volume, and volatility, *Review of Financial Studies* 36, 127-154.

Jones, Robert C., 1990, Designing factor models for different types of stock: What's good for the goose ain't always good for the gander, *Financial Analysts Journal* (March-April), 25-30.

Karafaith, Imre, 1988, Using dummy variables in the event methodology, *Financial Review* 23, 351-357.

Karpoff, J., 1987, The relation between price changes and trading volume: A survey, *Journal of Financial and Quantitative Analysis* 22, 109-126.

Kaul, Gautam, and M. Nimalendran, 1990, Price reversals: bid-ask errors or market overreaction?, *Journal of Financial Economics* 28, 67-93.

Keim, Donald B., 1985, Dividend yields and stock returns: Implications of abnormal January returns, *Journal of Financial Economics* 14, 473-489.

Keim, Donald B., 1988, Stock market regularities: A synthesis of the evidence and explanations, in: Elroy Dimson, ed., *Stock Market Anomalies* (Cambridge: Cambridge University Press).

Kim, Oliver, and Robert E. Verrecchia, 1994, Market liquidity and volume around earnings announcements, *Journal of Accounting and Economics* 17, 41-67.

Kryzanowski, Lawrence and Hao Zhang, 1993, Market behaviour around Canadian stock-split ex-dates, *Journal of Empirical Finance* 1 (June), 57-81.

Kyle, Albert S., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lakonishok Josef, and Edwin Maberly, 1990, The weekend effect: trading patterns of individual and institutional investors, *Journal of Finance* 45, 231-243.

Lamoureux, C.G., and W.D. Lastrapes, 1990, Heteroscedasticity in stock return data: volume versus GARCH effects, *Journal of Finance* 45, 221-230.

Lee, Charles M. C., Belinda Mucklow, and Mark J. Ready, 1993, Spreads, depths, and the impact of earnings information: an intraday analysis, *Review of Financial Studies* 6, 345-374.

Lehmann, Bruce N., 1990a, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* CV, 1-28.

Lehmann, Bruce N., 1990b, Residual risk revisited, *Journal of Econometrics* 45, 71-97.

Leland, Hayne and Mark Rubinstein, 1988, Comments on the market crash: Six months after, *Journal of Economic Perspectives* 2, 45-50.

Limmack, R.J. and C.W.R. Ward, 1990, The October 1987 stock market crash: An explanatory analysis of share price models, *Journal of Banking and Finance* 14, 273-289.

Litzenberger, Robert H. and Krishna Ramaswamy, 1982, The effects of dividends on common stock prices: Tax effects or information effects, *Journal of Finance* 37, 429-444.

Ljung, G.M. and G.E.P. Box, 1978, On a measure of lack of fit in time series models, *Biometrika* 65, 297-303.

Lo, Andrew W., and A. Craig Mackinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.

Lockwood, Larry, and Scott Linn, 1990, An examination of stock market return volatility during overnight and intraday periods, 1964-1989, *Journal of Finance* 45, 591-601.

Longstaff, F.A., 1989, Temporal aggregation and continuous-time capital asset pricing model, *Journal of Finance* 44, 871-887.

Madhavan, Ananth, 1992, Trading mechanisms in securities markets, *Journal of Finance* 47, 607-641.

Mech, Timothy S., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307-344.

Mei, Jianping, 1993, Explaining the cross-section of returns via a multi-factor APT model, *Journal of Financial and Quantitative Analysis* 28, 331-345.

Meltzer, Allan H., 1989, Overview, in: R. Kamphuis, R. Kormendi, and J. Watson, eds., *Black Monday and the future of financial markets* (Homewood, IL: Irwin).

Miller, Merton H., 1989, The Crash of 1987: Bubble or fundamental?, Working Paper, University of Chicago.

Mitchell, Mark L., and J. Harold Mulherin, 1994, The impact of public information on the stock market, *Journal of Finance* 49, 923-950.

Mitchell, Mark L. and Jeffry M. Netter, 1989, Triggering the 1987 stock market crash, *Journal of Financial Economics* 24, 37-68.

Moran, P.A.P., 1948, Some theorems on time series, *Biometrica* 35, 255-260.

Pagan, A., 1984, Econometric issues in the analysis of regressions with generated regressors, *International Economic Review* 25, 221-247.

Pagan, A., and G.W. Schwert, 1990, Alternative models for conditional stock volatility, *Journal of Econometrics* 45, 267-290.

Park, Tae H. and Lorne N. Switzer, 1995, Index participation units and the performance of index futures markets: evidence from the Toronto 35 index participation units market, *Journal of Futures Markets* 15, 187-200.

Roll, Richard, 1988, The international crash of October 1987, in: R. Kamphuis, R. Kormendi, and J. Watson, eds., *Black Monday and the future of financial markets* (Homewood, IL: Irwin).

Roll, Richard, 1984, A simple implicit measure of bid/ask spread in an efficient market, *Journal of Finance* 39, 1127-1139.

Roll, Richard, 1989, Price volatility, international market links, and their implications for regulatory policies, *Journal of Financial Service Research* 3, 211-246.

Schwert, G. William, 1989, Why does stock market volatility change over time?, *Journal of Finance* 44, 1115-1153.

Schwert, G. William, 1990, Stock volatility and the crash of '87, *Review of Financial Studies* 3, 77-102.

Schwert, G. William, and Paul Seguin, 1990, Heteroscedasticity in stock returns, *Journal of Finance* 45, 1129-1156.

Scott, L.O., 1987, Option pricing when the variance changes randomly, *Journal of Financial and Quantitative Analysis* 22, 419-438.

Seppi, Duane J., 1992, Block trading and information revelation around quarterly earnings announcements, *Review of Financial Studies* 5, 281-305.

Seyhun, H. Nejat, 1990, Overreaction or fundamentals: Some lessons from insiders' response to the market crash of 1987, *Journal of Finance* 45, 1363-1388.

Stoll, Hans R. and Robert E.Whaley, 1990a, Stock market structure and volatility, *Review of Financial Studies* 3, 37-71.

Stoll, Hans R. and Robert E. Whaley, 1990b, The dynamics of stock index and stock index futures returns, *Journal of Financial and Quantitative Analysis* 25, 441-468.

Subrahmanyam, Avanidhar, 1991, A theory of trading in stock index futures, *Review of Financial Studies* 4, 17-51.

Tauchen, G. and M. Pitts, 1983, The price variability-volume relationship on speculative markets, *Econometrica* 51, 485-505.

Thompson, Rex, 1985, Conditioning the return-generating process in firm-specific events: A discussion of event study methods, *Journal of Financial and Quantitative Analysis* 20, 151-168.

Wang, J., 1994, A model of competitive stock trading volume, *Journal of Political Economy* 102, 127-168.

White, Halbert, 1980, A heteroskedaticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, *Econometrica* 48, 817-838.

Wiggins, J.B., 1987, Option values under stochastic volatility: Theory and empirical estimates, *Journal of Financial Economics* 19, 351-372.

Wood, R.A., T.H.McInish, and J.K. Ord, 1985, An investigation of transaction data for NYSE stocks, *Journal of Finance* 40, 723-739.

Appendix: Toronto 35 Index Composition

Company Name	Symbol	Shares
Alcan Aluminium	AL	1500
BCE Inc.	B	1500
Bank of Montreal	BMO	1000
Bank of Nova Scotia	BNS	1000
Bow Valley Industrials	BVI	1000
CAE Industrials	CAE	1500
Canadian Imperial Bank	CM	1500
Canadian Pacific Ltd	CP	2000
Canadian Tire Cl A	CTR.A	2000
Echo Bay Mines	ECO	1000
Gulf Canada Resources	GOU	500
Imperial Oil Cl A	IMO.A	500
Imasco Ltd	IMS	1000
Lac Minerals	LAC	750
Laidlaw Cl B	LDM.B	1500
Macmillan Bloedel	MB	1000
Moore Corp.	MCL	1000
Inco Ltd.	N	1000
National Bank	NA	1000
Noranda Inc.	NOR	1000
Northern Telecom	NTL	1000
Nova Corp. of Alberta	NVA	3000
Placer Dome	PDG	2100
Power Corp.	POW	1000
Ranger Oil	RGO	1000
Royal Bank	RY	2000
Sears Canada	SCC	1500
Stelco Series A	STE.A	500
Southam Inc.	STM	750
TransAlta Utilities	TAU	2000
Toronto-Dominion Bank	TD	2000
Teck Corp. Cl B	TEK.B	1000
Thomson Corp.	TOC	2000
TransCanada Pipelines	TRP	1000
Seagram Co.	VO	500

Table 2 1

Correlation of estimated volatility with microstructure variables

Volatility is estimated by using the IWLS procedure by Schwert (1990) VOL is volume EVOL is expected volume UVOL is unexpected volume NT is number of trades SPD is the percent quoted spread and QD is quote depth defined as the sum of bid and ask depths COM refers to company ticker

COM	VOL	EVOL	UVOL	NT	SPD	QD
AL	3361	2351	1216	2501	0078	- 0069
B	2499	2762	2031	3522	1215	- 1732
BMO	0876	2544	0780	3461	1750	1329
BNS	2917	2556	2284	2673	1340	1817
BVI	3020	2620	2699	4070	1186	- 0397
CAE	1783	2556	1480	5140	1453	- 1032
CM	2464	2867	1934	3507	2698	- 1468
CP	1660	2793	1404	4091	0979	- 1500
CTR A	1643	3782	0095	1286	0411	0087
ECO	3293	3830	2100	4458	0830	0591
GOU	1244	2117	1021	3829	1756	0567
TMO A	3097	3063	2468	4696	1926	0610
IMS	1912	2261	1582	3587	2336	1163
LAC	3482	3239	2729	4686	0834	0904
LDM B	2455	2471	2027	4401	0654	0668
MB	2681	2542	2214	3589	1118	1408
MCL	1818	1851	1478	3909	1507	1655
N	0615	2699	0543	4451	0811	1733
NA	2397	1255	2125	2732	1551	- 1365
NOR	2274	2614	1794	4038	1172	0963
NTL	3408	2580	2750	4378	1360	- 0826
NVA	2534	1546	2060	2587	1594	2232
PDG	4046	3722	2949	4770	0439	1034
POW	2593	2263	2232	2594	2370	0932
RGO	1794	0232	2042	3686	1010	- 0869
RY	0960	2795	0726	3746	1323	- 1138
SCC	1782	1191	1693	4409	1887	- 1485
STE A	2160	2773	1723	4519	2707	- 1001
STM	1754	1899	1518	4236	2155	1376
TAU	2327	1892	2075	1274	1961	1376
TD	1718	1981	1307	3480	1085	- 1784
TEK B	2748	2110	2365	4297	1682	- 1083
TOC	2710	2210	2299	4151	1611	- 1313
TRP	3452	1066	3297	2528	1505	1761
VO	1977	2002	1711	4044	2575	- 0721
TIPS	1781	2433	1514	2387	1350	- 1178

