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INTRA-DAY PRICE VOLATILITY: A REFLECTION OF TRADING FRICTION

by

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Abstract

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The ability of an equity market to accommodate a series of trades and incorporate new information into stock prices with minimal price volatility is an important aspect of its quality. If price discovery is marked by price swings, runs and reversals, then short period (intra-day) volatility is heightened in the market. In this study, we use return series with various differencing intervals that are as short as half-hour and as long as two weeks to investigate the short-term volatility accentuation in five equity markets: the Nasdaq Stock Market and the New York Stock Exchange in the US, and the London Stock Exchange, Deutsche Boerse and Euronext Paris in Europe. In all these markets, we investigate the individual stocks that make up a major index during the calendar year 2000.

A variance-ratio statistic and market model tests are employed to investigate the quality of these five markets. Results confirm an intra-day reverse J-shaped pattern of half-hour volatility in these markets. (However, we are not able to find the same pattern in intra-day volume in all markets.) In addition, we find evidence of an intra-week pattern in volatility with higher volatility on Monday opening periods and Friday closing periods.

The evidence also suggests an accentuation of volatility during longer periods, such as 24-hour intervals. This accentuation appears to subside when we extend our differencing interval to longer periods such as one-week or two-week returns.

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Chapter 1: Introduction

The ability of an equity market to accommodate a series of trades and incorporate new information into stock prices with minimal price volatility is an important aspect of its quality. If the price discovery process is marked by price swings, runs and reversals, in other words if the price discovery process is not efficient, then intra-day volatility will be heightened in the market. Heightened intra-day volatility makes trading more difficult and hence may scare liquidity away. Furthermore, increased intra-day volatility can invite more speculative short-term trading into the market (day trading). Even though some traders might be able to profit from it, high intra-day volatility is costly to the market in aggregate. It discourages trades, lowers portfolio performance for most traders and makes portfolio returns more uncertain for everybody.

This dissertation investigates intra-day price volatility accentuation both inter-temporally and across several stock markets, and assesses it as an inverse measure of equity market quality. We investigate stock price volatility in several differencing intervals that are as short as half-hour to as long as two weeks in five different equity markets in the US and in Europe.

In an ideal world, with informationally efficient markets, prices adjust instantaneously to new information arrival into the market. As a result, volatility is caused solely by the permanent price shifts due to new information. However, it has been established in the academic literature (and is widely accepted among industry practitioners) that trading itself creates price runs and reversals even in the absence of new information and the price discovery process is less efficient than described above.

Price changes that are not motivated by new information, but are created by the trading process itself, are generally referred to as trading friction (noise) in academic studies.[1] These price changes that are due to trading friction are temporary (transient) in nature since they stem from temporary pricing errors. On the other hand, price adjustments that are due to new information are referred to as innovation and are expected to create permanent price shifts.

Trading friction creates runs and reversals in stock prices over the short run. Consequently, if a market is characterized by high trading friction, then we expect to see a volatility accentuation for shorter measurement intervals compared with longer measurement intervals. In this study, we use accentuated intra-day volatility (compared to longer period volatility) to assess the level of trading friction in a market. Since more accentuated short-term volatility implies higher trading friction, it can be used as an inverse measure of the quality of a market.

The relationship between short-term volatility and trading costs[2] has been analyzed in the financial economics literature. Hasbrouck and Schwartz (1988), Stoll (2000) and Bessembinder and Rath (2002) are some of the studies that find evidence of the link between accentuated volatility and heightened transaction costs. However,

[1] Several studies also define "informational" friction as the price over or undershooting in response to new information (e.g. Stoll 2000).

[2] Trading friction and trading costs are used interchangeably in this study since high trading friction translates into a cost of trading borne by traders. However, it should be emphasized that by trading costs we refer solely to price discovery errors and not costs such as commissions, fees or taxes.

inferring trading costs from volatility is a complex and tricky process. There are multiple reasons for this and the co-existence of various factors that collectively create both positive and negative correlation in the transactions data is an important one.

In general, the dynamic pattern of price discovery is characterized by multiple factors that simultaneously create runs and reversals in the price series of securities. Runs are the result of factors such as momentum trading, market impact of large trades, and overreaction to news announcements. These factors introduce positive autocorrelation into the stock price series. On the other hand, the reversals of these trends and other factors such as the bid-ask bounce introduce negative autocorrelation[3]. It is important to note that even though all the factors mentioned co-exist simultaneously in the stock price series, they impact the stock prices separately. For example, while there might be momentum trading that introduces positive autocorrelation into the price series, the bid-ask bounce or the reversal of the market impact of a large order will also co-exist in the price series, and create a counter impact to the price run caused by the momentum trading.

A commonality across the above-mentioned factors is that they exhibit themselves in shorter intervals and, as a result, the choice of length of measurement becomes an important empirical question. Of course, the extent of impact of the different factors varies substantially in terms of time. For example, the market impact of a large trade will not typically last as long as the overreaction to an important news announcement. More generally, while a measurement interval of a day is too long since the above mentioned

[3] These issues are discussed in depth in chapter 4, the analytical framework.

factors get washed out in longer periods, a too short period such as 5 minutes would be insufficient for these factors to manifest themselves and hence too short to capture them. With these considerations in mind, we measure volatility at several differencing intervals and capture the relative effect of trading friction in shorter differencing intervals compared to longer differencing intervals. For this purpose we measure and compare volatility at intra-day half hour, open to close, close to close, open to open, one week, and two week intervals.

Since the purpose of this study is to investigate further the relationship between short-term volatility and transaction costs, it can be viewed as an extension of several studies that sought to make this connection in different ways. Schwartz and Whitcomb (1977) is an early study that provides evidence of negative autocorrelation in common stock returns by looking at the market model residuals and establishes the deviation from independence in stock returns in shorter measurement intervals. Hasbrouck and Schwartz (1988) and Lo and MacKinlay (1988) use variance ratios to establish that short-term volatility is accentuated compared to longer-term volatility. Hasbrouck and Schwartz, further show that accentuated short-term volatility is linked with heightened transaction costs. Stoll (2000) also shows that higher opening volatility is an indication of higher trading friction in the market.

A key innovation in the current study is that we look at the heightened volatility at different periods of the trading day. We divide the trading day into half hour periods and focus on the price pattern of each half hour period across days. In other words, we investigate the volatility of each of the half hour periods (the opening half hour, closing half hour etc.) separately. [4] The advantage of looking at different time periods across days, as opposed to consecutive periods during the day, is that it helps us break the effect of positive correlation in stock returns in consecutive periods, and capture more clearly how the trading friction changes throughout the day. As a result, we are able to investigate the intra-day patterns in stock price volatility. We give particular attention to the volatility accentuation following the opening, as this period is generally regarded as one where trading friction is highest.

We investigate intra-day volatility patterns in five different market centers. By investigating this issue across different market centers with different market structures, we establish the universality of the positive link between volatility and trading costs. We are also able to draw conclusions on whether or not there is any significant variation across different market structures on this issue[5].

Intra-day volatility is an important measure of friction. Demsetz (1968) describes trading friction as the price concession needed for an immediate transaction. Even though Demsetz refers mainly to the bid-ask spread, an immediate price concession can also be viewed as the difference between the buying and selling prices of the same asset within a very short period of time. In a highly volatile market, there is a greater chance that the stock price will be considerably different from its current price after a short time. Therefore, the price concession for such a transaction will be larger in more volatile markets. If volatility is clearly higher during certain periods of the trading day, then this

[4] The methodology, and the underlying thinking behind it, is discussed in further detail in Chapter 6.

[5] The opening procedures of all the five markets are discussed in detail in Chapter 3.

uncertainty makes trading more difficult (or costly) during those periods, and might cause traders to shy away from the market. [6]

If high volatility causes traders to wait before entering the market, then the prices discovered in the market will reflect the beliefs of only the subset of traders who do choose to trade. In other words, stock prices discovered in that market will be less accurate. There is anecdotal evidence that large institutional traders tend to stay away from the market during the first half hour of trading (unless of course when they need to trade due to new information or due to several portfolio rebalancing needs). This study will also investigate the intra-day patterns in trading volume across the five markets studied. If the institutional traders do stay away from the market at the open, then we expect to see less volume and fewer trades of large size during the beginning of the day.

In this study, we attempt to capture the intra-day patterns of volatility by dividing the trading day into half hour periods, such as 9:30 to10:00, 10:00 to 10:30 etc. In a trading day that is six hours long we have twelve half hour periods. Half-hour intervals are commonly used both in the academic literature (e.g. Coughenour 2001) and in the popular media, such as the Wall Street Journal, to report intra-day statistics pertaining to equity trading. We do not include overnight periods in the intra-day study and concentrate only on the price changes during the official trading hours. [7] We expect that overnight information would already be reflected in the first price of the day. Since our

[6] Chordia, Roll, and Subrahmanyam (2000) report that recent market volatility induces a decrease in trading activity using daily data.

[7] Recent studies (e. g. Amihud and Mendelsohn (1987)) show that the overnight returns are likely to come from a different distribution from the trading day.

emphasis is trading friction that stems from non-information related sources, we disregard the overnight price changes when calculating our short-term returns.

We calculate the logarithmic return for each of the half hour periods (for each stock) and create a time-series of these returns for each half hour period across days over the duration of our data. Then, we calculate the volatility of stock returns for each of the half hour intervals. In other words, we try to capture the relative volatility of different periods during the trading day, such as the opening half hour or the closing half hour. The underlying assumption of this approach is that we expect today's opening half hour stock price behavior to be less correlated with either tomorrow's or yesterday's opening half hour stock price behavior[8]. In other words, half hour intervals across days are not expected to be as highly autocorrelated as half hour intervals that follow each other consecutively. As a result, we should be able to capture the accentuated intra-day volatility and the level of trading friction more accurately by employing this approach.

As noted, this study uses data from 5 different markets. The New York Stock Exchange and the Nasdaq Stock Market in the U. S., and Deutsche Boerse, Euronext Paris, and the London Stock Exchange in Europe. In each of these markets, we study the individual stocks that comprise a major index (Nasdaq 100 and S&P 100 in the US, FTSE 100 in England, CAC 40 in France and DAX 30 in Germany) during the calendar year 2000.

The study enhances and extends the existing literature in several ways: It investigates intra-day stock price volatility as a way of capturing the trading friction

[8] We also statistically check for this autocorrelation using a Durbin-Watson test.

during the trading day. To that extent, it is an attempt to expand the studies on trading friction (that use daily data) that were mentioned earlier (e.g. Stoll (2000)). We are also contrasting short-term volatility with long-term volatility (such as from daily and weekly return series) to measure the extent of volatility accentuation during shorter periods. In addition, we show that there are day-of-the-week effects in volatility patterns. Finally, we use market model tests to show that even though trading friction is more pronounced at the open and close of trading for all stocks, these pricing errors are not correlated across stocks. We also use data from five different equity markets, in the US and in Europe, with a wide spectrum of different market structures and opening procedures employed. As a result, we are able to investigate whether or not patterns of volatility differ across various market centers and market opening procedures. Instead of using data on stock indices, we use tick-by-tick data on individual stocks in each market. Since price discovery and trading friction occur on an individual stock basis, we use individual stock price data in all markets in order to capture trading friction more accurately.