Table 2 2

Granger-Causality Tests from Microstructure Variables to Volatility

COM	Number of Trades Granger-Cause Volatility LR test	Volume Granger-Cause Volatility LR test	Spread Granger-Cause Volatility LR test	Quote Depth Granger-Cause Volatility LR test
AL	16 260*	4 623	16 713*	5 277
B	39 139**	13 947*	43 732**	8 229
BMO	61 932**	3 881	26 636**	6 195
BNS	41 827**	14 684*	33 394**	37 925**
BVI	12 366	6 498	26 795**	5 476
CAE	33 490**	25 652**	27 331**	3 443
CM	27 321**	9 751	23 013**	12 797*
CP	31 174**	2 554	25 671**	7 647
CTR A	15 774*	4 994	24 881**	17 165**
ECO	12 900*	4 073	9 645	8 109
GOU	11 288	15 631*	22 761**	6 265
IMO A	24 366**	8 435	19 509**	11 694
IMS	11 414	6 884	11 616	3 385
LAC	18 306**	11 204	22 917**	3 481
LDM B	28 682**	13 123	5 322	8 392
MB	37 347**	6 518	27 967**	7 489
MCL	16 157*	2 903	21 174**	13 753*
N	10 979	11 338	6 762	22 182**
NA	40 423**	12 167	51 814**	5 557
NOR	32 711**	17 949**	31 344**	21 872**
NTL	30 101**	4 318	9 609	15 908*
NVA	23 689**	36 411**	85 849**	22 946**
PDG	49 235**	16 173*	23 724**	10 570
POW	10 551	17 949**	73 144**	13 722*
RGO	34 444**	6 407	44 880**	1 472*
RY	38 822**	2 883	19 066**	8 506
SCC	21 705**	2 559	5 172	27 970**
STE A	30 500**	6 539	30 319**	3 943
STM	24 510**	72 219**	29 838**	8 588
TAU	5 854	14 606*	88 436**	14 210*
TD	48 700**	12 629*	37 217**	14 884*
TEK B	16 130*	5 365	16 269*	8 232
TOC	19 556**	11 449	56 022**	1 782
TRP	16 369*	6 092	66 762**	27 503**
VO	23 000**	2 999	9 645	14 605*
TIPS	20 378**	10 267	40 165**	14 301*

* (**) denotes statistical significance at 5% (1%) level Test statistic follows a $\chi^2(6)$ distribution

Table 2 3

Conditional Form of the Granger-Causality Tests

COM	Number of Trades Granger-Cause Volatility LR test	Volume Granger-Cause Volatility LR test	Spread Granger-Cause Volatility LR test	Quote Depth Granger-Cause Volatility LR test
AL	18 442**	5 414	18 895**	6 335
B	37 621**	12 085	42 215**	7 004
BMO	65 062**	3 510	29 765**	6 092
BNS	43 308**	14 985*	34 876**	35 206**
BVI	11 798	6 899	26 228**	5 990
CAE	30 081**	21 941**	23 921**	5 771
CM	23 624**	10 264	24 315**	13 139*
CP	31 681**	2 660	26 178**	6 976
CTR A	15 759*	4 903	24 866**	19 538**
ECO	14 565*	4 376	11 310	9 006
GOU	10 801	14 694*	22 274**	6 828
IMO A	24 998**	8 910	20 141**	14 963*
IMS	14 115*	7 102	14 317*	4 049
LAC	19 478**	10 646	24 089**	3 281
LDM B	27 695**	12 784*	4 334	4 636
MB	42 495**	7 134	33 114**	13 188*
MCL	16 522*	3 411	21 539**	15 693*
N	11 896	11 211	7 679	21 915**
NA	43 973**	11 856	55 363**	7 028
NOR	35 851**	18 560**	34 484**	23 003**
NTL	28 870**	4 230	8 377	20 019**
NVA	26 083**	33 065**	88 242**	22 166**
PDG	49 868**	16 844**	24 357**	12 361
POW	11 439	14 314*	74 032**	15 034*
RGO	33 455**	6 804	43 891**	14 442*
RY	41 093**	2 887	21 337**	11 964
SCC	21 694**	2 805	5 161	28 819**
STE A	30 172**	6 079	29 991**	5 459
STM	27 491**	73 183**	32 819**	11 518
TAU	7 199	17 204**	89 782**	17 845**
TD	48 162**	11 982	36 678**	24 258**
TEK B	17 792**	5 259	17 931**	9 764
TOC	17 715**	11 592	54 181**	1 544
TRP	14 954*	7 800	65 347**	31 303**
VO	21 165**	2 504	7 810	13 759*
TIPS	14 907*	8 283	34 694**	15 279*

* (**) denotes statistical significance at 5% (1%) level Test statistic follows a $\chi^2(6)$ distribution

Table 2 4

Granger-Causality Tests from Volatility to Microstructure Variables

COM	Volatility Granger-Cause Number of Trades LR test	Volatility Granger-Cause Volume LR test	Volatility Granger-Cause Spread LR test	Volatility Granger-Cause Quote Depth LR test
AL	34 205**	25 754**	6 628	10 104
B	21 568**	7 522	19 187**	28 031**
BMO	20 630**	7 164	8 964	10 885
BNS	21 716**	5 478	7 616	16 754*
BVI	-0 334	3 513	12 527	8 941
CAE	20 798**	17 596**	5 544	8 414
CM	-0 356	1 417	5 351	9 294
CP	6 783	-2 689	4 723	9 660
CTR A	3 684	5 906	7 095	12 066
ECO	67 073**	25 645**	10 932	17 262**
GOU	4 480	15 845*	3 648	15 322
IMO A	25 750**	35 766**	12 207	10 926
IMS	1 366	37 122**	11 480	9 225
LAC	4 817	13 206*	4 029	14 550*
LDM B	91 339**	53 725**	2 505	52 211**
MB	9 900	72 017**	17 066**	5 970
MCL	3 673	4 211	5 165	3 710
N	25 959**	50 990**	12 686*	4 282
NA	21 063**	15 109*	16 050*	5 908
NOR	8 627	12 804	13 857*	21 946**
NTL	37 417**	40 134**	7 759	36 281**
NVA	41 513**	22 576**	9 872	13 140*
PDG	35 776**	57 115**	15 678*	7 894
POW	27 988**	7 630	6 095	4 130
RGO	13 362*	2 629	5 246	5 707
RY	4 563	3 476	10 333	7 651
SCC	11 780	-4 325	14 543*	5 674
STE A	32 273**	17 098**	6 279	7 563
STM	14 147*	5 634	26 857**	4 483
TAU	49 033**	0 656	17 481**	11 512
TD	9 091	69 227**	9 289	12 643*
TEK B	8 311	10 313	5 294	6 540
TOC	27 845**	55 799**	54 950**	11 532
TRP	25 901**	195 200**	11 471	28 386**
VO	13 210*	36 391**	32 519**	4 606
TIPS	10 463	7 216	1 619	10 598

* (**) denotes statistical significance at 5% (1%) level Test statistic follows a $\chi^2(6)$ distribution

Table 2 5

Regression of estimated volatility on trade and quote variables is given by

$$\sigma_t = a + b_1 VOL_t + b_2 VOLR_t + b_3 NT_t + b_4 DUM_t + b_5 SPD_{t-1} + b_6 QD_{t-1} + b_7 OP_t + b_8 MON_t + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t$$

where VOL is volume VOLR is volume when the trades during the interval are classified as a sell order (i e VOLR=VOL if $p_t < m_{t-1}$ where p_t is price at time t and m_{t-1} is the average of bid and ask quotes at time t-1 otherwise VOLR = 0) SPD is the percent quoted spread QD is quote depth defined as the sum of bid and ask depths OP is the indicator variable for opening intervals and MON is the indicator variable for Monday The dependent variable is estimated volatility based on the IWLS procedure introduced by Schwert (1990) Durbin-Watson statistics and adjusted R are provided * (**) denotes statistical significance at 5% (1%) level Test statistics for individual coefficients are t-statistics (in parentheses) computed using White (1980) standard errors Test statistics for lagged volatility coefficients are F-statistics for the hypothesis that the sum of the 13 coefficients is zero

COM	VOL	VOLR	NT	DUM	SPD	QD	OP	MON	σ LAGS	DW	A R
AL	1366	- 0117	8077	- 1234	2373	-1 8247	2816	2194			
	(2 98)**	(- 25)	(8 25)**	(-8 70)**	(7 61)**	(-5 79)**	(6 09)**	(1 27)	[2 43]*	1 981	2281
B	0382	0955	2165	- 0002	2981	- 7809	1440	0302			
	(1 81)	(3 01)**	(7 89)**	(- 00)	(9 10)**	(-6 39)**	(5 58)**	(34)	[4 32]**	1 999	2243
BMO	0039	1183	5932	- 0262	3292	-1 0724	2239	- 0683			
	(1 42)	(4 52)**	(9 60)**	(-2 19)*	(10 93)**	(-5 38)**	(7 51)**	(- 68)	[6 23]**	2 038	2534
BNS	1815	- 0712	2839	- 0878	3399	-1 5787	4678	1132			
	(3 87)**	(-1 01)	(4 68)**	(-3 16)**	(9 95)**	(-8 29)**	(8 53)**	(58)	[4 12]**	2 003	2262
BVI	4967	- 3479	3 1248	- 0624	0998	-1 8911	2003	2355			
	(5 27)**	(-2 17)*	(5 62)**	(-3 47)**	(7 21)**	(3 79)**	(6 02)**	(1 82)	[8 23]**	2 009	2662
CAE	0178	0107	5 7240	0069	1647	-2 3218	1114	6572			
	(53)	(14)	(9 75)**	(22)	(6 18)**	(-6 62)**	(1 45)	(2 20)*	[9 87]**	1 935	3153
CM	0942	0532	9295	- 0430	2600	-1 4648	3442	9265			
	(3 49)**	(1 11)	(8 68)**	(-3 75)**	(9 12)**	(-5 16)**	(7 59)**	(62)	[5 54]**	2 000	2626
CP	1125	- 1009	6730	- 0402	3113	-1 0943	1924	- 0175			
	(4 18)**	(-3 75)**	(10 50)**	(-1 11)	(10 67)**	(-5 62)**	(5 05)**	(- 12)	[3 46]**	1 975	2337
CTR A	0435	0970	1 2949	- 0505	1581	-2 5635	1557	- 1284			
	(99)	(1 36)	(9 37)**	(-4 79)**	(7 68)**	(-6 78)**	(4 78)**	(-1 01)	[5 97]**	1 988	1764
ECO	3738	- 1754	3 6403	- 1481	2024	-3 1073	9253	6738			
	(2 20)*	(- 83)	(6 38)**	(-5 31)**	(6 83)**	(-3 65)**	(8 94)**	(2 09)*	[3 75]**	1 985	2968
GOU	1415	- 1002	3 8687	- 0917	1451	-3 2870	3233	2311			
	(1 07)	(- 70)	(7 22)**	(-3 79)**	(8 45)**	(-5 55)**	(6 95)**	(1 14)	[6 34]**	2 009	2334
IMO A	2277	0438	1 3823	- 0108	1568	-3 2712	2188	1323			
	(2 35)*	(39)	(6 38)**	(- 87)	(5 88)**	(-5 38)**	(8 21)**	(1 46)	[3 62]**	1 989	3060
IMS	0905	- 0177	1 8741	- 0499	1437	-2 0491	2026	0546			
	(1 60)	(- 25)	(9 01)**	(-5 02)**	(5 95)**	(-4 17)**	(6 26)**	(50)	[12 03]**	1 997	2248
LAC	2149	- 0396	2 4102	- 1090	2258	-2 7404	6982	3258			
	(3 25)**	(- 46)	(9 65)**	(-4 57)**	(8 39)**	(-5 83)**	(9 10)**	(1 11)	[7 08]**	1 954	3138