A further incentive for this study is a recent requirement by the Securities and Exchange Commission for markets to provide detailed disclosure of their execution quality. However, there is no single metric to measure execution quality (also known as market quality). Even the Commission writes in its Report on the Comparison of Order Executions Across Equity Market Structures (2001) that "There is no single, all-encompassing measure of market quality. For example, although effective spread is an important component, some investors may prefer a fast execution at a guaranteed price to a slower execution with the possibility of price improvement. In addition, effective spread measures the handling of a single trade, without considering the ability of a market structure to absorb a series of trades with minimal price volatility. " Consequently, our study can be seen as an investigation of intra-day price volatility as a single (inverse) measure of market quality and thus one of the metrics to compare order executions across different equity market structures. [9]

Since a major function of a marketplace is to establish the prices of the assets traded in it, then the quality of the market can be measured by how efficient it is in performing this task. The complexity of finding the price that best reflects the broad market is particularly magnified at times of stress. Examples include periods around critical news releases, major market moves, and following a period of non-trading such as the overnight close. A central premise of this study is that the quality of a market can best be evaluated during the stressful periods. Market openings are an excellent candidate to focus on – they are stressful, and they occur daily. Consequently, this study examines the dynamic behavior of prices that characterize market openings. More specifically, it assesses price volatility during the trading day, with an emphasis on the beginning of the trading day.

After establishing that volatility is a meaningful measure of market quality, the study assesses how the Nasdaq, New York Stock Exchange, Euronext Paris[10], Deutsche Boerse and the London Stock Exchange stocks fare according to this measure. The

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[9] Nasdaq (in its web-page) lists volatility as one of their four metrics to measure market quality, and publishes monthly reports of the volatility of Nasdaq 100 and the Nasdaq Composite indices.

[10] Euronext is a market born from the merger of the exchanges of Amsterdam, Brussels and Paris. In this study, data from only Euronext Paris is used.

remainder of the dissertation is organized as follows. Chapter 2 provides a literature review. Chapter 3 reviews the opening procedures in the alternative market centers studied. Chapter 4 establishes the analytical framework of the study. Chapter 5 describes the data. Chapter 6 is a discussion of the methodology and empirical results. Chapter 7 concludes the study.

Chapter 2: Literature Review

Market quality has been a subject of national debate since the 1970s. Even though market quality has been a focus of national debate due to the recent requirement by the Securities and Exchange Commission for stock markets to provide detailed disclosure of their execution quality, there is no single agreed upon metric to assess it. Academic literature on market quality is vast, with different researchers focusing on different aspects of market quality. These studies are either broad investigations that look at measures such as spread, depth, volatility and liquidity for different market centers (e. g. Chordia, Roll and Subrahmanyam (2000) and Stoll (2000)). Or they are more specific studies that concentrate on how different market structures respond to important rule changes (e. g. Chakravarty, Wood and Harris (2002) investigate the impact of decimalization).

In a comprehensive study that investigates liquidity and trading activity in the NYSE over the period of 1988 to 1998, Chordia, Roll, and Subrahmanyam (2000) find a relative lack of change in absolute daily prices (0. 56%) compared to average absolute change in daily liquidity variables (about 2%), average absolute change in daily depth variables (about 4-5%), and average absolute change in daily trading activity variables (15-20%). In this study, the authors use quoted and effective spreads and depth as the measures of daily liquidity and volume and number of daily transactions are used as the measures of trading activity.

This relative lack of change in absolute daily prices is a surprising result given the high levels of intra-day volatility documented in the current study and elsewhere, and suggests that there are big gyrations during the trading day that are not manifest in longer periods, even on a daily basis. In the current study, one area we investigate is how short term (intra-day) stock price volatility compares to the stock price volatility of longer measurement intervals such as daily and weekly intervals.

It has been suggested in the academic literature that the day of the week might have an effect on liquidity and trading. In fact, Chordia et al find that market is more liquid and trading activity is higher on Tuesdays through Thursdays compared to Mondays and Fridays. We also investigate the day of the week effect (or a weekly seasonality) in this study. Foster and Wiswanathan (1990, 1993) also show that trading volume is low and adverse selection costs are high on Mondays compared to other days.

An emerging sub-field of research in market quality is a transaction level analysis of the period surrounding the opening of trading after a period of non-trading (e. g. the overnight period or a trading halt). Typically these studies find that the opening of trading after a period of non-trading is a stressful period, and that informal[11] or formal[12] mechanisms are necessary to improve the efficiency of the opening. In a recent study, Cao, Ghysels and Hatheway (2000) document the price discovery that takes place in the Nasdaq market during the pre-opening period (8:00 am to 9:30 am). The authors present

[11] Such as the price signaling between the market makers in the Nasdaq market in the pre-opening period.

[12] Examples include the opening call auctions in Euronext Paris, and Deutsche Boerse or the specialist intervention in the opening auction of the NYSE.

evidence that market makers signal to each other the direction they think the price will move in through posting non-binding bid and ask quotes. Through this price signaling activity, there is price discovery before the market opens and the opening price reflects the cumulative information of all market makers that participated in the pre-opening. The authors maintain that most of the price signaling is done through locked or crossed quotes[13]. Biais, Hillion, Spatt (1999) provide an analysis of the Paris Bourse pre-opening period and show that there is price discovery during the pre-opening even in the absence of specialist intervention.

Madhavan and Panchapagesan (2000) examine the process of price discovery at the New York Stock Exchange single-price opening auction. The authors argue that the presence of designated dealers (i. e specialists) facilitates price discovery relative to a fully automated call auction market without intermediation. They maintain that this reflects the information specialists gain from observing the evolution of the limit order book and the requirement they have to provide price stabilization.

Increased volatility is also expected following intra-day trading halts since trading halts are periods without any formal price discovery process. In fact, Lee, Ready and Seguin (1994) investigate the pattern of volume and volatility following the NYSE trading halts and find that the implementation of trading halts increase, rather than decrease, both volume and volatility following the halt[14]. Christie, Corwin and Harris

[13] Locked quotes are the quotes where the best bid and the best ask are the same. Crossed quotes are the quotes where the best bid is higher than the best ask.

[14] Corwin and Lipson (2000) also investigate the impact of trading halts on the NYSE.

(2002 JF), on the other hand, in a similar study find that the post trading halt period is associated with unusually high volatility and share volume in the Nasdaq market. In the spirit of the above studies, this study also puts emphasis on the stock price behavior during the opening of trading.

Trading friction in financial markets measures the difficulty with which an asset is traded. Stoll (2000[15]) is a recent study that investigates trading friction for the NYSE stocks. Stoll's study follows in the footsteps of Cohen, Hawawini, Maier, Schwartz, and Whitcomb (CHMSW) (1980 and 1983) and Demsetz (1968). Demsetz describes trading friction as the price concession needed for an immediate transaction. CHMSW (1980) further argue that "to understand better the behavior of markets, the effects of friction must be modeled". In his study, Stoll states that trading frictions are particularly pronounced at the opening of a market and can be captured by measuring the opening volatility. Stoll's definition of opening volatility takes into consideration only the first price of the day, and not the price changes immediately following the opening. More specifically, he measures the accentuated volatility at the open (compared to volatility at the close) using the following metric

$$OV = |O_t - O_{t-1}| - |C_t - C_{t-1}|$$

where O_t = the opening price on day t and C_t = the closing price on day t. He finds, for a sample of NYSE/AMSE and Nasdaq stocks over the period of December 1, 1997 to February 28, 1998, that opening volatility is significantly higher than closing volatility

[15] Originally presented as the presidential address at the 1999 American Finance Association meetings, this study is later published in the Journal of Finance in its August 2000 issue.

for both samples and also OV is slightly larger in the Nasdaq sample compared to NYSE/AMSE.

There are two types of friction, real and informational, that might be causing the accentuated opening volatility. First, high opening volatility might be due to real friction, such as imperfections in the opening procedures of the different market centers. For example, in the NYSE each stock has a designated Specialist whose duty it is to establish the opening price of that stock. On the other hand, in the Nasdaq market there are multiple market makers for each stock and there is a lack of a clear opening procedure. As a result, in the Nasdaq market trading is opened by multiple market makers quoting their own bid and ask prices. [16] Second, high opening volatility might be reflecting informational friction such as overreactions to news announcements that came in during non-trading hours by the traders who are trying to discover the equilibrium price. In the absence of friction at the open (i. e. in the case of perfect market efficiency) opening volatility should not be different from closing volatility. In other words, it should not matter whether you use the opening or the closing prices to calculate the volatility.

Stoll's finding that all market centers experience accentuated opening volatility lends support to the existence of informational friction. Furthermore, his finding that Nasdaq stocks have a higher OV compared to NYSE/AMSE stocks suggest that different opening procedures employed by these markets might affect the extent of trading friction experienced. On the other hand, Stoll's study focuses on daily data and he writes "I

[16] The study by Cao, Ghysels and Hatheway (2000) shows that market makers in the Nasdaq market discover prices in the pre-trading period (8:00 am to 9:30 am) by signaling to each other the direction they think the price will move in through posting non-binding bid and ask quotes.

summarize friction measures by day and consequently ignore important intra-day variations first investigated by Wood, McInish and Ord (1985) and Chan, Christie and Schultz (1995)".

A sample of stocks that move from Nasdaq to NYSE is analyzed by Bessembinder and Rath (2002). Their sample comes from stocks that moved from Nasdaq to NYSE over the period of 1996-2000 and the author finds that the return volatility of these stocks decreases substantially following the move. According to Bessembinder and Rath, this decrease in volatility is due to lower transaction costs in the NYSE.

Stoll's definition of opening volatility is in the spirit of Amihud and Mendelson (1987) and Stoll and Whaley (1990). Before Amihud and Mendelson (1987), daily volatility was traditionally calculated from close to close returns. Theirs was the first academic study that compared the variance of the open-to-open returns to the close-to-close returns of the stocks of the DJ Industrial Index. They found that open-to-open returns had a higher variance compared to the close-to-close returns[17]. Stoll and Whaley (1990) also compare open-to-open returns to close-to-close returns for all NYSE stocks from 1982 to February 1986 and document the same phenomenon[18]. In addition, the authors investigate the relationship between volume and volatility, and find an inverse relationship between volume and daytime volatility, but a positive relationship between

[17] Gerety and Mulherin (1994) extend this line of research and calculate 24 hour return variances on an hourly basis in addition to the opening and the closing variances. The authors find that the variance decreases monotonically from the open to the close.

[18] For an early paper on stock returns during trading hours versus non-trading hours see Oldfield and Rogalski (1980).

volume and overnight volatility. Jones, Kaul and Lipson (1994), on the other hand, show that the positive volatility-volume relation documented by numerous researchers actually reflects the positive relation between volatility and the number of transactions. Thus, according to the authors, it is the occurrence of transactions per se, and not their size, that generates volatility[19].