Table 2 5 (Continued)

COM	VOL	VOLR	NT	DUM	SPD	QD	OP	MON	σ LAGS	DW	A R
LDM B	0630	- 0267	7378	- 1388	3449	-2 2354	5665	2076			
	(1 03)	(37)	(2 59)**	(-2 85)**	(4 19)**	(-3 55)**	(8 24)**	(92)	[5 16]**	1 890	2704
MB	2207	0089	1 4072	- 0493	1815	-2 3671	2028	- 1054			
	(2 41)*	(08)	(8 45)**	(-2 83)**	(8 98)**	(-7 25)**	(5 51)**	(- 76)	[7 74]**	2 032	2280
MCL	0134	0773	1 8854	- 0572	2003	-2 7827	2058	0984			
	(32)	(1 42)	(10 24)**	(-4 96)**	(7 23)**	(-7 30)**	(6 05)**	(79)	[4 21]**	1 986	2295
N	- 0041	0045	1 2768	- 0535	2257	-2 8920	3758	- 0124			
	(- 38)	(42)	(9 96)**	(-3 93)**	(7 41)**	(-7 50)**	(8 26)**	(- 10)	[3 84]**	1 975	2996
NA	2339	- 0793	1 3105	- 0943	2078	-1 6570	3171	- 3126			
	(3 52)**	(- 94)	(7 48)**	(-5 40)**	(12 06)**	(-6 74)**	(6 12)**	(-1 51)	[9 74]**	2 000	2110
NOR	1384	- 0799	1 7458	- 0525	1794	-1 8595	2993	1045			
	(2 78)**	(-1 42)	(9 33)**	(-3 58)**	(9 00)**	(-6 36)**	(7 54)**	(67)	[6 48]**	2 032	2562
NTL	1489	1389	1 4570	- 0312	3348	-3 2482	2846	0636			
	(3 18)**	(1 15)	(9 21)**	(-2 32)*	(7 57)**	(-7 44)**	(6 43)**	(45)	[2 75]*	2 002	2758
NVA	1283	- 0231	8204	1142	4004	-2 3815	1804	- 0180			
	(3 72)**	(- 55)	(7 87)**	(86)	(13 83)**	(-9 63)**	(2 73)**	(- 08)	[6 07]**	2 017	1812
PDG	1894	- 0146	9302	- 0981	2511	-1 8487	5543	2220			
	(2 96)**	(- 20)	(6 39)**	(-4 34)**	(5 42)**	(-4 22)**	(9 30)**	(99)	[1 69]	1 981	3124
POW	4456	1027	9774	- 0602	1626	-1 2787	1697	1074			
	(4 78)**	(50)	(4 61)**	(-5 61)**	(8 74)**	(-4 10)**	(6 49)**	(90)	[11 92]**	2 027	2033
RGO	0122	0295	2 4283	- 1140	2325	-1 0658	3230	- 2286			
	(95)	(2 34)*	(6 27)**	(-4 50)**	(10 50)**	(-4 36)**	(5 54)**	(- 99)	[7 67]**	2 007	2184
RY	0635	- 0611	8894	- 0424	2748	-1 2711	2643	- 5845			
	(2 02)*	(-1 89)	(9 68)**	(-2 79)**	(8 93)**	(-5 18)**	(8 06)**	(- 05)	[5 83]**	2 033	2296
SCC	0847	1035	9 4841	- 0298	0580	-1 9182	2102	- 1042			
	(1 49)	(72)	(6 55)**	(- 81)	(4 70)**	(-4 94)**	(4 39)**	(- 55)	[7 15]**	2 020	2497
STF A	1970	4530	4 5800	- 0298	1713	-5 3048	3715	- 3018			
	(1 73)	(1 77)	(7 65)**	(- 87)	(6 83)**	(-4 93)**	(5 17)**	(- 98)	[5 96]**	1 993	2824
STM	2181	- 1644	5 7193	- 0358	1247	-2 5246	2239	- 0786			
	(1 80)	(79)	(6 21)**	(-1 40)	(6 62)**	(-3 44)**	(6 01)**	(- 50)	[4 21]**	2 003	2412
TAU	3046	- 1512	2786	- 0401	2637	- 8322	1811	0406			
	(6 34)**	(-2 64)**	(4 63)**	(-3 02)**	(11 91)**	(-5 17)**	(5 74)**	(30)	[16 97]**	2 020	1945
TD	0698	- 0978	7396	- 0714	2808	-1 8070	3791	0196			
	(1 66)	(-1 94)	(6 37)**	(-3 49)**	(9 30)**	(-6 93)**	(7 77)**	(12)	[2 81]*	2 020	2139
TEK B	1550	- 0280	2 6818	- 0955	1287	-2 2786	3067	0225			
	(2 80)**	(- 34)	(5 64)**	(-4 70)**	(6 58)**	(-5 16)**	(8 30)**	(- 14)	[3 64]**	2 016	2687
TOC	1257	- 0492	2 7967	0234	2414	- 6827	1500	- 1204			
	(3 72)**	(- 94)	(13 52)**	(2 11)*	(9 70)**	(-3 43)**	(4 45)**	(- 89)	[9 11]**	1 999	2493
TRP	0819	2883	4438	- 0410	3011	-1 2028	1491	- 3477			
	(1 51)	(1 46)	(3 31)**	(-3 21)**	(9 96)**	(-6 80)**	(4 99)**	(-3 05)**	[3 01]*	1 916	2618
VO	1601	- 1300	1 7231	- 0291	1898	-6 1519	1644	0093			
	(1 72)	(-1 28)	(10 68)**	(-3 77)**	(5 26)**	(-2 22)*	(6 67)**	(10)	[6 04]**	1 966	2330
TIPS	4302	- 1343	8138	- 6157	3058	- 4492	2411	0100			
	(1 34)	(- 34)	(2 41)*	(-4 32)**	(9 08)**	(-4 45)**	(8 01)**	(80)	[11 91]**	2 017	1717

Table 2 6

Regression of estimated volatility on unexpected volume and quote variables is given by

$$\sigma_t = a + b_1 UVOL_t + b_2 DUM_t + b_3 SPD_{t-1} + b_4 QD_{t-1} + b_5 OP_t + b_6 MON_t + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t$$

where UVOL is unexpected volume DUM is the indicator variable for no trade outcomes SPD is the percent quoted spread QD is quote depth defined as the sum of bid and ask depths OP is the indicator variable for opening intervals and MON is the indicator variable for Monday The dependent variable is estimated volatility based on the IWLS procedure introduced by Schwert (1990) Durbin-Watson statistics and adjusted R are provided An ARIMA(0 (1 2 3)(13) 3) model is used to partition volume into expected and unexpected components * (**) denotes statistical significance at 5% (1%) level Test statistics for individual coefficients are t-statistics (in parentheses) computed using White (1980) standard errors Test statistics for lagged volatility coefficients are F-statistics for the hypothesis that the sum of the 13 coefficients is zero

COM	UVOL	DUM	SPD	QD	σ LAGS	DW	A R
AL	2642	- 2003	1824	-1 1699			
	(6 57)**	(-15 32)**	(5 73)**	(-3 66)**	[5 04]**	2 050	1915
B	0760	- 0574	2377	- 4437			
	(2 09)*	(-1 57)	(7 00)**	(-3 47)**	[7 04]**	2 030	1721
BMO	0128	- 0973	2100	- 1890			
	(1 33)	(-9 85)**	(6 84)**	(- 92)	[12 29]**	2 056	1682
BNS	1821	- 1510	2876	- 8886			
	(2 80)**	(-5 82)**	(8 31)**	(-4 88)**	[6 49]**	2 031	2009
BVI	4634	- 1536	0882	-1 5163			
	(2 84)**	(-11 51)**	(6 17)**	(-2 94)**	[9 38]**	2 029	2275
CAE	2010	- 2276	1182	-1 1612			
	(1 95)	(-10 44)**	(5 04)**	(-2 99)**	[20 96]**	2 042	1611
CM	1805	- 1178	2029	- 9230			
	(5 70)**	(-13 08)**	(9 05)**	(-3 11)**	[8 57]**	2 026	2287
CP	0173	- 1690	2056	- 7402			
	(2 81)**	(-4 86)**	(6 53)**	(-3 59)**	[5 70]**	2 016	1254
CTR A	1957	- 1217	1273	-1 9064			
	(4 43)**	(-13 93)**	(5 99)**	(-5 17)**	[7 68]**	2 010	1219
ECO	7910	- 2937	1586	-1 9864			
	(5 69)**	(-15 03)**	(5 57)**	(-2 41)*	[6 43]**	2 008	2576
GOU	1138	- 2449	1322	-2 0315			
	(1 17)	(-16 19)**	(7 21)**	(-3 38)**	[7 96]**	2 017	1807
IMO A	5443	- 0709	1009	-2 3468			
	(6 16)**	(-10 48)**	(3 58)**	(-3 89)**	[9 91]**	2 020	2422
IMS	2269	- 1251	1186	-1 0512			
	(4 26)**	(-16 15)**	(4 89)**	(-2 16)*	[14 43]**	2 019	1830
LAC	4257	- 2785	1522	-1 3727			
	(6 94)**	(-15 01)**	(5 81)**	(-2 80)**	[10 47]**	2 032	2429

Table 2 6 (Continued)

COM	UVOL	DUM	SPD	QD	σ LAGS	DW	A R²
LDM B	0689	- 2079	1944	1213			
	(1 41)	(-6 91)**	(3 42)**	(17)	[5 36]**	2 050	1598
MB	3622	- 1293	1271	-1 4331			
	(4 35)**	(-7 91)**	(6 26)**	(-4 49)**	[12 53]**	2 033	1759
MCL	1951	- 1479	1480	-1 5889			
	(4 86)**	(-17 48)**	(5 14)**	(-4 37)**	[7 24]**	2 017	1641
N	0041	- 1540	1253	-1 5935			
	(2 37)*	(-16 07)**	(3 97)**	(-4 27)**	[11 43]**	2 033	2243
NA	2743	- 1855	1726	- 9687			
	(5 35)**	(-12 79)**	(9 95)**	(-3 97)**	[12 54]**	2 031	1780
NOR	1909	- 1520	1402	-1 3295			
	(3 45)**	(-13 00)**	(6 73)**	(-4 61)**	[10 98]**	2 049	2010
NTL	4431	- 1167	2625	-2 4181			
	(5 94)**	(-10 27)**	(5 90)**	(-5 71)**	[6 24]**	2 037	2196
NVA	1777	0015	3531	-1 8375			
	(6 58)**	(01)	(11 89)**	(-7 30)**	[8 08]**	2 041	1456
PDG	3415	- 2029	1754	- 9722			
	(4 89)**	(-11 46)**	(3 70)**	(-2 25)**	[3 38]**	2 043	2581
POW	5740	- 1000	1483	- 9510			
	(6 05)**	(-13 04)**	(7 96)**	(-3 00)**	[12 78]**	2 038	1913
RGO	0593	- 2588	1917	- 5765			
	(7 65)**	(-17 07)**	(8 60)**	(-2 21)*	[9 38]**	2 034	1713
RY	0257	- 1388	2049	- 6466			
	(1 00)	(-10 91)**	(6 52)**	(-2 55)*	[9 31]**	2 044	1615
SCC	2392	- 2808	0394	-2 2138			
	(2 37)*	(-15 46)**	(3 05)**	(-4 74)**	[8 34]**	2 016	1736
STE A	7190	- 2326	1455	-3 3942			
	(3 57)**	(-10 08)**	(5 33)**	(-3 02)**	[15 46]**	2 023	2036
STM	2811	-19788	1052	-1 8593			
	(1 40)	(-15 26)**	(5 54)**	(-2 34)*	[7 62]**	2 042	1752
TAU	2109	- 0763	2405	- 5176			
	(4 74)**	(-6 14)**	(10 81)**	(-3 40)**	[17 67]**	2 033	1810
TD	0768	- 1642	2091	- 8154			
	(1 49)	(-9 81)**	(6 78)**	(-3 62)**	[7 61]**	2 042	1574
TEK B	2939	- 1960	1082	-1 8788			
	(5 98)**	(-19 26)**	(5 46)**	(-4 35)**	[5 36]**	2 047	2232
TOC	2651	- 0955	2056	- 6766			
	(7 08)**	(-9 90)**	(8 10)**	(-3 29)**	[9 77]**	2 022	1775
TRP	2348	- 0821	2681	- 8836			
	(1 94)	(-5 12)**	(7 81)**	(-4 66)**	[3 70]**	2 014	2025
VO	3625	- 0929	1250	-4 6909			
	(2 68)**	(-12 57)**	(3 25)**	(-2 00)*	[8 74]**	2 009	1725
TIPS	4737	- 8961	2939	- 3997			
	(1 91)	(-9 16)**	(8 57)**	(-3 97)**	[12 38]**	2 017	1656

Table 2 7

Regression of estimated volatility on volume components and quote variables is given by

$$\sigma_t = a + b_1 EVOL_t + b_2 UVOL_t + b_3 DUM_t + b_4 SPD_{t-1} + b_5 QD_{t-1} + \sum_{i=1}^{13} c_i \sigma_{t-i} + e_t$$

where EVOL is expected volume UVOL is unexpected volume DUM is the indicator variable for no trade outcomes SPD is the percent quoted spread QD is quote depth defined as the sum of bid and ask depths OP is the indicator variable for opening intervals and MON is the indicator variable for Monday Durbin-Watson statistics and adjusted R are provided An ARIMA(0 (1 2 3)(13) 3) model is used to partition volume into expected and unexpected components The dependent variable is estimated volatility based on the IWLS procedure introduced by Schwert (1990) * (**) denotes statistical significance at 5% (1%) level Test statistics for individual coefficients are t statistics (in parentheses) computed using White (1980) standard errors Test statistics for lagged volatility coefficients are F statistics for the hypothesis that the sum of the 13 coefficients is zero

COM	EVOL	UVOL	DUM	SPD	QD	σ LAGS	DW	A R
AL	1293	2670	- 1950	1922	-1 3827			
	(2 24)*	(6 48)**	(-14 32)**	(5 98)**	(-4 17)**	[3 99]**	2 039	1925
B	1083	0764	- 0537	2395	- 4892			
	(1 43)	(2 08)*	(-1 47)	(7 04)**	(-3 63)**	[6 05]**	2 021	1728
BMO	1106	0128	- 0958	2134	- 2155			
	(1 09)	(1 32)	(-9 63)**	(6 87)**	(-1 05)	[12 13]**	2 055	1682
BNS	2700	1845	- 1396	3127	-1 1799			
	(4 25)**	(2 80)**	(-5 44)**	(8 82)**	(-5 90)**	[4 53]**	2 017	2058
BVI	8933	4655	- 1526	0898	-1 6177			
	(1 70)	(2 85)**	(-11 39)**	(6 30)**	(-3 12)**	[7 27]**	2 013	2285
CAE	1 4770	2038	- 2148	1069	-1 5541			
	(2 59)**	(1 93)	(-9 75)**	(4 30)**	(-3 70)**	[16 73]**	2 026	1676
CM	2985	1822	- 1130	2112	-1 0982			
	(2 65)**	(5 58)**	(-12 25)**	(9 30)**	(3 59)**	[6 33]**	2 021	2306
CP	1190	0173	- 1678	2077	- 7766			
	(1 09)	(2 80)**	(-4 83)**	(6 58)**	(-3 68)**	[5 46]**	2 015	1254
CTR A	0789	1959	- 1215	1276	-1 9216			
	(25)	(4 42)**	(-13 75)**	(6 01)**	(-5 19)**	[7 40]**	2 009	1217
ECO	1 3503	8097	- 2792	1793	-3 1762			
	(3 35)**	(5 60)**	(-13 75)**	(6 24)**	(-3 50)**	[4 86]**	1 994	2611
GOU	0199	1138	- 2448	1323	-2 0372			
	(06)	(1 17)	(-16 04)**	(7 24)**	(-3 34)**	[7 72]**	2 017	1804
IMO A	6293	5498	- 0687	1083	-2 6854			
	(2 45)*	(6 14)**	(-9 88)**	(3 86)**	(-4 25)**	[7 17]**	2 010	2439
IMS	3699	2290	- 1241	1221	-1 2057			
	(1 18)	(4 28)**	(-15 98)**	(5 07)**	(-2 33)*	[12 54]**	2 014	1833
LAC	4756	4293	- 2705	1619	-1 7022			
	(2 27)*	(6 93)**	(-14 48)**	(6 06)**	(-3 36)**	[8 51]**	2 011	2449

Table 2 7 (Continued)

COM	EVOL	UVOL	DUM	SPD	QD	σ LAGS	DW	A R
LDM B	1852	0703	- 1973	2341	- 3105			
	(2 57)*	(1 42)	(-6 31)**	(3 70)**	(47)	[2 62]*	2 038	1650
MB	9292	3645	- 1269	1400	-1 6644			
	(3 76)**	(4 33)**	(-7 75)**	(5 96)**	(-5 15)**	[9 33]**	2 017	1798
MCL	1746	1966	- 1460	1517	-1 7488			
	(1 23)	(4 84)**	(-16 97)**	(5 21)**	(-4 56)**	[6 52]**	2 015	1642
N	0107	0041	- 1539	1254	-1 5976			
	(11)	(2 37)*	(-16 07)**	(3 99)**	(-4 25)**	[11 20]**	2 033	2241
NA	1816	2751	- 1839	1738	-1 0128			
	(1 57)	(4 96)**	(-12 53)**	(3 93)**	(-4 09)**	[11 52]**	2 016	1791
NOR	4035	1935	- 1482	1492	-1 5477			
	(2 40)*	(3 44)**	(-12 47)**	(7 22)**	(-5 02)**	[8 78]**	2 038	2033
NTL	3835	4515	- 1130	2773	-2 8557			
	(3 36)**	(6 03)**	(-10 01)**	(6 16)**	(-6 47)**	[3 93]**	2 051	2222
NVA	2520	1879	0162	3617	-2 0222			
	(4 35)**	(6 49)**	(12)	(12 29)**	(-7 87)**	[5 70]**	2 023	1521
PDG	4844	3485	- 1909	1935	-1 3755			
	(4 84)**	(4 91)**	(-10 36)**	(4 01)**	(-3 06)**	[1 93]	2 011	2648
POW	1 0658	5765	- 0987	1509	-1 0793			
	(2 38)*	(6 05)**	(-12 81)**	(8 13)**	(-3 35)**	[11 24]**	2 033	1925
RGO	0073	0593	- 2586	1921	- 5964			
	(90)	(7 62)**	(-17 07)**	(8 62)**	(-2 28)*	[9 35]**	2 034	1713
RY	0631	0257	- 1382	2050	- 6596			
	(48)	(99)	(-10 82)**	(6 52)**	(-2 59)**	[9 17]**	2 043	1613
SCC	0170	2392	- 2808	0394	-2 2131			
	(- 04)	(2 37)*	(-15 46)**	(3 05)**	(-4 74)**	[8 24]**	2 016	1734
STE A	2 0053	7278	- 2245	1338	-3 8801			
	(2 54)*	(3 55)**	(-9 75)**	(5 09)**	(-3 46)**	[12 22]**	2 016	2061
STM	1 5360	2838	- 1965	1071	-2 0841			
	(1 44)	(1 40)	(-15 11)**	(5 62)**	(-2 75)**	[6 64]**	2 026	1798
TAU	4045	2110	- 0740	2428	- 5602			
	(2 09)*	(4 67)**	(-5 93)**	(10 91)**	(-3 66)**	[16 35]**	2 019	1822
TD	1043	0779	- 1615	2149	- 9422			
	(1 77)	(1 47)	(-9 36)**	(6 96)**	(-3 94)**	[6 02]**	2 040	1582
TEK B	0441	2942	- 1958	1083	-1 8943			
	(25)	(5 96)**	(-19 18)**	(5 46)**	(-4 30)**	[5 05]**	2 045	2230
TOC	1353	2659	- 0946	2061	- 7325			
	(94)	(7 06)**	(-9 69)**	(8 13)**	(-3 40)**	[9 08]**	2 017	1775
TRP	1004	2381	- 0806	2764	- 9941			
	(1 21)	(1 93)	(-4 75)**	(8 36)**	(-5 03)**	[2 31]*	1 988	2047
VO	- 1480	3616	- 0933	1235	-4 6155			
	(- 40)	(2 67)**	(-12 38)**	(3 20)**	(-1 95)*	[8 50]**	2 009	1723
TIPS	1795	4748	- 8888	2922	- 4008			
	(1 57)	(1 89)	(-9 05)**	(8 52)**	(-3 99)**	[11 68]**	2 011	1712