The importance of the differencing interval when measuring variance has been established in the literature. Hasbrouck and Schwartz (1988), and Lo and MacKinlay (1988) are two studies that show that the variance estimated for the same data sample, however at different sampling frequencies, give different results. This is in contrast to a random walk model of stock returns that would give the same number for variance no matter how the sampling frequency is set as long as the same calendar period is investigated. Furthermore, if stock prices follow a random walk then we expect to find evidence of neither positive nor negative autocorrelation.

Lo and MacKinlay show that while a positive autocorrelation is observed for equity portfolios (leading to more depressed short term volatility compared to long term volatility), the pattern of individual stocks prices give evidence of negative autocorrelation (leading to increased short term volatility compared to long term volatility). While Lo and MacKinlay focus on longer differencing intervals such as weekly and monthly intervals, Hasbrouck and Schwartz focus on shorter intervals. More specifically, Hasbrouck and Schwartz compare short-term (half hour) variance to long-

[19] Coughenour (2001) extends the analysis of Jones, Kaul and Lipson (1994) to an intraday setting, and Huang and Masulis (1999) document similar phenomena using London Stock Exchange data.

term (two days) variance and show that the short-term variance is accentuated compared to long-term variance for individual stocks. In addition, the authors argue that the short-term accentuated volatility is due to heightened transaction (execution) costs. The transaction (execution) cost in this context is defined as the cost of trading an asset quickly and is incurred by the active traders (market order traders) as opposed to passive traders (limit order traders).

Intra-day patterns in volatility, and volume were first documented by Wood, McInish and Ord (1985), Jain and Joh (1988) and Harris (1986). Subsequently, this area has been investigated by other academic studies including Madhavan et al (1997) and Gerety and Mulheren (1994). Generally, these studies find a U-shape in volume and volatility across the markets studied. One of the more important differences between these studies and the current one is that, in these studies, patterns of stock indices are investigated as opposed to the patterns of individual stocks that are investigated in the current study. Price discovery takes place on an individual stock basis, and one of the primary reasons for the accentuated intra-day volatility is the errors in price discovery for the individual stocks that occur during the trading day. By investigating individual stocks, we would like to capture the extent of this phenomenon[20]. Furthermore, another important difference between our study and some of the studies mentioned above is that these studies calculate and contrast the volatility of 24-hour returns, albeit beginning the 24 hour period at different times of the day. In other words, they measure 9:30 to 9:30

[20] Campbell et. al (2001) report that over the period between 1962 to 1997 there has been a noticeable increase in firm-level volatility relative to market volatility.

volatility, 10:00 to 10:00 volatility etc. In addition to measuring open to open and close to close (ie. 24 hour) volatilities, in this study we also concentrate on shorter term volatility by investigating the pattern of intra-day half hour and open to close volatilities.

The intra-day pattern of the bid-ask spread has also been investigated in the academic literature. These studies show that there is some variation across different market structures in terms of the pattern of the spread. More specifically, even though Wood and McInish (1992) find that spreads in the NYSE have a U-shaped pattern during the day, other studies investigating the bid-ask spread in dealer markets do not find a similar shape. Chan, Christie and Schultz (1995) use a sample of Nasdaq stocks and find that spreads are relatively stable throughout the trading day but narrow significantly during the last hour of trading. Kleidon and Werner (1993), on the other hand, identify a pattern of declining intra-day spreads during the trading day in the London Stock Exchange.

Admati and Pfleiderer (1988) provide a theoretical explanation for the intra-day U-shaped patterns in volume and volatility in which concentrated-trading patterns arise endogenously as a result of the strategic behavior of liquidity traders and informed traders. In this model, information comes to the market randomly throughout the day, inducing the informed traders to act upon their information when they receive it. On the other hand, liquidity traders can time their trades and they choose to concentrate their trading at the open and at the close. The rationale for this behavior is their attempt to minimize the adverse selection costs they would incur when they trade against the informed traders by increasing their chances of trading with another liquidity trader through bunching together. As a result, due to the strategic behavior of traders, the trading is concentrated at the open and the close, creating the U-shaped patterns of volume and volatility.

Several other models, generally labeled as the price formation models (e. g. Dow and Gorton (1993), Grundy and McNichols (1989) and Leach and Madhavan (1993)), explain the heightened volatility at the open by the high level of information asymmetry at the open. According to these models, information asymmetry decreases over the day as the prices are discovered through trading. These models predict that volatility should also decrease as the trading day progresses as the information asymmetry decreases and prices reflect the market consensus better.

There are several empirical studies that document the price discovery that takes place through trading. For example, Fleming and Remolina (1999) show, using US Treasury Market data, that prices adjust to new information arrival over a two stage prolonged period as opposed to an immediate adjustment. The authors show that in the first stage, prices adjust sharply to just released new information, showing trading is not essential for price discovery. However, high volume and volatility are observed over the prolonged second stage, indicating a residual disagreement about among traders. After this second stage volume and volatility returns to normal levels. Finally, Chordia and Swaminathan (2000) show that the stocks with lower trading volume respond more slowly to new information in market returns compared to the stocks with higher trading volume, once again indicating the importance of trading to price discovery.

Several researchers argue that the trading costs should increase towards the end of the trading day, creating more volume and volatility near the closing of trading. Examples include Bessembinder (1994), and Brock and Kleidon (1992). These studies argue that traders (and market-makers) try to rebalance their portfolios at the end of the trading day to minimize the costs of carrying inventory overnight, causing the observed increases in volume and volatility. In other words, the pressure of the approaching market close creates an environment with higher volume and volatility.

Since European markets make extensive use of the call-auction trading mode in addition to the continuous trading, we are able to make inferences on the relative merits of call auctions in this study. Schwartz (1993) defines a call market as a market where orders are batched for simultaneous execution at a single price when the market is "called".[21] This is in contrast to continuous trading where trading takes place "continuously" whenever a buy order meets a sell order during the trading hours.

Madhavan (2000) also discusses call auctions in a recent study. He defines the network externalities puzzle as the existence of geographical and temporal fragmentation in trading despite the positive externalities of consolidation such as pooling of information and better price discovery. Temporal consolidation of trading would take the form of a call auction that aggregates the buy and sell orders for execution at a certain point in time. The price of the call auction is the price that maximizes the number of executions. During our study period, there has been relatively important rule changes in

[21] Call auction trading is discussed and analyzed from several different angles at a recent book titled "The electronic call auction: Market mechanism and Trading" edited by Schwartz (2001).

the European markets regarding call auction trading as London Stock Exchange introduced a closing call auction and Deutsche Boerse increased the number of intra-day call auctions to two.

Chapter 3: Opening Procedures in Alternative Markets

Opening of trading following a period of non-trading such as the overnight or weekend market close is a particularly stressful period for market participants. It is during this time that all the information that accumulated during the non-trading period needs to be incorporated into stock prices. As a result, during the opening period there is greater uncertainty regarding the stock prices' ability to reflect new information. Furthermore, the variation across market participants in regards to the interpretation of news (also known as heterogeneous expectations) could also add to the stress of this particular period. As a result, market openings are characterized by higher volatility than the rest of the day[22].

Since the opening interval is an important period of price discovery, many equity markets employ special protocols to facilitate the start of trading. Domowitz and Madhavan discuss both the importance and the challenges of the opening procedures in an article in a book edited by Schwartz (2001). The authors write that "efficient price discovery is a crucial function for securities market. Opening procedures play an especially important role in facilitating price discovery following the enforced trading halt induced by the overnight or weekend non-trading period. Indeed, many markets use special opening procedures designed to provide traders with information regarding

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[22] Domowitz and Madhavan (2001) argue that the increased uncertainty following the opening can translate into not only more volatile prices but also less liquidity at the open.

market clearing prices with a view toward enhancing liquidity and reducing intra-day price volatility".

The perspective that Domowitz and Madhavan hold, not uncommon in the market microstructure literature, is that the particular opening protocol chosen by the market can indeed influence how successful it is in discovering prices. Since this study investigates five different equity markets, we can indirectly[23] assess whether or not there are any significant variations in price behavior during the opening across markets. All of the five markets we study are structured differently, and they employ unique protocols to open the market in the morning. This chapter provides an overview of the different opening procedures followed by the equity markets included in our study.

New York Stock Exchange has a formal opening procedure that may be characterized as an intermediated opening. For each stock on the NYSE, there is a designated specialist whose duty it is to set the opening price. As a matter of fact, the specialist has a broader obligation to maintain a fair, competitive, orderly and efficient market and to provide price continuity for the stocks that he or she is responsible for.

Prior to the opening, the specialist observes the overnight accumulation of the limit orders on the limit order book. In addition, market orders are accumulated prior to the open on the Opening Automated Report System (OARS). These orders might come electronically through the SuperDOT system, or they might also come from the floor

[23] We do not directly test for differences across markets, rather we try to establish the importance of the opening period across different market structures.

brokers.[24] Even though the specialists provide indications of the order imbalance to the floor community before the open, they are the only ones who know the individual orders that make up the limit order book and market orders (and hence the order imbalance).

At 9:30, the specialists choose the prices at which the market will open. At this price, all the market on open orders and limit orders (with prices at or better than the opening price) trade. In addition to these obligations and setting the price of the stock, the specialist is also allowed to trade the stock proprietarily, and as a result enjoys, as a trader, the unique informational advantage that stems from being able to observe the order flow. At the open, the specialists, once they set the opening price, must absorb any excess demand or supply at the opening prices from their inventories.

Even though the specialist typically trades at the open either to offset a buy/sell order imbalance or as a proprietary trader, it has been shown that their relative trading volume in larger and more liquid stocks is significantly less than their trading volume in smaller and less liquid stocks. As a result, we expect that the specialist intervention will be less for our NYSE sample that consists of very large capitalization and highly liquid stocks.

Furthermore, in the NYSE, the specialist can delay the opening of a stock, if he or she deems necessary, for short periods of time such as 10-15 minutes[25]. The reasons for a delayed opening can include a large buy/sell order imbalance or an important pending

[24] Sofianos and Werner (2000) report that floor participation at the open is low, especially for more active stocks.

[25] The specialist can delay the opening longer as well but needs to get the approval of a designated floor official in that case.

news announcement. Since volatility is scaled according to time in our study, a delayed opening may create a bias in our findings. In other words, instead of measuring the price change from 9:30 to 10:00 for our first half-hour period, we could be measuring the price change from 9:45 to 10:00 (if we consider a 15-minute delay in the opening) and still treat it as a half hour period. However, this is a bias on the conservative side since its effect would be to decrease the extent of the opening volatility spike that we observe. Furthermore, given that, for our sample of large and liquid stocks, opening delays are relatively rare, we consider this an acceptable bias.