Figure 1

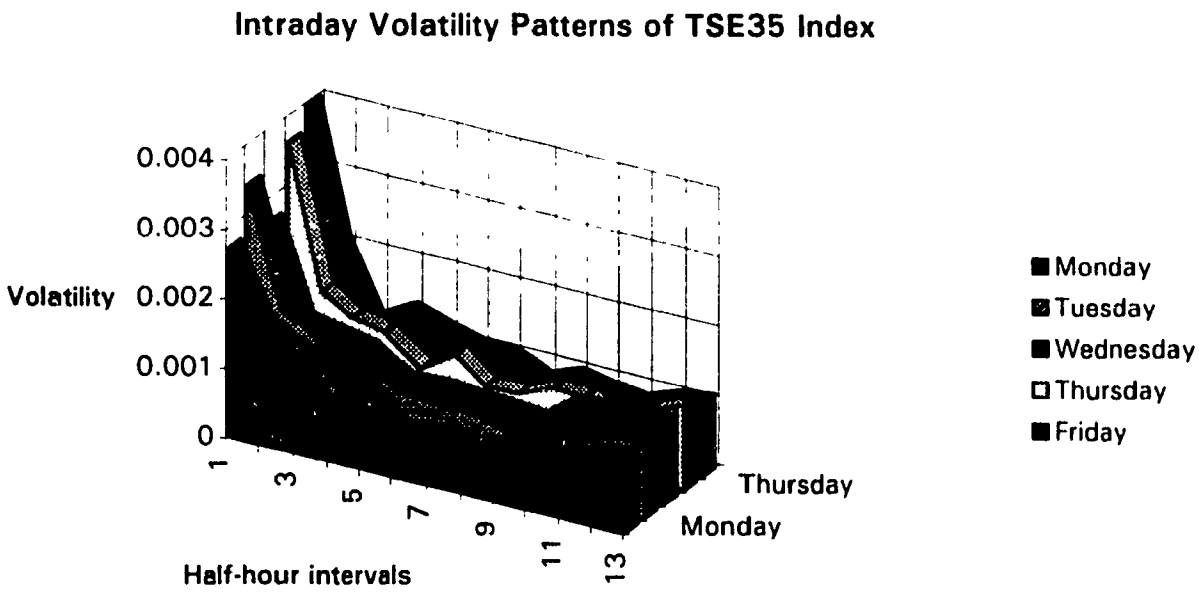
Intraday Volatility Patterns of TSE35 Index
Volatility
0.004
0.003
0.002
0.001
0
1
3
5
7
9
11
13
Half-hour intervals
Thursday
Monday
Monday
Tuesday
Wednesday
Thursday
Friday

Table 3 1

The average returns for TSE35 stocks are equally weighted returns using the average of bid and ask quotes R_{it} for individual stocks The hypothesis that variance ratios are equal to one is tested for both interday and intraday intervals The t-statistics in parentheses are based on the distribution of the subperiod variance ratios * (**) denotes statistical significance at the 5% (1%) level

Panel A: Interday volatility patterns

The variance ratios of the average returns of the TSE35 stocks are calculated for four weekdays relative to Monday

	[illegible]	[illegible]	[illegible]	[illegible]
Average of	1 5635	1 0926	1 5287	1 8930
TSE35 Stocks	(1 46)	(0 62)	(2 76)*	(3 77)**

Panel B: Intraday Volatility Patterns

The variance ratios of the average returns of the TSE35 stocks are calculated for 12 half-hour intervals relative to the sixth interval (i e Noon to 12 30 p m)

	σ^2_1/σ^2_6	σ^2_2/σ^2_6	σ^2_3/σ^2_6	σ^2_4/σ^2_6	σ^2_5/σ^2_6	σ^2_7/σ^2_6	σ^2_8/σ^2_6	σ^2_9/σ^2_6	σ^2_{10}/σ^2_6	σ^2_{11}/σ^2_6	σ^2_{12}/σ^2_6	σ^2_{13}/σ^2_6
Average of	15 1493	3 3876	2 1908	1 6851	1 3536	0 9743	0 9892	1 0036	1 3133	1 2862	1 6985	1 7076
TSE35 Stocks	(4 97)**	(4 61)**	(2 40)*	(3 43)**	(1 54)	(-0 18)	(-0 05)	(0 02)	(1 22)	(1 17)	(1 46)	(2 85)*

Table 3 2

Panel A: Relative frequency of different trade sizes for stocks included in the TSE35 index

		Monday	Tuesday	Wednesday	Thursday	Friday
Small Trades	Number	5690	5560	5560	5526	5455
	Volume	0570	0538	0499	0445	0477
Medium Trades	Number	4089	4198	4195	4209	4258
	Volume	4826	4870	4506	4066	4690
Large Trades	Number	0221	0242	0245	0265	0287
	Volume	4604	4591	4995	5489	4832

Panel B: Relative frequency of different trade sizes for TIPs

		Monday	Tuesday	Wednesday	Thursday	Friday
Small Trades	Number	4580	4878	5053	4592	4522
	Volume	0091	0135	0109	0085	0080
Medium Trades	Number	3362	3481	3029	3445	3604
	Volume	0967	1197	0895	0939	0860
Large Trades	Number	2058	1641	1918	1963	1873
	Volume	8941	8668	8995	8976	9060

Table 3 3

Variance ratios of non-trading to trading periods

Volatility is estimated using the IWLS procedure suggested by Schwert (1990) The ratios of non-trading to trading volatilities for each company (COM) in the TSE35 index and TIPS are based on mean variance ratios for 13 subperiods The variance ratio is given by

$$VR = \frac{\sigma^2_{non\ trading}}{\sigma^2_{trading}}$$

The null hypothesis H. VR =0 is tested The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages * (**) denotes statistical significance at the 5% (1%) level

	Variance Ratio
Minimum	0 0539
	(3 40)**
Median	0 1413
	(7 59)**
Maximum	0 2106
	(7 41)**
TIPs	0 2929
	(8 48)**

Table 3 4

Variance ratios of medium trades relative to small and large trades

The ratios of medium-size trades to small/large trade volatilities for each of the companies (COM) in the TSE35 index and TIPS are based on mean variance ratios (VR) for 13 subperiods The VR is given by

$$VR = \frac{\sigma^2_{medium\ trades}}{\sigma^2_{small/large\ trades}}$$

The hypothesis H. VR=1 is tested The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages * (**) denotes statistical significance at the 5% (1%) level

	Variance Ratio
Minimum	3 0666
	(8 22)**
Median	8 0162
	(3 85)**
Maximum	11 9127
	(5 17)**
TIPS	1 8890
	(7 84)**

Table 3 5

Ratios of the variance of the bid-ask errors to the variance of transaction returns for the portfolio of TSE35 stocks and TIPS The variance ratio is defined as

$$VR = \frac{Var(RD_t)}{Var(R_n)}$$

where R_n is a transaction return and RD_t is the difference between a transaction return and a return using the average of bid and ask quotes The hypothesis H_0 VR=0 is tested for the average of TSE35 stocks and TIPS The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages * (**) denotes statistical significance at the 5% (1%) level

	Return Measurement Interval (k)			
	1 day	2 days	3 days	1 week
TIPs	0 1873 (6 27)**	0 1167 (4 40)**	0 0970 (3 31)**	0 0947 (2 12)*
Mean VR of TSE35 stocks	0 3521 (9 53)**	0 2129 (4 60)**	0 1862 (3 86)**	0 0889 (3 35)**

Table 3 6

Variance ratios for returns based on quote midpoints

The variance ratio is defined as

$$VR(k) = \left(\frac{1}{k}\right)\left(\frac{VAR(R_t^k)}{VAR(R_t)}\right)$$

where R_t and R_t^k are returns using the average of bid and ask quotes over one half-hour period and k-period measurement intervals, respectively The null hypothesis H_0 VR(k)=1 is tested for measurement intervals of one, two and three days and one week where k is 13, 26 39, and 65 respectively The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages The variance ratios for TSE35 stocks are averaged across stocks to obtain subperiod means * (**) denotes statistical significance at the 5% (1%) level 'COM' refers to company

COM	Return Measurement Interval			
	1 day	2 days	3 days	1 week
AL	0 8478	0 9817	1 0622	1 4737
	(-2 76)**	(-0 27)	(0 32)	(1 72)
B	0 9789	1 0954	1 0450	0 9557
	(-0 24)	(0 79)	(0 20)	(-0 19)
BMO	0 9025	1 1971	1 3479	1 8009
	(-1 48)	(1 91)	(2 47)*	(2 76)**
BNS	0 7117	0 7849	0 8642	0 9429
	(-4 46)**	(-1 78)	(-0 82)	(-0 55)
BVI	0 7089	0 6863	0 6588	0 8428
	(-4 09)**	(-3 31)**	(-3 32)**	(-0 99)
CAE	0 7710	0 6827	0 8792	0 9372
	(-2 80)**	(-4 31)**	(-0 80)	(0 43)
CM	0 7706	0 9307	0 9409	1 2348
	(-3 69)**	(-0 82)	(-0 66)	(1 03)
CP	0 8141	0 9106	0 9977	0 9389
	(-2 20)*	(-0 68)	(-0 08)	(0 57)
CTR A	0 7993	0 8636	0 8831	1 0723
	(-2 46)*	(-1 22)	(-1 18)	(0 24)
ECO	0 9563	0 9902	1 0612	1 1515
	(-0 59)	(-0 17)	((0 53)	(0 55)
GOU	0 8499	1 0836	1 0892	1 2003
	(-1 64)	(0 42)	(0 52)	(0 83)
IMO A	1.1507	1 4924	1 2288	1 9690
	(1 04)	(2 17)	(1 21)	(2 08)
IMS	0 8727	0 8682	1 0795	1 2533
	(-1 25)	(-1 33)	(0 52)	(0 92)
LAC	0 8273	0 7940	0 9271	0 8802
	(-1 85)	(-1 95)	(-0 43)	(-0 63)