In a recent study, Madhavan and Panchapagesan (2000) show that the specialist intervention facilitates the price discovery at the open in the NYSE and makes the opening price more efficient compared to a fully automated opening procedure (i.e. an opening call auction) without specialist intervention. The way the authors define efficiency of the opening price is by comparing that price to the future 3:00 pm price observed during the same day. The authors argue that this increased efficiency reflects the information specialists gain from observing the evolution of the limit order book and the requirement they have to provide price stabilization. However, needless to say, call auctions can be designed in a variety of ways. The comparison the authors make is between the specialist-intermediated opening at the NYSE and an automated call auction without full transparency[26] that would have taken place if there were no specialist intervention at the NYSE opening. It is not clear, however, whether the benefits of the

[26] Transparency in this context can be defined as the market participants' ability to observe the evolution of the limit order book before the market opening.

specialist intervention would have remained for a call auction that provides full transparency before the market open (such as the case with the opening protocol of Euronext Paris).

Compared to the NYSE that is a floor based auction market where there is only one specialist making the market per stock, the Nasdaq Stock Market consists of competing market makers and Electronic Communication Networks (ECNs) that enter the bid and the ask quotes. The highest bid and the lowest ask that are quoted are called the inside quotes, and trading takes place at these quotes. Contrary to the NYSE, Nasdaq does not have a formal opening procedure. Furthermore, Nasdaq does not have a trading floor.

In Nasdaq, market makers and ECNs start entering their bid and ask quotes to the system as early as 6:00 am. Until June 5, 2000, the quotes that were entered by the market makers before the 9:30 am market open were not binding but merely "indicative". However, On June 5, 2000 a new "trade or move" rule was implemented. According to this rule, the market makers that enter a locking or crossing quotation between 9:20:00 am and 9:29:59 am are required to either trade at that price or to change their quotations to unlock/uncross the market within 30 seconds. Formal trading starts at 9:30 am on the Nasdaq market and all the quotes entered become firm quotes. In other words, starting at

9:30 am market makers have an obligation to buy and sell the minimum share size[27] at the quoted prices.[28]

A recent study by Cao, Ghysels and Hatheway (2000) shows that even though there is no formal opening procedure at the Nasdaq market, the market makers do engage in informal price discovery during the pre-opening period of 8:00 am to 9:30 am. The authors present evidence that market makers signal to each other the direction in which they think the price will move, through posting non-binding bid and ask quotes. Through this price signaling activity, the market makers are able to communicate with each other information regarding price direction and level that leads to price formation. Communication via the price signaling activity described is imperative to Nasdaq, since direct verbal communication between dealer firms about market conditions have been discouraged with the implementation of SEC's new order handling rules.

As a result, there is price discovery in the Nasdaq market before the market opens and the opening price reflects the cumulative information of all market makers that participated in the pre-opening. According to these authors, this outcome is mutually beneficial for all the market makers in Nasdaq. It is also important to note that, in addition to revealing information about the stock prices, the market makers also reveal their identity when they post their quotes in the pre-opening period. Since market opening

[27] The minimum size requirement shows variation over time and is typically less for less active stocks.

[28] It is important to note that starting July 2002, Nasdaq will start phasing in the SuperMontage system. This system will imply important changes to several trading rules currently in place.

is a repeated game, market makers who try to exploit their information at the expense of other market makers might find fewer counter-parties to trade with in the future.

The European markets we investigate, the Deutsche Borse, Euronext Paris and London Stock Exchange, are all electronic order-driven markets, and in this respect they are relatively similar to the NYSE. However, none of them has a physical trading floor. Also, the London Stock Exchange comes from a dealer-market structure that used to resemble the Nasdaq Stock Market. All of these European markets open their trading in the morning with a call auction.[29] After the opening auction in each market, trading starts in the form of continuous trading. At the Euronext Paris and Deutsche Bourse the opening call auction takes place at 9:00 am. On the other hand, the opening call auction takes place at 8:00 am on the London Stock Exchange.[30] However, if we take into consideration the one-hour difference between England and the Continental Europe, then we see that the start of trading is synchronized for all three European markets studied.

One of the more important differences between Deutsche Borse and Euronext Paris with respect to their opening procedures is that Deutsche Borse has intermediated openings (with the help of a "kursmakler"), whereas the opening at the Euronext Paris is fully automated. Deutsche Borse has a specialist system that is similar to the specialist system of the NYSE. Again there is only one specialist in the Deutsche Borse, called "Kursmakler", for each stock, and one kursmakler can make the market for multiple

[29] All of these markets also close their trading with a call auction that takes place shortly after continuous trading stops. In addition, Deutsche Borse employs several intra-day call auctions during the trading day.

[30] Our analysis shows that this is not a "successful" call auction in the sense that volume traded at the opening call auction at the LSE is very small compared to the opening call auctions of the other European markets studied.

stocks. Furthermore, the kursmakler is also able to trade proprietarily for her account. At the opening call auction, it is the kursmakler who sets the opening price based on the order flow that came in during the non-trading period.

There are no specialists at Euronext Paris and as a result the opening price that is the outcome of the opening call auction depends solely on the orders that came in during the pre-opening period. The pre-opening period of the Euronext Paris is further characterized by a high degree of transparency, where the traders can observe the evolution of the limit order book. Furthermore, until it is very close to the opening, traders are able with relative ease to cancel the orders they placed. In contrast, the Deutsche Borse call auctions are characterized by a relative lack of transparency.

Biais, Hillion and Spatt (1999) investigate the price formation process during the pre-opening period at Paris Bourse. The authors show that the indicative opening price[31] is very informative in reflecting the overnight information accumulation. Learning among traders that leads to price discovery does take place during the pre-opening period. However, the high level of transparency, coupled with the ease with which traders can cancel their orders before the opening auction might let them "game" the market by withholding their most informative orders until the market is very close to opening (this phenomenon is also known as "suckering"). Pagano and Schwartz (2002) recently show that price discovery at the Euronext Paris' market opening (and close) was improved by the institution of a call auction to close the market in 1996.

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[31] The indicative price is the price that would have been the opening price if the call auction were held at that instance.

London Stock Exchange made a number of enhancements to their opening call auction on May 30th 2000, simultaneously with introducing the closing call auction. These enhancements were the availability of market orders in addition to the limit orders, calculation and dissemination of an indicative auction price during the call period, random end to the auction call period, auction call period extensions under specific situations such as significant price moves, and alignment of the matching algorithm with the other European markets.

Similar to the Nasdaq market, the London Stock Exchange also has a competing dealer market structure in addition to the electronic SETS system. There is a further aspect that distinguishes London Stock Exchange from the other markets studied. Trading on the LSE is dominated by the institutional traders, in contrast to a more balanced combination of retail and institutional trading observed in the other markets. Clearly, this is an important factor that might impact the trading culture on the LSE not only during the trading hours but also during the period that covers the opening.

Chapter 4: Analytical Framework

4.1 A Discussion of Variance Ratios

In this study, we use variance ratios to measure the extent of accentuated short-term volatility. Variance ratios are commonly used in the academic literature to compare the variances of data sampled at different frequencies. An important implication of random walk hypothesis is that variance of the random walk increments (measured by the natural logarithm of price relatives) is a linear function of the time period. In other words, if returns of stock prices follow a random walk, it should not matter whether we use hourly, daily or weekly time increments to measure the return variance. They should all give approximately the same variance once they are adjusted for the differencing interval.[32]

For example, let's take the following single period logarithmic return series and the double period logarithmic return series:

$$r_t(1) \equiv \ln(P_t) - \ln(P_{t-1})$$

$$r_t(2) \equiv r_t + r_{t-1} = \ln(P_t) - \ln(P_{t-1}) + \ln(P_{t-1}) - \ln(P_{t-2}) = \ln(P_t) - \ln(P_{t-2})$$

where $r_t(2)$ covers a time period double the period covered by $r_t(1)$. Furthermore, let's define Var ($r_t(1)$) as the variance of $r_t(1)$ and Var ($r_t(2)$) as the variance of $r_t(2)$.

[32] See Campbell, Lo and MacKinlay (1997) and Ronen (1997) for a detailed discussion of applications of variance ratios.

Clearly, for the same study period, if we have n observations for $r_t(1)$, then we should have n/2 observations for $r_t(2)$.

Under the random walk hypothesis, Var ($r_t(2)$) should be twice Var ($r_t(1)$) and the following variance ratio $\mathrm{VR}(2) = \frac{2\mathrm{Var}[r_t(1)]}{\mathrm{Var}[r_t(2)]}$ should be one. However, existence of serial autocorrelation in stock returns[33] causes the variance ratios to differ from one. Again we can demonstrate this for the two-period variance ratio as follows:

$$\mathrm{VR}(2) = \frac{2\,\mathrm{Var}[r_t(1)]}{\mathrm{Var}[r_t(2)]} = \frac{2\,\mathrm{Var}[r_t]}{\mathrm{Var}[r_t + r_{t-1}]}$$

$$\mathrm{Var}[r_t + r_{t-1}] = \mathrm{Var}[r_t] + \mathrm{Var}[r_{t-1}] + 2\,\mathrm{Cov}[r_t, r_{t-1}] = 2\,\mathrm{Var}[r_t] + 2\,\mathrm{Cov}[r_t, r_{t-1}]$$

$$\mathrm{VR}(2) = \frac{2\,\mathrm{Var}[r_t]}{2\,\mathrm{Var}[r_t] + 2\,\mathrm{Cov}[r_t, r_{t-1}]}$$

$$\mathrm{VR}(2) = [1 + \rho(1)]^{-1}$$

where $\rho(1)$ is the first order autocorrelation of the return series. Since the denominator of the above variance ratio is the variance of two-period returns series, we are only concerned with the first order autocorrelation. However, when the long-period return series are more than double the short-period return series, then we need to investigate higher order autocorrelation terms than the first order. This issue will be discussed in more detail later.

The VR(2) formula derived above shows that while a positive autocorrelation causes the VR(2) to be less than one, negative serial autocorrelation will cause the VR(2)

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[33] An early paper investigating serial autocorrelation in stock prices is Schwartz and Whitcomb (1977).

to be greater than one. In other words, under positive autocorrelation, variance of longer periods will be larger than sum of the variances of shorter periods. Under negative autocorrelation, variance of longer periods will be smaller than sum of the variances of shorter periods.

A simple example can be given to demonstrate this relationship between the direction of the autocorrelation and the magnitude of the variance ratio. If stock prices bounce back and forth between a high price and a low price constantly, then the returns are said to be negatively autocorrelated. In this case, we will observe a high short-term volatility due to the bounce. On the other hand, the level of the prices will not change much over time and the longer-term volatility will be relatively low. Conversely, if there is a momentum that causes prices to move predominantly in a certain direction, then we can say that the short-period returns are positively autocorrelated. In this case, even if the short-term changes in stocks prices are small, they will build up over time and create sizable changes in the level of stock prices over longer time periods. As a result, long-term volatility will be significantly higher than the sum of the short-term volatilities.

As Hasbrouck and Schwartz (1988) and Schwartz (1993) have discussed, inter-temporal correlation is attributable mainly to execution costs, and not to other factors such as new information or the price uncertainty that follows it. The reason behind this is that factors such as new information are not serially correlated. If new information is really new, then it should be unpredictable. Whether new information is bullish or bearish is a coin flip. Since information arrival in the market is not predictable then due to this uncertainty stock prices are assumed to follow a random walk.

Consequently, new information arrival should affect both long-term and short-term return variances proportionately, and a disproportionately higher accentuation in short-term return variance must be attributable only to the existence of execution costs including imperfect price discovery.[34] As Schwartz and Whitcomb (1977) have shown when prices follow a random walk, variance increases proportionately with increases in the length of the interval over which the price changes are measured. As such, variance ratios that compare long-term to short-term variances are useful tools to compare the level of execution costs inter-temporally and across market centers.

As mentioned earlier, the relationship between the variance ratio and serial autocorrelation in returns can also be extended to multiple period settings. Hasbrouck and Schwartz (1988) and Campbell at al (1997) show that an m-period variance ratio will be a function of the m-1 autocorrelation coefficients as follows:

$$\mathrm{VR}\,(\mathrm{m}) \equiv \frac{mVar[r_t(1)]}{Var(r_t(m))} = [1 + 2 \sum_{k=1}^{m-1} (\frac{m-k}{m}) \rho(k)]^{-1}$$

This equation shows that the m-period variance ratio is a function of the first m-1 autocorrelation coefficients, with linearly declining weights.[35] Similar to the earlier analysis, if higher-order intertemporal correlations are predominantly positive (negative),

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[34] Please see chapter 4.2 for a detailed discussion of execution costs.

[35] Campbell et al (1997) show that even for alternative processes to the random walk, variance ratios will have similar properties. For example, under an AR(1) alternative given by $r_t = \phi\, r_{t-1} + \varepsilon_t$

$$\mathrm{VR(m)} = [1 + 2 \sum_{k=1}^{m-1} (1 - \frac{k}{m}) \phi^k]^{-1} = [1 + \frac{2}{1-\phi} \left[\phi - \frac{\phi^m}{m} - \frac{\phi - \phi^m}{m(1-\phi)} \right]]^{-1}$$

then long term return variance will be greater (smaller) than the sum of short term return variances.

If higher order autocorrelation coefficients are pre-dominantly negative then we should observe accentuated short-term volatility in the equity prices. Hasbrouck and Schwartz make a direct link between accentuated short-term volatility and execution costs. The authors write "execution costs, although not directly observable, increase the instability of share prices over short periods of time, and we can measure the excessive volatility of short period price movements. An execution cost for a security can be inferred as that value that would itself account for an issue's short period volatility". Furthermore, the authors propose and test a metric to link execution costs to volatility.

4.2 A Discussion of Factors Creating Trading Friction (Execution Costs)

There are multiple reasons for intra-day stock prices to be excessively volatile. Market microstructure literature typically divides the causes of intra-day volatility into two: Public information shocks and other microstructure phenomena that are generally referred to as "friction" [Schwartz (1993), Stoll (2000), Madhavan, Richardson, and Roomans (1997)]. Examples of friction include the transaction prices that bounce between the bid and the ask price, the market impact of large buy and sell orders (or order imbalances that causes prices to move away from the prevailing level temporarily), and the effect of momentum trading and imperfections in the price discovery process that causes prices to gyrate around their prevailing level. Furthermore, in the case of new information, overreaction to news announcements may cause prices to overshoot temporarily, creating higher transitory volatility.[36] These problems are typically expected to be more acute for less liquid and smaller market capitalization stocks.

The common factor among all the above sources of heightened short-term volatility is that they are temporary in nature and they tamper out as the differencing interval is extended. Since they are factors that cause prices to move away from their prevailing levels (or away from the underlying value of a stock) without a fundamental (information related) reason, they get corrected over time. However, this mean reverting behavior introduces negative inter-temporal correlation into stock prices over smaller differencing intervals. In short, these factors can all be characterized as forces causing the prices to move away from their prevailing levels over shorter periods. Since they are not information related, there is no fundamental (and permanent) reason for the change in the price. In the absence of a real reason for the change in price, price reversals follow creating the price trends that are mean reverting (and characterized by runs and reversals) over the longer periods.

One basic reason for accentuated intra-day volatility is the bid-ask bounce since it introduces negative autocorrelation into transaction prices. All else equal, if trades alternate randomly between buyer initiated transactions (that occur at the ask) and seller initiated transactions (that occur at the bid), then the consecutive price changes will be negatively autocorrelated and the short-term volatility measures will be accentuated due to the bid-ask bounce. However, this is a relatively easy cost to isolate and measure if

[36]Several methods are employed in different markets to control the short-term volatility. Examples include the intervention of designated market makers with a responsibility to stabilize prices or the implementation of certain rules, such as trading halts, in the case of excessive volatility.

quote data are available in addition to transactions data. To avoid the effect of the bid-ask bounce, volatility of the returns can be measured from the changes of the midpoint of the bid and the ask price instead of the transaction price. Furthermore, the effect of the bid-ask spread is likely to have become minimal with the advent of decimalization.

The market impact of large buy or sell orders (that are not placed by traders acting on new information) or order imbalances cause stock prices to move away temporarily from their prevailing levels by creating extra demand or extra supply. Large buy orders and buy order imbalances drive the prices up by creating higher demand, and large sell orders and sell order imbalances drive the prices down by creating extra supply. High market impact for large trades shows that the effective bid-ask spread is wider for larger orders, implying higher transaction costs. However, these effects are transitory in nature if these trades are not caused by new information and, as a result, prices revert back to their prevailing levels. Consecutively, the outcome of market impact is again reversal behavior in stock prices and hence negative autocorrelation.

Due to the price impact cost of trading large order sizes, institutional traders typically break up their large orders and trade over a more extended period to avoid driving stock prices to their disadvantage. In addition to uninformed traders, according to Madhavan et al (1997), informed traders also have an incentive to break up their large orders if they believe that breaking up their orders will help their identity to remain anonymous.

Breaking up of large orders into smaller trades is one of the reasons for the momentum trading observed in the market. Herding behavior among traders is another factor creating momentum trading.[37] Under momentum trading, buy trades are followed by more buy trades and sell trades are followed by more sell trades. In other words, when prices are moving in a certain direction, traders who see this trend place more orders that further enhance the trend. Again, a stock's price running up too high, and/or down too low due to momentum trading, translates into accentuated intra-day volatility.

One reason for this behavior is a lack of perfect informational efficiency in the market (eg. Grossman and Stiglitz 1980). When traders do not have the perfect information set, they try to infer information from the direction of the stock price and they join the herd. Also, if traders observe that there is significant momentum trading for many stocks, then they would also try to profit from this momentum by identifying it early on. (There are several investment consultancy companies that promise their clients the service of alerting them to the start of a momentum move so that they can get on board early and profit from it.)

Measuring the intra-day accentuated volatility is more difficult when there is heavy momentum trading that causes runs in the stock prices. Under momentum trading, stock returns are positively autocorrelated for shorter periods of time and this positive autocorrelation causes volatility measures to underestimate shorter-term volatility. On the other hand, since these runs can not and do not persist forever without an underlying fundamental reason, reversals of the price trends eventually occur and cause the prices to move in the opposite direction creating accentuated volatility due to this reversal

[37] There are several recent papers discussing herding behavior and momentum trading in securities markets. examples are Hong, Lim and Stein (2000) and Stein and Hong (1999).

behavior. It is the interplay of this run and reversal behavior of stock prices that emphasize the importance of higher order autocorrelations. If higher order autocorrelation factors are predominantly negative, indicating the reversal behavior of stock prices, then we observe the accentuated short-term volatility in stock prices.

Imperfection in the price discovery process is another factor that accentuates the short-term price volatility. In the absence of perfect informational efficiency in the marketplace, traders try to infer information about the fundamental value of the stock through the trades of others and by trading with each other. As a result of these trades by traders with imperfect information sets, prices move in directions that are not always justified by the fundamental values of the stocks. In other words, in the absence of perfect information in the market, price over or undershooting occurs. However, when these price trends are temporary in nature, and prices return to their more correct levels over the longer time periods.

Similarly, when new information comes to the market, investors typically do not have a common interpretation of it, and thus news cannot be translated instantaneously into new share prices. Divergent interpretations of the news announcements (also known as heterogeneous expectations) cause the stock prices to become more volatile following the news arrival.[38] Price formation models (eg. Dow and Gorton 1993) argue that information is incorporated into stock prices through an extended trading period. However, this adjustment period is not without friction and short-term volatility does get

[38] Fleming and Remolina (2001) show that Treasury bond prices have a two-stage adjustment process to new information arrival, where volatility is relatively high during the second stage.

more accentuated following news releases. This temporary overshooting of prices due to new information is generally referred to as informational friction (Schwartz1993, Stoll 2000).

The common characteristic across all the factors described above is that each will cause the price of a stock to bounce between a lower value at one moment, and a higher value at another moment. As a result, due to trading friction, it is reversal behavior and not random walk that characterizes short-period price movements. Even with momentum trading that causes price runs, reversal behavior is expected. With momentum trading, prices move in one direction predominantly, overshoot their mark, and consequently reversals take place.

Reversals are associated with an accentuation of the volatility of returns measured over shorter differencing intervals. However, their effect is increasingly muted as the measurement interval is lengthened and the impact of trading friction disappears over the longer period. While price change introduced by new information is permanent, price changes that occur due to factors that create trading friction are temporary. As a result, if long period (such as weekly or monthly) returns are analyzed, one might conclude that prices are relatively stable. On the other hand, if one focuses on the intra-day prices, one might alternatively conclude that they are relatively volatile. It is this relative accentuation over the shorter differencing intervals (compared to longer differencing intervals) that we intend to focus on through using variance ratios.

Chapter 5: Data

5.1 US Markets

Two domestic markets are studied: The New York Stock Exchange and the Nasdaq Stock Market. Intraday trades and quotes data for both markets were obtained from the TAQ (Trades and Quotes) database of the NYSE. The trade files include the time of each transaction (stamped to the nearest second), its price and size, the exchange on which the trade took place and various other specifications relating to the transaction. The quote files include the time each quote update was entered (stamped to the nearest second), the bid price and the ask price, the corresponding sizes associated with the bid and the ask prices, the market center that entered the quote update (in the case of Nasdaq, also the identity of the market-maker that entered the quote update), and various other specifications relating to the quote entry.

For Nasdaq stocks, only the inside quotes (lowest ask and highest bid) are included in the database. These inside quotes are called the NBBO (national best bid and offer). For NYSE stocks, all quotes are included in the TAQ database, including autoquotes by regional exchanges. Autoquoting is a method employed by regional exchanges when they want to remove themselves from quote competition. To accomplish this goal, these exchanges generate a new quote of their own by adding a delta to the ask and subtracting a delta from the bid of the current quote, for only 100 shares bid and offered. As a result, they signal to the market that they are out of price competition.[39] The inclusion of autoquotes is a potential source of bias when employing the TAQ database. This bias is mentioned in Chordia, Roll and Subrahmanyam (2000). To avoid the bias that might stem from autoquoting, we eliminate the quotes that are placed on the regional exchanges.