	Return Measurement Interval			
COM	Table 3 6 Continued			
	1 day	2 days	3 days	1 week
LDM B	0 9877	1 2317	1 1373	1 3242
	(-0 19)	(1 22)	(0 63)	(1 13)
MB	0 8407	0 9000	0 8951	1 4140
	(-2 13)	(-1 07)	(-0 65)	(1 34)
MCL	0 9732	1 1208	0 9544	1 0157
	(-0 33)	(0 95)	(-0 37)	(-0 01)
N	1 2353	1 4973	1 6642	1 8683
	(2 41)*	(2 95)**	(-2 47)*	(3 04)**
NA	0 7209	0 7676	0 7605	0 8894
	(-4 00)**	(-2 09)	(-1 82)	(-0 59)
NOR	0 8905	1 0112	0 9691	1 2414
	(-1 42)	(0 03)	(-0 28)	(1 52)
NTL	1 1886	1 4109	1 2153	1 4817
	(1 75)	(2 73)**	(1 20)	(1 24)
NVA	0 6236	0 5834	0 5339	0 6398
	(-5 78)**	(-5 79)**	(-5 03)**	(-2 27)*
PDG	1 0456	0 9976	1 1141	0 8969
	(0 48)	(-0 08)	(0 73)	(-0 51)
POW	0 6299	0 6248	0 6473	0 8322
	(-9 05)**	(-6 39)**	(-3 55)**	(-1 16)
RGO	0 7602	0 7374	0 6112	0 5692
	(-3 18)**	(-2 88)**	(-4 17)**	(-3 86)**
RY	0 7252	0 9038	1 0538	1 3998
	(-3 16)**	(-0 69)	(0 23)	(1 13)
SCC	0 9000	1 0233	0 9938	1 1206
	(-0 87)	(0 07)	(-0 08)	(0 38)
STE A	0 8451	1 0219	1 0623	1 3671
	(-1 59)	(0 07)	(0 24)	(1 21)
STM	0 9097	1 0468	1 1964	1 4753
	(-0 78)	(0 28)	(0 88)	(1 51)
TAU	0 6112	0 5184	0 5448	0 6009
	(-11 58)**	(-11 07)**	(-5 94)**	(-4 52)**
TD	0 7475	0 9798	0 8738	1 2807
	(-2 92)**	(-0 20)	(-0 93)	(0 85)
TEK B	0 9294	1 1252	1 2784	1 4570
	(-1 02)	(0 77)	(0 74)	(1 63)
TOC	0 7797	0 7390	0 9050	1 2696
	(-2 34)*	(-3 18)**	(-0 79)	(0 96)
TRP	0 6522	0 7178	0 6538	0 8368
	(-3 87)**	(-2 06)	(-2 27)*	(-0 97)
VO	1 3358	1 7886	1 9455	2 2985
	(4 14)**	(4 07)**	(3 02)**	(2 60)*
Mean VR of TSE35 Stocks	0 8656	0 9746	1 0022	1 1981
	(-1 63)	(-0 25)	(-0 05)	(0 72)
TIPS	0 4392	0 4912	0 5424	0 6519
	(-15 83)**	(-7 69)**	(-5 45)**	(-2 44)*
Index portfolio	1 3078	1 6741	1 8846	2 6458
	(2 88)**	(3 13)**	(3 26)**	(2 99)**

Table 3 7

Variance ratios on transaction returns

The variance ratio is defined as

$$VR(k) = \left(\frac{1}{k}\right)\left(\frac{VAR(R_t^k)}{VAR(R_t)}\right)$$

where R_t and R^k_t are transaction returns over one half-hour period and k-period measurement intervals respectively The null hypothesis H_0 VR(k)=1 is tested for measurement intervals of one two and three days and one week where k is 13 26 39 and 65 The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages The variance ratios for TSE35 stocks are averaged across stocks to obtain subperiod means * (**) denotes statistical significance at the 5% (1%) level

COM	Return Measurement Interval			
	1 day	2 days	3 days	1 week
AL	0 8958	1 0426	1 1206	1 6218
	(-1 48)	(0 30)	(0 60)	(1 90)
B	1 0150	1 1643	1 2073	1 0107
	(0 08)	(1 10)	(0 90)	(-0 02)
BMO	0 8292	1 0728	1 2624	1 6176
	(-3 03)**	(0 86)	(2 31)*	(2 09)
BNS	0 6367	0 7712	0 7996	0 8600
	(-5 47)**	(-1 83)	(-1 35)	(1 29)
BVI	0 4307	0 3799	0 3542	0 4187
	(-14 95)**	(-10 29)**	(-15 33)**	(-6 95)**
CAE	0 5260	0 3907	0 5215	0 5605
	(-5 53)**	(-9 59)**	(-3 69)**	(-2 62)*
CM	0 7422	0 9531	0 9670	1 2622
	(-3 77)**	(-0 55)	(-0 37)	(0 98)
CP	0 7627	0 8927	1 0320	0 9448
	(-2 70)**	(0 79)	(0 12)	(0 45)
CTR A	0 5763	0 6124	0 5651	0 6574
	(-7 66)**	(-4 59)**	(-6 68)**	(2 63)*
ECO	0 8450	0 9067	0 9817	1 0930
	(-2 04)	(-1 02)	(-0 22)	(0 28)
GOU	0 5781	0 6422	0 6701	0 7110
	(-5 39)**	(-2 59)*	(-3 22)**	(1 75)
IMO A	1 0150	1 3511	1 1062	1 9208
	(0 08)	(1 67)	(0 66)	(1 79)
IMS	0 6584	0 7006	0 8164	0 9699
	(-6 72)**	(-4 65)**	(-1 98)	(-0 27)
LAC	0 6421	0 6832	0 7090	0 7887
	(-4 43)**	(-3 20)**	(-1 97)	(0 92)

Table 3 7 Continued				
	1 day	2 days	3 days	1 week
LDM B	1 1537	1 4332	1 3818	1 5187
	(1 71)	(1 90)	(1 48)	(1 67)
MB	0 6014	0 6408	0 6509	0 9633
	(-6 10)**	(-4 96)**	(-2 29)*	(-0 25)
MCL	0 7444	0 8957	0 8026	0 7837
	(-3 71)**	(-1 12)	(-1 44)	(-1 31)
N	1 3357	1 6408	1 8471	2 0739
	(2 66)*	(3 12)**	(2 87)**	(3 13)**
NA	0 4088	0 3947	0 4594	0 4190
	(-11 01)**	(-9 82)**	(-5 70)**	(-5 92)**
NOR	0 6764	0 7274	0 6886	0 8592
	(-5 15)**	(-2 73)**	(-2 83)**	(-1 44)
NTL	1 2659	1 5789	1 3274	1 6478
	(2 14)	(3 17)**	(1 77)	(1 41)
NVA	0 3582	0 3536	0 2905	0 3725
	(-15 67)**	(-10 05)**	(-11 33)**	(-5 91)**
PDG	1 0262	1 0517	1 0921	0 9641
	(0 24)	(0 31)	(0 54)	(-0 19)
POW	0 3431	0 3370	0 3747	0 4034
	(-15 11)**	(-11 98)**	(-7 59)**	(-5 05)**
RGO	0 4991	0 4443	0 3700	0 2954
	(-7 74)**	(-8 87)**	(-8 71)**	(-11 75)**
RY	0 6361	0 7912	0 8653	1 2768
	(-4 67)**	(-1 65)	(-0 92)	(0 84)
SCC	0 6026	0 5435	0 5970	0 6191
	(-5 99)**	(-4 38)**	(-3 89)**	(-2 14)
STE A	0 7373	0 8216	0 8290	1 0493
	(-2 43)*	(-1 00)	(-0 88)	(0 09)
STM	0 7829	0 8142	0 9934	1 0757
	(-1 96)	(-1 33)	(-0 09)	(0 22)
TAU	0 2950	0 2379	0 2322	0 2703
	(-27 86)**	(-33 91)**	(-23 63)**	(-17 36)**
TD	0 7265	0 8911	0 7249	1 2235
	(-2 87)**	(-0 76)	(-2 13)	(0 71)
TEK B	0 7538	0 8855	1 0335	1 1432
	(-5 08)**	(-1 06)	(0 08)	(0 59)
TOC	0 4695	0 4363	0 5159	0 7195
	(-9 37)**	(-8 77)**	(-6 73)**	(-1 81)
TRP	0 3793	0 3969	0 3170	0 4051
	(-8 90)**	(-6 66)**	(-8 86)**	(-5 34)**
VO	1 2712	1 7542	2 0411	2 2789
	(1 81)	(3 02)**	(2 56)*	(2 17)
TIPS	0 4296	0 4646	0 4761	0 5825
	(-15 27)**	(-8 23)**	(-8 17)**	(-3 21)**
Mean VR of TSE35 Stocks	0 7206	0 8184	0 8442	0 9942
	(-3 62)**	(-1 63)	(-1 14)	(-0 11)

Table 3 8

Variance ratios on quote-based returns

The variance ratio is defined as

$$VR(k) = \left(\frac{1}{k}\right)\left(\frac{VAR(R_t^k)}{VAR(R_t)}\right)$$

where R_t and R^k_t are quote-based returns over one half-hour period and k-period measurement intervals respectively The null hypothesis H_0 VR(k)=1 is tested for measurement intervals of one two and three days and one week where k is 13 26 39 and 65 respectively The t-statistics in parentheses are calculated using standard errors based on the distribution of the subperiod averages The variance ratios for TSE35 stocks are averaged across stocks to obtain subperiod means * (**) denotes statistical significance at the 5% (1%) level 'COM' refers to company

Panel A: Quote-based returns R_{1t}:

$$\begin{aligned} R_{1t} &= (Ask_t - Ask_{t-1})/m_{t-1} && \text{if} \quad m_t > m_{t-1}, \\ &= (Bid_t - Bid_{t-1})/m_{t-1} && \text{if} \quad m_t < m_{t-1}, \\ &= 0 && \text{otherwise} \end{aligned}$$

is used to calculated variance ratios

	Return Measurement Interval (k)			
	1 day	2 days	3 days	1 week
Mean VR of TSE35 stocks	0 5133 (-8 86)**	0 5482 (-6 95)**	0 5581 (-5 52)**	0 6547 (2 91)*
TIPs	0 4847 (-9 24)**	0 5326 (-6 34)**	0 5995 (-4 16)**	0 6730 (2 52)*