The study period is the calendar year 2000. We include in our study the stocks that make up a major index for both market centers. For Nasdaq, we choose the stocks that were a part of the Nasdaq 100 index on December 31, 2000 and for NYSE, we choose the stocks that were a part of the S&P 100 index on December 31, 2000. Of course, the S&P 100 index contains a few Nasdaq stocks and we eliminate these stocks from our NYSE sample. Furthermore, we eliminate from both samples the stocks that were included into the indices mid-year. As a result, we end up with 72 stocks for our NYSE sample and 78 stocks for our Nasdaq sample. The list of stocks for both market centers can be found in Appendix A. We divide the calendar year into two six-month periods and run our tests separately for these two periods in order to check for robustness.

TAQ data is not error filtered. The following filters and corrections were used to remove errors: Any trade prices that were non-positive were eliminated. Any quotes where the bid-ask spread was more then $3, or where the bid was larger than or equal to the ask, or where either the bid or the ask were non-positive were eliminated from the data. The data were adjusted for stock splits, and cash and stock dividends. The out of

[39] For a discussion of autoquoting behavior of the regional exchanges see Chakravarty, Wood and Harris (2002).

sequence trades and other erroneous data entries were eliminated. Also, the days where trading was stopped earlier than the usual close, were eliminated. Finally, the end of the trading day is defined as 4:05 pm rather than 4:00 pm due to possible delays in time stamping the trades and quotes around the close.

5.2 European Markets

The three foreign markets that are studied include the Euronext Paris (Paris Bourse), Deutsche Boerse and the London Stock Exchange. For each market we study the transaction records, during the year 2000, of stocks that make up a major index. We use the BDM database of the Paris Bourse for the transactions of the stocks that make up the CAC 40 index, and the Transaction Data Service database of the London Stock Exchange for the transactions of the stocks that make up the FTSE 100 index. The transactions database of the stocks that make up the DAX 30 index was obtained from the Deutsche Boerse.

Trading hours at the Paris Bourse at the beginning of 2000 were 9:00 am to 5:00 pm. The hours were extended on April 1st to 9:00 am to 5:30 pm. The market opens with a call auction within the first minutes after 9:00 am, and there is another call auction that takes place about 5 minutes after the close. We divide the study period into two intervals: the first interval is from January 1st to March 31st and the second period is from April 2nd to December 31st. The first interval corresponds to the shorter trading hours and the second interval corresponds to the longer trading hours.

Trading hours for Deutsche Boerse at the beginning of the year were 9:00 am to 5:30 pm, but they were extended to 9:00 am to 8:00 pm on June 2nd, 2000. Similar to the Paris Bourse, trading opens with an opening call auction that takes place within the first few minutes after 9:00 am. There is an intraday call auction a few minutes after 1:00 pm. Also, again similar to the Paris Bourse, there is a call auction that takes place about 5-10 minutes after the close. Before the extension of trading hours, the closing call was around 5:40 pm. After the extended trading hours, this call is kept as the second intraday call auction and the closing call auction takes place few minutes after 8:00 pm. Again, we divide the study period into two intervals. The first interval is from January 1st to May 31st, corresponding to the shorter trading hours, and the second interval is from June 3rd to December 31st, corresponding to the longer trading hours.

Trading hours for the London Stock Exchange are 8:00 am to 4:30 pm. If the one-hour time difference between England and Continental Europe is taken into consideration, then the trading starts at the same time in all three markets. A closing call auction was introduced on May 30th 2000 to the London Stock Exchange. Starting with this date, trading has been ending with a call auction that takes place several minutes after 4:30 pm. We again divide the study period into two intervals. The first interval is from January 1st to May 29th, corresponding to the period without the closing call auction, and the second interval is from June 1st to December 31st, corresponding to the period with the closing call auction.

We include in our study all the stocks that were a part of the DAX 30 and CAC 40 indices as of December 31, 2000, and those for which we have uninterrupted data for the whole year. Our sample selection criteria for the London Stock Exchange stocks are slightly stricter than Deutsche Boerse and Euronoxt Paris. We treat each of the two periods separately and select the stocks that remained in the index throughout the corresponding study period. The reason is twofold: First, the composition of the FTSE 100 index goes through revisions more often than both the DAX 30 and the CAC40; and second, since there are more stocks in the FTSE 100 index than both DAX 30 or the CAC40, the elimination of several stocks will not diminish the number of stocks we study significantly.

Finally, for all three markets we eliminated the stocks that traded (over the full span of trading days) in less than 90% of all half hour intervals.[40] As a result, this methodology gives us a sample of 28 stocks for the Deutsche Boerse, and 39 stocks for the Paris Bourse. In the London Stock Exchange, during the first study period we have 85 stocks and during the second study period we have 88 stocks. The list of the stocks included in the final sample is in appendix B.

A common error filter is to check for returns that appear too large for a given interval. The data were checked for half hour returns that are more than plus or minus 15%. The French and German data were free of these extreme returns. On the other hand, less than 0.06% of half hour returns of English data had extreme returns and they were eliminated. Also, six days that had a market-wide trading halt in Deutsche Boerse were eliminated. Finally, the data were filtered for any observations with missing volume

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[40] We use the same rule for the US samples. However, it does not lead to the elimination of any stock for the US markets.

information.

Chapter 6: Empirical Methodology and Results

In this study, we employ several variance ratio tests to measure the level of short-term variance accentuation inter-temporally and across market centers. For this purpose, we calculate the variance of the same stock for the same study period at different differencing intervals. If stock prices follow a random walk, then all the variances are expected to have the same value once scaled according to time.[41]

We define the following differencing intervals: Intra-day (half-hour) variances, open-to-close variances, open-to-open variances, close-to-close variances, one-week variances and two-week variances. We then calculate the ratios of shorter period variances to longer period variances in order to measure the extent of variance accentuation or diminution at shorter differencing intervals.

In addition to the variance ratio tests, we also investigate the pattern of intra-day prices from other perspectives: we investigate the intra-day patterns in volatility and whether these patterns show variability across days (intra-week patterns), we examine the intra-day patterns in the trading volume, and finally, through running several market model tests, we investigate the correlation among stocks during each intra-day (half-hour) period.

Section 6.1 describes the methodology and findings relating to the intra-day patterns of variance and volume. This section also discusses the findings on inter-day variance analysis. Section 6.2 defines the longer period variance measures. Section 6.3

[41] Please see chapter 4 for a detailed discussion of variance ratios.

discusses the additional procedures of calculating the variance ratios and the findings. Finally, section 6.4 presents the findings on market model regression R-squares.

6.1 Intra-Day and Intra-Week Patterns

6.1.a Intra-Day Variance and Volume

We capture the intra-day patterns of volatility by dividing the trading day into several half-hour periods. For example, in a market with a trading day that is six and a half hours long (eg. New York Stock Exchange and Nasdaq) we have thirteen half-hour periods: such as 9:30 to10:00, 10:00 to 10:30 ... 3:30 to 4:00. We choose half-hour periods as our intra-day interval because even though half-hour is a short period, it still is long enough to capture the microstructure effects described in chapter 4. Furthermore, for our study we need at least two trades to take place per interval. As we decrease the length of the differencing interval, the frequency of non-trading increases and our results become less informative. Half-hour intervals are also commonly used both in the academic literature (e.g. Coughenour 2001) and in the popular media, such as the *Wall Street Journal*, to report intra-day statistics pertaining to equity trading.

We concentrate mainly on the trading hours in this study and disregard overnight price changes in calculating the opening half-hour returns. We are interested in the trading friction that is created by the trading process. The first price of the day is expected to reflect only the change in price due to the information flow that came in overnight. In this study our focus is the volatility due to friction that exacerbates the price discovery errors (temporary price changes) and not the volatility due to information flow (permanent price changes). As a result, disregarding overnight price changes when calculating intra-day volatilities does not bias our results.

The reason for dividing the trading day into several sub-periods is twofold. First, focusing on a certain half-hour interval across days helps to break the effect of the factors that create the inter-temporal autocorrelation that were described in chapter 4. Since factors such as momentum trading and market impact that were described earlier build over time, investigating consecutive periods would lead us into underestimating their effect on trading costs. The underlying assumption of this approach is that we do expect today's opening half-hour stock price behavior to be less correlated with both tomorrow's and yesterday's opening half-hour stock price behaviors compared to consecutive half-hour intervals. Since half-hour intervals across days are expected to be less strongly autocorrelated as the half-hour intervals that follow each other consecutively, we should be able to capture the behavior of intra-day stock prices and the accentuated intra-day volatility more accurately.

Second, we are able to investigate how the trading friction changes across the trading day, and whether certain periods of the day could be characterized by having higher levels of execution costs. We calculate the volatility of stock returns for each of the half-hour intervals separately in an attempt to capture the relative volatility of different periods of the trading day, such as the opening half-hour or the closing half-hour.

For each of the half hour intervals, we take the first trade price and the last trade price of the interval.[42] If there are less than two trades per interval, we eliminate that interval from our sample. However, for most of the stocks that we are investigating (that are all large capitalization stocks for each market center) we do not have the problem of non-trading. For each interval, we calculate the natural logarithm of the return corresponding to that interval using the following formula:

$$r_{i,j,t} = \ln\left(\frac{P_{i,j,t}}{P_{i,j-1,t}}\right) \qquad j=1,2,3,\dots 13$$

where i is the subscript for the individual stock, j is the subscript for the intra-day period and t is the subscript for the trading day. We create a separate return series for each of the half hour intervals of the day (i.e we keep j and i as constant and calculate the return series across t). As a result, we have 13 intra-day half hour return series per stock for the study interval. We then calculate both the standard deviation, $\sigma_{i,j}$ and the variance, $\sigma^2_{i,j}$, of each stock per interval.

We also calculate the average standard deviation, $\sigma_j = \frac{1}{m}\sum_{i=1}^{m}\sigma_{i,j}$ across stocks in a market for each study period for each intra-day period, where m is the number of stocks in our sample per study period. The findings for σ_j for all markets and study periods are presented in Figures 1 through 10. In these figures, the horizontal axis denotes the intra-

[42] We do not include the overnight period in calculating the intra-day half hour returns. For the first half-hour period, we take the first trade of the day as the opening price of that interval. This is a source of concern for the NYSE stocks, since for some stocks trading does not start exactly at 9:30 but is delayed several minutes. However, this will bias this study by underestimating the first half hour variance and thus is an acceptable bias.

day half hour periods throughout the trading day and the vertical axis denotes the corresponding average intra-day volatility for each of the half hour intervals. In order to make the charts comparable across markets and study periods, we present each intra-day half hour volatility as a percentage of opening half hour volatility. For example, for the New York Stock Exchange first study period, intra-day volatility for the second intra-day half-hour is 80%. This denotes that from 10:00 am to 10:30 am volatility in this market is on average only 80% of the 9:30 am to 10:00 am volatility. Since our emphasis is on patterns of volatility as opposed to the levels of volatility in different markets, we do not match our samples across different market centers. Rather we investigate the intra-day patterns in the largest and most liquid stocks in every market.

The relationship between volume and volatility is an interesting empirical question. In addition to the old Wall Street adage "It takes volume to move the prices," there are several academic studies that show that there is a positive relationship between volume and volatility. On the other hand, there are also several academic studies that suggest that high volatility is followed by low volume or that volatility discourages trades from the market.

Even though the focus of this study is not the relationship between volume and volatility, we are also interested in intra-day volume patterns. We expect that if a certain part of the day is characterized by higher trading costs (higher trading friction and inefficient price discovery) then investors might be more wary of trading during that part of the day. In this case, we would expect to see a lower trading volume during higher volatility periods. Also, it might be the lack of volume that creates the excessive volatility. In a market without liquidity, the impact of individual trades would be greater in moving the prices in comparison to a market with more participants. On the other hand, if it is volume (or trading activity) that creates the volatility, then we should observe higher volatility during the periods that have higher relative volume.

Intra-day volume is calculated as the cumulative volume traded across all stocks per market per study period for each half hour interval. In other words, for each of the intra-day half hour periods, we add up all the volume executed for all the stocks in our sample for each market and study period. Since trading volume shows significant variation across different market centers, we present volume traded per half-hour period as a percentage of total volume traded per day. For example, 14 % during the first half hour period in the NYSE means on average 14% of the daily trading volume is executed during the first half hour in this market. In this way, we attempt to make the intra-day trading across markets and time periods comparable. Furthermore, by presenting the intra-day volume as a percentage of daily volume, we avoid the bias that would have been created by double counting in the Nasdaq market.[43] The findings are reported in Figures 11 through 18. [44] In these figures, the horizontal axis denotes the intra-day half hour periods throughout the trading day. The vertical axis denotes the cumulative intra-

[43] Studies show that in Nasdaq volume is "double" counted due to high market maker intermediation in trading.

[44] For the two US markets, we present the findings on intra-day volume only for the January-February 2000 period. Unlike the European markets where the trading hours were extended for Deutsche Boerse and Euronext Paris and closing calls were instituted at the London Stock Exchange, there were no rule changes for the US markets that should influence the trading volume.

day volume for each of the half hour intervals as a percentage of daily trading volume executed during that half-hour interval.

In all the markets, findings confirm a U-shaped intra-day volatility pattern, with a more pronounced spike at the beginning of the trading day. These findings confirm that the period following the opening and just before the end of trading are periods of particular stress, and require particular attention. Our findings also show a U-shaped intra-day pattern for trading volume in the US markets. However, we fail to find a similar U-shaped pattern for intra-day volume in the European markets. In the European markets, heavier trading occurs towards the end of the trading day.

The spike in volatility at the beginning of the day is especially pronounced for the London Stock Exchange for both of our study periods. Opening half-hour volatility in the London Stock Exchange is more than 3 times the mid-day volatility. On the other hand, volume in the morning period in this market is the lowest among the five markets. Only about 2% of daily volume is executed in the first half hour at the LSE compared to 14% for Nasdaq and NYSE, 5% for Deutsche Boerse and 7% for Euronext Paris. This is an unexpected result in the light of several academic studies that find a positive link between volume and volatility. The finding suggests reluctance on the part of LSE traders to trade during the highly volatile morning hours. This issue merits further investigation.

Deutsche Boerse data allow us to isolate the volume traded during the opening and intra-day call auctions as well as the closing call auctions. The call auctions in the Deutsche Boerse are the most successful, in terms of volume traded, across the call auctions in all three European markets. For both of the study periods there is heavy trading at the intra-day call auctions. On the other hand, the volatility during these intervals does not have any particular accentuation.

On June 2nd, 2000, trading hours at the Deutsche Boerse were extended from 9:00-5:30 to 9:00-8:00. However, the findings show that the extended hours were not very successful as the trading activity from 5:30 to 8:00 is much lower compared to the rest of the day. In addition, volatility is also significantly lower during the extended hours. Furthermore, average volume traded per stock on a trading day remains almost the same across both periods. As a result, the effect of extending the trading hours has been spreading the volume over a longer trading day. These findings suggest that there is a memory carry-over. Namely, that 5:30 remains the effective close even after the trading hours were extended. Due to this reason, we calculate two sets of variance ratios for Deutsche Boerse second period: first, with the effective close of 5:30 pm and, second, with the actual close of 8:00 pm.

Similar to Deutsche Boerse, the trading hours on the Euronext Paris have been extended by half an hour by changing the close from 5:00 pm to 5:30 pm on April 1st, 2000. Contrary to Deutsche Boerse, this extension appears to have been successful as the trading volume is the highest during the period 5:00 to 5:30 pm.

Finally, one striking finding regarding the domestic markets is the similarity in the intra-day patterns of both volume and volatility in Nasdaq and the NYSE. Both volume and volatility are U-shaped with a bigger spike at the open in both markets. One difference between the two markets at the close is that although volume is marginally lower at Nasdaq compared to the NYSE (11.62% and 12.55% respectively), volatility at

Nasdaq is relatively higher than volatility at the NYSE. We should caution that we are not referring to the "level" of neither volume nor volatility, simply to their pattern over the trading day in this analysis.

6.1.b Intra-Week Patterns

Intra-day volatility patterns show that volatility is accentuated in all markets studied during the beginning of trading in the morning and towards the close of trading. This result clearly suggests that these are periods characterized by less efficient price discovery (high trading friction). However, the underlying reasons for the greater uncertainty (and the more difficult price discovery) are different for the opening and closing periods. Price discovery in the morning is more difficult compared to the rest of the trading day mainly because there is information cumulated during the non-trading hours that needs to be translated into prices during this period. Furthermore, following a period of non-trading there could be greater heterogeneity in interpretation of the new information and, thus, more variation in opinions about the direction of stock prices.[45] On the other hand, towards the end of the day trading becomes more stressful due to the impending close of trading. Namely, as the market close approaches traders feel a need to close their positions and/or rebalance their portfolios before the non-trading period ends in order to minimize the risk of carrying their positions overnight. This increased

[45] Price formation models such as Dow and Gorton (1993) suggest prices are formed and information is incorporated into prices through trading. As a result, at the beginning of the trading day there might be more divergent opinions about the new information or the direction of prices. If traders "communicate" through trading, then divergence of opinions should decrease as the trading day progresses.

trading pressure translates into increased volume and accentuated volatility in stock prices.

We expect that if the above explanations are correct in explaining the intra-day volatility patterns, then we could see even higher levels of stress (and accentuated volatility) during the market open on Mondays and during the market close on Fridays. Since weekends have a two-day long stretch of non-trading in the markets we study, we expect there to be more information accumulation during the weekend period compared to the mid-week overnight period.[46] As a result, the trading periods immediately following the weekend (Monday open) and just before the weekend (Friday close) are expected to be characterized by higher trading friction compared to the mid-week opening and closing periods.

In order to test for the day of the week effects, we calculate the intra-day variances described in Section 6.1.a for each day of the week separately. We then compare the Monday opening half-hour volatility to the mid-week (Wednesday) opening half-hour volatility and the Friday closing half-hour volatility to the mid-week (Wednesday) closing half-hour volatility.

Findings are summarized in Table 1. Results support our expectations since in the majority of markets Monday opening half-hour and Friday closing half-hour variances are more accentuated compared respectively to the opening and closing half-hours of

[46] Assuming information arrival is distributed randomly across days. However, to investigate this issue more comprehensively the pattern of news releases for each market should be analyzed. For instance, even though Nasdaq firms prefer to release news after the close of trading, NYSE firms tend to release news in the pre-opening period.

Wednesday. On the other hand, the results are statistically different from unity only in a few cases. One notable exception is the London Stock Exchange. For this market, opening volatility is statistically more accentuated on Mondays for both study periods and the Friday closing volatility is more accentuated during the second study period. This result is consistent with our intra-day analysis where we find that the London Stock Exchange is the market with the highest opening half-hour accentuation in our study.

We also find that the Friday closing call auction in Deutsche Boerse is significantly more volatile in the second study period compared to the mid-week closing call auction. The second study period corresponds to the extended trading hours in this market. This finding suggests that even though there is not much trading during the extended hours, the last call auction before the weekend is an important vehicle of price discovery. Finally, we find conflicting results for Nasdaq in terms of inter-day effects. However, Nasdaq is more unique compared to the other markets studied in the sense that there is heavier overnight and pre-opening trading in this market. As a result, the importance of the opening and closing half-hour periods might be undermined by this characteristic of Nasdaq.

6.2 Longer-period Variances

We also calculate the variance of each stock in our sample for longer differencing intervals than the intra-day periods. The following variances (for all stocks across the five markets and two study periods) are calculated: open-to-close variance, open-to-open variance, close-to-close variance, one-week variance and two-week variance.

6.2.a Open-to-Close Variance:

For each stock, we create a return series using the opening price of the trading day and the closing price of the trading day. Following the usual practice in the academic literature, we set the closing time to be 5 minutes later than the official closing time. The open-to-close return is calculated with the following formula,

$$r_{i,j,t} = \ln(\frac{P_{i,13,t}}{P_{i,0,t}})$$

where i is the subscript for the individual stock, $P_{i,0,t}$ is the first price of the day for stock i (j=0) and $P_{i,13,t}$ is the last price of the day for stock i (j=13). These returns do not contain the overnight period consistent with our intra-day analysis. We then calculate the variance of open-to-close returns per each stock $\sigma^2_{oc,i}$.

6.2.b Open-to-Open Variance:

We calculate the open-to-open return series for each stock. This return is calculated with the following formula,

$$r_{i,j,t} = \ln(\frac{P_{i,0,t}}{P_{i,0,t-1}})$$

where i is the subscript for the individual stock i, $P_{i,0,t-1}$ is the first price of the day for stock on day t-1, $P_{i,0,t}$ is the first price of the day for stock i on day t (t measures a 24 hour interval). We then calculate the variance of open-to- open returns per each stock $\sigma^2_{oo,i}$.

6.2.c Close-to-Close Variance:

We calculate the close-to-close return series for each stock. We again set the closing time at 4:05 pm. The close-to-close return is calculated with the following formula,

$$r_{i,j,t} = \ln(\frac{P_{i,13,t}}{P_{i,13,t-1}})$$

where i is the subscript for the individual stock i, $P_{i,13,t-1}$ is the last price of the day for stock on day t-1, $P_{i,13,t}$ is the last price of the day for stock i on day t (t measures a 24 hour interval). We then calculate the variance of close-to-close returns per each stock $\sigma^2_{cc,i}$.

6.2.d Weekly Variance:

We calculate the weekly return series for each stock. The weekly return is calculated with the following formula,

$$r_{i,j,t} = \ln(\frac{P_{i,13,5t}}{P_{i,13,5t-5}})$$

where i is the subscript for the individual stock i, $P_{i,13.5t}$ is the last price of the day for stock at t, $P_{i,13.5t-5}$ is the last price of the day for stock i 5 trading days (1 week) earlier. We then calculate the variance of one-weekly returns per each stock $\sigma^2_{ow,i}$.