Panel B: Quote-based returns R_{2t}:

$$\begin{aligned} R_{2t} &= (Bid_t - Bid_{t-1})/m_{t-1} && \text{if} \quad m_t > m_{t-1}, \\ &= (Ask_t - Ask_{t-1})/m_{t-1} && \text{if} \quad m_t < m_{t-1}, \\ &= 0 && \text{otherwise} \end{aligned}$$

is used to calculate variance ratios

	Return Measurement Interval (k)			
	1 day	2 days	3 days	1 week
Mean VR of TSE35 stocks	0 4524 (-14 40)**	0 4943 (-9 31)**	0 5061 (-7 08)**	0 6005 (3 63)**
TIPs	0 4482 (-13 54)**	0 4863 (-8 51)**	0 5431 (-5 81)**	0 6175 (-3 75)**

TABLE 4 1

The Pearson correlation coefficients Rho for various pairs of firm-specific screens are reported below The probabilities > |R| under H. Rho = 0 are reported in the parentheses 'BETA' refers to the measure of systematic risk 'DIV' to the dividend yield 'P/E' to the price-to-earnings ratio 'D/EQ' to the debt-to-equity ratio and 'SIZE' to the size based on the market value of the common equity

	BETA	DIV	P/E	D/EQ	SIZE
BETA	1 00000 (0 0000)	-0 04466 (0 3209)	0 08773 (0 0509)	0 04390 (0 3992)	0 03635 (0 4104)
DIV	-0 04466 (0 3209)	1 00000 (0 0000)	-0 13003 (0 0030)	-0 02062 (0 6860)	0 03621 (0 4099)
P/E	0 08773 (0 0509)	-0 13003 (0 0030)	1 00000 (0 0000)	-0 02697 (0 5969)	-0 02416 (0 5825)
D/EQ	0 04390 (0 3992)	-0 02062 (0 6860)	-0 02697 (0 5969)	1 00000 (0 0000)	0 12164 (0 0160)
SIZE	0 03635 (0 4104)	0 03621 (0 4099)	-0 02416 (0 5825)	0 12164 (0 0160)	1 00000 (0 0000)

TABLE 4 2

The abnormal returns (AR's) for the three sets of screen-sorted portfolios for the event date [0] for the one and two-beta models and their respective t-values are reported below The screens are beta (β) size as measured by market value of common equity, and dividend yield Portfolios one and ten contain the deciles of securities with the smallest and largest screen values, respectively "*" and "**" indicate statistical significance at the 0 05 and 0 01 levels respectively

	1 β Model		2 β Model	
Portfolio	AR[0]	t-value	AR[0]	t-value
Panel A:	Beta-sorted portfolios			
1	-0 17	-9 06**	-0 06	-4 99**
2	-0 08	-7 41**	-0 04	4 89**
3	-0 07	-9 33**	-0 05	-7 84**
4	-0 05	-6 92**	-0 04	-6 84**
5	-0 04	-5 97**	-0 05	-7 07**
6	-0 02	-2 13*	-0 03	2 94**
7	-0 03	-3 85**	-0 06	-7 93**
8	-0 01	-1 08	-0 05	6 05**
9	0 02	1 66	-0 03	-3 74**
10	0 07	5 12**	-0 03	-3 18**
Panel B:	Size-sorted Portfolios			
1	-0 03	-1 51	-0 03	-2 18*
2	-0 04	-2 52*	-0 06	-4 87**
3	-0 04	-3 39**	-0 05	4 77**
4	-0 06	-4 40**	-0 04	3 88**
5	-0 06	-4 64**	-0 06	6 40**
6	-0 04	-4 57**	-0 06	-7 01**
7	-0 05	-6 36**	-0 05	-7 74**
8	-0 02	-2 97**	-0 05	7 21**
9	-0 04	-6 69**	-0 05	11 66**
10	-0 01	-2 68**	-0 01	3 42**
Panel C:	Dividend-yield-sorted portfolios			
1	-0 04	-3 66**	-0 05	5 41**
2	-0 04	-4 69**	-0 04	-5 81**
3	-0 03	-4 63**	-0 05	-7 75**
4	-0 05	-6 72**	-0 06	-9 81**
5	-0 02	-3 13**	-0 04	-6 63**
6	-0 04	-4 93**	-0 06	-10 34**
7	-0 04	-5 93**	-0 04	-6 81**
8	-0 03	-4 42**	-0 04	-6 92**
9	-0 03	-4 80**	-0 03	-5 90**
10	-0 02	-2 12**	-0 02	-3 52**

TABLE 4 3

The cumulative abnormal returns (CAR's) for the three sets of screen-sorted portfolios for six time intervals for the one-beta model and their respective t-values (in parentheses for portfolios 1 through 10) are reported below The screens are beta size as measured by market value of common equity and dividend yield Portfolios one and ten contain the deciles of securities with the smallest and largest screen values respectively The F-values for a joint test of the hypothesis of no difference in the portfolio CAR's from zero for all ten portfolios jointly are presented below in the parenthesis for each time interval on the row labelled "jointly" The F-values for a joint test of the hypothesis of no difference in the CAR's from zero for the two extreme portfolios (portfolios one and ten) are presented in the parenthesis for each time interval on the row labelled "Extreme" "*" and "**" indicate statistical significance at the 0 05 and 0 01 levels respectively

	CAR[t1,t2]					
Port.	[-5,-1]	[0, 5]	[1, 5]	[-20,-1]	[1, 20]	[-20,20]
Panel A:	Beta sorted Portfolios					
1	-0 13**	-0 36**	-0 18**	-0 05	-0 25**	-0 48**
	(-4 21)	(-8 94)	(-6 01)	(-0 90)	(-4 46)	(-5 23)
2	-0 04*	-0 18**	-0 10**	-0 09**	-0 11**	-0 28**
	(-2 53)	(-8 00)	(-5 88)	(-2 82)	(-3 46)	(-5 45)
3	-0 06**	-0 12**	-0 05**	-0 07**	-0 06**	-0 21**
	(-4 53)	(-7 67)	(-3 96)	(-3 24)	(-2 69)	(-5 70)
4	-0 03*	-0 10**	-0 05**	-0 05*	-0 08**	-0 19**
	(-2 29)	(-5 97)	(-3 56)	(-2 10)	(-3 62)	(-5 01)
5	-0 05**	-0 11**	-0 06**	-0 09**	-0 09**	-0 24**
	(-4 45)	(-7 37)	(-5 17)	(-4 54)	(-4 23)	(-6 97)
6	-0 06**	-0 08**	-0 05**	-0 07*	-0 07*	-0 18**
	(-3 49)	(-3 82)	(-3 13)	(-2 42)	(-2 44)	(-3 55)
7	-0 05**	-0 05**	-0 02	-0 06*	-0 04	-0 14**
	(-3 53)	(-3 26)	(-1 27)	(-2 50)	(-1 89)	(-3 76)
8	-0 04	-0 04	-0 02	-0 02	-0 06	-0 10
	(-1 10)	(-1 59)	(-1 15)	(-0 68)	(-1 86)	(-1 84)
9	-0 03	-0 02	-0 03	-0 04	-0 10**	-0 13*
	(-1 75)	(-0 76)	(-1 72)	(-1 13)	(-3 07)	(-2 36)
10	-0 02	0 09**	0 02	-0 03	-0 06	-0 03
	(-1 00)	(2 83)	(0 93)	(-0 74)	(-1 36)	(-0 47)
Jointly	(3 58)**	(17 16)**	(9 32)**	(1 68)	(5 23)**	(5 03)**
Extreme	(21 38)**	(122 74)**	(57 46)**	(0 37)	(54 88)**	(28 83)**

Panel B:	Size-sorted Portfolios					
1	-0 07*	-0 11**	-0 08*	-0 08	-0 10	-0 21
	(-2 11)	(-2 77)	(-2 49)	(-1 57)	(-1 84)	(-2 36)
2	-0 05*	-0 15**	-0 11**	-0 07	-0 16**	0 29**
	(-2 11)	(-4 80)	(-4 58)	(-1 63)	(-3 78)	(-4 08)
3	-0 06**	-0 12**	-0 07**	0 09*	-0 12**	-0 08
	(-3 08)	(-4 47)	(-3 31)	(2 57)	(-3 31)	(-1 35)
4	-0 07**	-0 15**	-0 08**	-0 13**	-0 17**	-0 37**
	(-2 97)	(-5 05)	(-3 58)	(-3 25)	(-4 19)	(-5 63)
5	-0 06**	-0 11**	-0 04*	-0 12**	-0 11**	-0 29**
	(-2 82)	(-4 30)	(-2 26)	(-3 30)	(-2 97)	(-5 04)
6	-0 07**	-0 11**	-0 06**	-0 10**	-0 11**	-0 25**
	(-4 63)	(-5 63)	(-4 19)	(-3 79)	(-4 18)	(-5 96)
7	-0 04*	-0 11**	-0 05**	-0 05	-0 09**	-0 20**
	(-2 90)	(-6 05)	(-3 66)	(-1 87)	(-3 67)	(-4 86)
8	-0 04**	-0 08**	-0 05**	-0 06*	-0 08**	-0 17**
	(-2 76)	(-4 87)	(-3 99)	(-2 38)	(-3 30)	(-4 38)
9	-0 02**	-0 04**	-0 00	-0 05**	-0 01	0 10**
	(-2 64)	(-3 69)	(-0 47)	(-3 24)	(-0 43)	(3 74)
10	-0 00	-0 01	-0 00	-0 00	0 01	-0 00
	(-0 54)	(-1 47)	(-0 17)	(-0 34)	(0 92)	(-0 08)
Jointly	(1 36)	(4 05)**	(4 56)**	(7 41)**	(5 40)**	(5 58)**
Extreme	(2 01)	(6 03)*	(7 75)**	(0 73)	(5 01)*	(4 12)*

	CAR[t1,t2]					
Port.	[-5,-1]	[0, 5]	[1, 5]	[-20,-1]	[1, 20]	[-20,20]
Panel C:	Dividend-yield-sorted Portfolios					
1	-0 07**	-0 13**	-0 08**	-0 10**	-0 13**	-0 29**
	(-3 54)	(-5 44)	(-4 31)	(-3 16)	(-4 17)	(-5 48)
2	-0 06**	-0 09**	-0 05**	-0 07*	-0 07**	-0 18**
	(-3 81)	(-4 99)	(-3 35)	(-2 60)	(-2 70)	(-4 30)
3	0 04**	-0 06**	-0 02	-0 03	-0 03	-0 10**
	(-3 32)	(-3 53)	(-1 83)	(-1 44)	(-1 48)	(-2 73)
4	-0 03*	-0 05**	-0 00	-0 05*	-0 04	-0 14**
	(-2 43)	(-3 20)	(-0 13)	(-2 54)	(-1 80)	(-4 12)
5	-0 01	-0 03*	-0 01	-0 03	-0 03	-0 09**
	(-1 02)	(-2 23)	(-1 06)	(-1 75)	(-1 75)	(-2 97)
6	-0 02*	-0 04*	-0 00	-0 04	-0 05*	-0 12**
	(-2 02)	(-2 56)	(-0 16)	(-1 78)	(-2 39)	(-3 57)
7	-0 00	-0 09**	-0 05**	-0 02	-0 06**	-0 12**
	(-0 37)	(-6 14)	(-4 49)	(-0 95)	(-3 19)	(-3 68)
8	-0 01	-0 07**	-0 03**	-0 03	-0 03	-0 10**
	(-0 50)	(-4 42)	(-2 91)	(-1 17)	(-1 73)	(-3 12)
9	-0 03*	-0 06**	-0 03*	-0 04	-0 03	-0 11**
	(-2 58)	(-3 84)	(-2 20)	(-1 87)	(-1 19)	(-2 87)
10	-0 03*	-0 03	-0 01	-0 03	0 01	-0 04
	(-2 30)	(-1 89)	(-1 08)	(-1 42)	(0 26)	(-1 10)
Jointly	(1 14)	(4 26)**	(5 84)**	0 87	(4 01)**	(3 28)**
Extreme	(1 87)	(19 31)**	(23 77)**	(3 25)	(27 48)**	(21 05)**

TABLE 4 4

The cumulative abnormal returns (CAR's) for the set of beta-sorted portfolios for six time intervals for the two beta model and their respective t-values (in parentheses for portfolios 1 through 10) are reported below. Portfolios one and ten contain the deciles of securities with the smallest and largest beta values respectively. The F-values for a joint test of the hypothesis of no difference in the portfolio CAR's from zero for all ten portfolios jointly are presented below in the parenthesis for each time interval on the row labelled "Jointly". The F-values for a joint test of the hypothesis of no difference in the CAR's from zero for the two extreme portfolios (portfolios one and ten) are presented in the parenthesis for each time interval on the row labelled "Extreme".

	CAR[t1,t2]					
Portfolio	[-5,-1]	[0, 5]	[1, 5]	[-20,-1]	[1, 20]	[-20, 20]
1	-0 10**	-0 17**	-0 10**	0 02	0 17**	0 23**
	(-4 62)	(-5 78)	(-4 54)	(0 47)	(-4 06)	(3 51)
2	-0 05**	-0 13**	-0 09**	-0 09**	-0 11**	-0 25**
	(-3 39)	(-6 61)	(-5 65)	(-3 15)	(3 72)	(5 51)
3	-0 05**	-0 10**	-0 05**	-0 06**	0 07**	0 19**
	(-4 50)	(-6 81)	(-4 21)	(-2 78)	(3 16)	(5 50)
4	-0 03**	-0 09**	-0 05**	-0 05*	0 09**	0 19**
	(-3 03)	(-6 42)	(-4 29)	(-2 22)	(4 12)	(5 61)
5	-0 03**	-0 12**	-0 07**	-0 07**	0 10**	0 22**
	(-2 93)	(-8 45)	(-6 74)	(-3 12)	(4 95)	(6 81)
6	-0 02	-0 09**	-0 06**	-0 03	0 08*	0 14**
	(-1 51)	(-4 29)	(-3 80)	(-0 84)	(2 51)	(2 74)
7	-0 02	-0 11**	-0 05**	-0 03	-0 08**	0 16**
	(-1 90)	(-6 79)	(-4 40)	(-1 15)	(3 17)	(-4 46)
8	-0 00	-0 13**	-0 08**	-0 02	-0 11**	-0 17**
	(-0 06)	(-6 94)	(-5 43)	(-0 64)	(-3 97)	(-4 18)
9	-0 00	-0 12**	-0 08**	0 01	-0 13**	0 15**
	(-0 20)	(-5 76)	(-5 23)	(0 28)	(-4 17)	(3 31)
10	0 01	-0 11**	-0 07**	0 03	0 10*	0 11*
	(0 83)	(-4 62)	(-4 10)	(0 82)	(-2 90)	(2 13)
Jointly	(8 14)**	(0 96)	(4 06)**	(1 01)	(1 23)	(0 97)
Extreme	(21 37)**	(4 27)*	(0 01)	(0 36)	(0 34)	(0 62)

TABLE 4 5

The beta characteristics for the set of beta-sorted portfolios are reported below The beta for the pre-event estimation period (β') is reported for the one-beta model The beta for the post-estimation period (β") and the difference between the betas for the post- and pre-estimation periods (Δβ) are reported for the two-beta model N is the number of securities included in each portfolio The reported beta value for each portfolio is the equally-weighted average of the beta values for each portfolio Portfolio one (ten) contains the decile of securities with the lowest (highest) beta "*" and "**" indicate statistical significance at the 0 05 and 0 01 levels respectively

			1β Model	2β Model		
Portfolio	Screen	N	β'	β"	Δβ	t-value
1	-0 64	95	-0 64	0 20	0 84	5 99**
2	-0 03	95	-0 03	0 25	0 28	2 99**
3	0 14	95	0 14	0 28	0 13	1 79
4	0 29	95	0 29	0 34	0 04	0 67
5	0 42	95	0 42	0 41	-0 01	-0 19
6	0 54	95	0 54	0 49	-0 04	-0 42
7	0 68	95	0 68	0 45	-0 23	-3 04**
8	0 87	95	0 87	0 52	-0 35	-4 01**
9	1 14	95	1 14	0 66	-0 47	-4 87**
10	1 73	94	1 73	0 78	-0 95	-8 42**

F-value of 67 03** for H Δβ = = Δβ = 0

TABLE 4 6

The changes in the risk premium λ for residual volatility and tests of their significance (t-values) for the beta sorted portfolios are reported below The λ_j estimates are obtained from the following GARCH-M model

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \lambda_j h_{jt} D_{[0,170]} + \varepsilon_{jt}$$

$$h_{jt} = c_j + a_j \varepsilon_{jt-1}^2 + b_j h_{jt-1}$$

Portfolios one and ten contain the deciles of securities with the smallest and largest beta values respectively "*" and "**" indicate statistical significance at the 0 05 and 0 01 levels respectively

Portfolio	α	β	c	a	b	λ
1	0 54E-2**	0 35**	0 14E-1**	0 44**	0 43**	16 84**
	(3 43)	(6 90)	(11 53)	(9 37)	(2 59)	(3 51)
2	0 61E-3*	0 21**	0 30E-2**	0 57**	0 72**	3 48
	(1 65)	(8 30)	(6 93)	(15 04)	(14 79)	(0 50)
3	0 11E-3	0 84**	0 63E-2**	0 62**	0 26	3 24
	(0 22)	(67 49)	(8 03)	(5 88)	(0 95)	(0 38)
4	0 93E-3**	0 30**	0 25E-2**	0 55**	0 75**	3 05
	(3 22)	(11 52)	(7 71)	(15 79)	(20 36)	(0 54)
5	0 38E-3	0 47**	0 18E-2**	0 61**	0 76**	4 51
	(1 39)	(23 08)	(5 96)	(14 12)	(19 42)	(0 63)
6	0 17E-3	0 89**	0 32E-2**	0 76**	0 66**	4 28
	(0 45)	(69 64)	(6 63)	(10 22)	(12 13)	(0 66)
7	0 68E-3**	0 67**	0 22E-2**	0 62**	0 72**	3 08
	(2 54)	(34 55)	(6 33)	(11 81)	(11 77)	(0 43)
8	0 82E-3**	0 78**	0 32E-2**	0 81**	0 43**	5 40
	(2 56)	(54 07)	(9 66)	(12 61)	(5 39)	(1 06)
9	0 10E-2**	0 80**	0 32E-2**	0 53**	-0 77**	9 75
	(2 28)	(44 79)	(5 27)	(10 37)	(-14 14)	(1 10)
10	0 82E-3*	0 90**	0 40E-2**	0 64**	0 67**	1 25
	(1 92)	(40 70)	(7 60)	(9 51)	(9 92)	(0 17)

TABLE 4 7

The cumulative abnormal returns (CAR's) for the beta-sorted portfolios for the time period [0.5] for the GARCH (1 1) model are represented by T_j Portfolios one and ten contain the deciles of securities with the smallest and largest beta values respectively "*" and "**" indicate statistical significance at the 0 05 and 0 01 levels respectively The estimated GARCH model is

$$R_{jt} = \alpha_j + \beta_j R_{mt} + T_j D_{[0,5]} + \varepsilon_{jt}$$

$$h_{jt} = c_j + a_j \varepsilon_{jt-1}^2 + b_j h_{jt-1}$$

Note that T represents the CAR over the period [0 5] since $D_{[0,5]}$ is a dummy variable that equals one for $0 \leq t \leq 5$

Portfolio	α	β	c	a	b	T
1	0 28E-2**	0 18**	0 01**	0 56**	0 00	-0 35E-1**
	(2 24)	(3 44)	(30 88)	(10 72)	(0 00)	(-6 97)
2	0 50E-3	0 21**	0 3E-2**	0 58**	0 72**	-0 19E-1**
	(1 49)	(6 77)	(6 82)	(14 63)	(14 81)	(-4 02)
3	0 75E-3**	0 27**	0 24E-2**	0 54**	0 75**	-0 14E-1**
	(2 57)	(9 03)	(8 06)	(15 58)	(23 28)	(-3 92)
4	0 72E-3**	0 34**	0 27E-2**	0 56**	0 66**	-0 16E-1**
	(2 45)	(15 01)	(6 94)	(12 24)	(8 37)	(-5 59)
5	0 38E-3	0 41**	0 19E-2**	0 63**	0 74**	-0 21E-1**
	(1 47)	(16 12)	(6 08)	(13 51)	(16 95)	(-6 69)
6	0 73E-3**	0 51**	0 23E-2**	0 66**	0 75**	-0 12E-2
	(2 32)	(12 22)	(5 70)	(13 67)	(20 01)	(-0 25)
7	0 64E-3**	0 63**	0 23E-2**	0 63**	0 71**	-0 14E-1**
	(2 48)	(27 28)	(6 31)	(12 13)	(11 93)	(-4 91)
8	0 84E-3**	0 68**	0 34E-2**	0 89**	0 43**	-0 10E-1**
	(2 90)	(26 67)	(9 57)	(16 43)	(5 86)	(-4 52)
9	0 67E-3*	0 81**	0 33E-2**	0 53**	0 75**	0 84E-2*
	(1 64)	(19 80)	(5 61)	(11 98)	(13 49)	(1 95)
10	0 81E-3*	1 00**	0 38E-2**	0 58**	0 71**	0 13E-1**
	(1 89)	(24 50)	(7 01)	(10 79)	(12 08)	(2 63)