6.2.e Two-Weekly Variance:

We calculate the two-weekly return series for each stock. The two-weekly return is calculated with the following formula,

$$r_{i,j,t} = \ln\left(\frac{P_{i,13.10t}}{P_{i,13.10t-10}}\right)$$

where i is the subscript for the individual stock i, $P_{i,13.10t}$ is the last price of the day for stock at t, $P_{i,13.10t-10}$ is the last price of the day for stock i 10 trading days (2 weeks) earlier. We then calculate the variance of the two-weekly returns per each stock $\sigma^2_{tw,i}$.

6.3 Variance Ratios

To calculate the variance ratios, we scale each variance described in Sections 6.1 and 6.2 above to a 24-hour variance. For example, the variance of one-week returns, that covers 5 trading days, is divided by 5 to make it comparable to the variance of close-to-close returns.[47] The scaled variances are as follows,

[47] This methodology was discussed in detail in chapter 4.

INT: $\sigma^2_{j,t}$ * (n+1)

OC: $\sigma^2_{oc,t}$ * (n+1/n)

OO: $\sigma^2_{oo,t}$

CC: $\sigma^2_{cc,t}$

OW: $\sigma^2_{ow,t}$ * (1/5)

TW: $\sigma^2_{tw,t}$ * (1/10)

where n is the number of half hour periods per one trading day[48], j is the subscript for the intra-day half-hour period, and i is the subscript for the particular stock.

In Table 2, we report the following longer period variance ratios for all the markets: OC / TW, OO / TW, CC / TW, OW / TW. In all of these variance ratios, the denominator (the longer differencing interval) is the scaled two-week variance. Since we expect that trading friction would get washed out over the longer term, two-week variance should be capturing the true volatility (that stems from permanent, information related price shifts) of the securities investigated instead of accentuated volatility due to trading friction. As a result, through using this set of variance ratios, we are able to investigate whether or not open-to-close, open-to-open, close-to-close, and one-week variances are accentuated.

Findings show that one-week variance is statistically indistinguishable from two-week variance for all markets. This finding confirms that trading friction is washed out

[48] For INT and OC, we multiply by n+1 in order to adjust for the overnight period price changes.

when variance is calculated in sufficiently long differencing intervals. Clearly, a one-week differencing interval is long enough for the volatility accentuation due to friction to dampen appreciably. On the other hand, open-to-open variance is significantly accentuated in the London Stock Exchange and Euronext Paris for both of the study periods, and in Nasdaq and Deutsche Boerse for at least one of the study periods. The results for the close-to-close variance are less consistent than open-to-open variance results. We find that close-to-close variance is accentuated in comparison with the two-week variance in the London Stock Exchange, Euronext Paris and the Deutsche Boerse for only one study period in each market. This result is consistent with the academic literature that find opening variances to be higher than closing variances.[49]

Open-to-close variance, on the other hand, is not statistically greater than two-week variance for all the markets except for the London Stock Exchange. Since the open-to-close period does not include the overnight period, this result implies that there is significant price volatility overnight (that might be due to information arrival overnight). The second period (July-December 2000) for the NYSE is an outlier in the sense that the variance ratios are pre-dominantly less than 1, albeit not statistically significantly except for the OC/TW, during this period. This was a period of important change in the NYSE since decimalization has been introduced during this period. Certainly, this might be the factor explaining the findings. However, the impact of decimalization needs to be investigated more formally before reaching any firm conclusions.

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[49] For example, Amihud and Mendelsohn (1987) and Stoll (2000).

In Table 3, the percentages of stocks (for each market and study period) that have variance ratios more than unity are reported. As expected, these percentages are consistent with the variance ratios we calculated, and show that, for most of the markets, shorter period volatilities are accentuated.

In Tables 4 through 13, we report the results for the shorter period variance ratios for all the markets: INT / OC, INT / OO, INT / CC, INT / OW, INT / TW. In all of these variance ratios, the numerator (the shorter differencing interval) is the scaled intra-day half-hour variance. The denominator, on the other hand, is varied in order to capture the intra-day volatility accentuation compared to various longer period volatilities. We report the variance of each half-hour period of the day compared to the variance of open-to-close, open-to-open, close-to-close, one-week and two-week variance. Below the variance ratios in these tables, we also report the percentage of stocks that have variance ratios greater than unity.

The findings show that, for all markets and study periods, the opening of the markets is characterized by highly accentuated volatility. In all the markets, this accentuated opening volatility lasts for at least one hour into the trading day. The accentuation is most notable for the London Stock Exchange. In this market, the opening volatility accentuation is much higher than the other four markets studied, and it persists for a longer period: more than two hours into the trading day.

We find more mixed results for the period towards the close of markets. We find that the closing half-hour volatility is accentuated for Nasdaq, London Stock Exchange, and Euronext Paris only. Again, the volatility accentuation at the close is more pronounced for the London Stock Exchange. Furthermore, we find that there is significant price discovery at the closing call of the London Stock Exchange that was introduced at the start of our second study period. On the other hand, we do not find a particular volatility accentuation (or diminution) for the closing call auctions of Euronext Paris or Deutsche Boerse.

Finally, the results for the mid-day half-hour period variances are also consistent across market centers. They show that variance ratios are significantly less than unity during the mid-day half-hour periods. This result indicates that accentuated intra-day volatility that has been reported in the popular media and some academic studies is experienced mainly during the opening and (sometimes) closing periods of the trading days. The findings provide strong support for our assertion that the opening and closing periods of the day are periods of particular stress, and that price discovery is particularly difficult during these periods.

6.4 Market Model R-Squares

It is of interest whether or not the price discovery errors (that are particularly pronounced at the opening and closing half-hour intervals) are correlated among stocks. For instance, when one stock overshoots, do other stocks tend to overshoot as well, or are the extreme behaviors of the stock prices during the open and close uncorrelated with each other? To answer this question, we run the following market model regression for each stock and each half-hour interval during the day:

$$r_{i,j,t} = \beta_1 + \beta_2 * r_{m,j,t} + \varepsilon$$

where $r_{i,j,t}$ is the logarithmic return of stock i during intra-day interval j on day t, and $r_{m,j,t}$ is the logarithmic return of the equally-weighted index of all stocks (for each stock market and study period) during intra-day interval j on day t.

We take the R-square of each regression and calculate an average R-square across stocks for each half-hour period for each market and study period. An average R-square that is low would indicate that the individual stock price changes are not correlated with each other. Similarly, a high R-square would mean that the stocks tend to move in the same direction as each other. To make the results comparable with each other across markets, we present our findings as ratios in Table 14. In the numerator, we have the average R-square during the opening half-hour period (Column A), the average R-square during the closing half-hour period (Column B), and the average R-square during the closing call period (Column C). In the denominator, we have the average R-square of all the "mid-day" half-hour periods. For example, for the Nasdaq Stock Market, we calculate the R-squares for all the half-hour periods from 10:00 am to 3:30 pm and average them to find the average mid-day R-square. If the R-squares are stable across different half-hour periods during the day, then we expect all the above ratios to equal unity.

As shown in Table 14, during both of the study periods, the opening half-hour R-squares are lower than the mid-day R-squares for NYSE, Nasdaq and the London Stock Exchange. On the other hand, they are higher than mid-day R-squares for Euronext Paris and Deutsche Boerse during both of the study periods.[50] On the other hand, the ratio of the R-squares of the closing half-hour to the mid-day half-hour is approximately 1 for all markets except for the London Stock Exchange. Once again, London Stock Exchange has the lowest ratios among all markets for both the opening and the closing periods. This finding is in accordance with the results that show that the opening and closing half-hour periods are particularly volatile in the London market.

[50] This finding might be due to the successful opening call auctions that both Deutsche Boerse and Euronext Paris employ to start trading in the morning. London stock Exchange also opens the market with a call auction, however the volume at this opening call auction is extremely low.

Chapter 7: Discussion and Future Research

An essential function of a marketplace is to bring buyers and sellers together to discover the prices of securities traded in it. However, the process of price discovery in any equity market is not without trading friction. Trading friction can be defined as all of the factors that collectively create pricing errors (that lead to less than efficient price discovery). Examples of factors that create pricing errors include the bid-ask spread that causes prices to alternate between the bid price and the ask price, the price impact of large trades that push the prices up for a buyer-initiated transaction or down for a seller-initiated transaction, herding behavior (momentum trading) that leads to price runs up or down, and under or overreaction to news announcements.

There are two important commonalities between the factors that create the trading friction. First, they create turbulence around the prevailing level of the security price. Second, their impact is only temporary in nature. That is, prices revert back to the prevailing level over a longer period. For instance, the price impact of any large buy trade cannot permanently raise the level of prices[51] and the price level is, consequently, bound to revert back. Similarly, there are trades at both the bid price and the ask price in any series of transactions that follow each other. Finally, no price inflation (or deflation) due to momentum trading or as an overreaction to a news announcement can persist over the longer period. These factors do indeed affect the prices, but, their impact is not

[51] Assuming the large trade is not information related.

permanent. Prices get corrected and revert back to their previous levels over the longer period.

As a result, due to the above two commonalities, trading friction is expected to lead into accentuated volatility over the short term. In other words, short-term accentuated volatility can be viewed as symptomatic of a market with increased inefficiencies in the price discovery process. Despite the fact that some temporary pricing errors may be unavoidable in an equity market, it is certainly desirable to minimize the level of trading friction that is the outcome of avoidable inefficiencies in the price discovery process. A market with less trading friction is certainly more efficient in discovering prices and will be a preferable trading venue for most market participants. It is from this perspective that we view short-term accentuated volatility as an inverse measure of market quality.

In this dissertation, we investigate the level of short-term volatility accentuation and contrast it to longer-term volatility in five different equity markets: The New York Stock Exchange and NASDAQ in the US, and The London Stock Exchange, Deutsche Boerse, and Euronext Paris in Europe. For each market, we repeat our investigation for two separate study periods to check for the consistency of our results. Also, in all the markets in this study, we choose the most liquid stocks during each study period. The reason to investigate five markets and two study periods for each of them is to find the common features across these markets, and to establish that accentuated short-term volatility is a phenomenon shared by a wide array of equity market structures.

The five markets we choose represent a wide array in terms of the structures of these markets. The New York Stock Exchange is an order-driven market with a trading floor. The Nasdaq Stock Market is a dealer market, however with a growing order-driven electronic trading component (the Electronic Communication Networks). The European markets are all electronic trading platforms, however with distinctive characteristics in each. The London Stock Exchange, for instance, has evolved from a dealer-market structure and is still influenced by this culture. Deutsche Boerse is the only market in this study that employs intra-day call auctions, and Euronext Paris is a market with a relatively high level of transparency.

We choose the largest stocks that are part of a major index in each market for two reasons: First, the academic literature shows that a lack of liquidity is a factor that creates swings in security prices. However, it is our aim to establish that accentuated short-term volatility is an outcome of price discovery errors and not simply a product of a lack of liquidity. Second, since we are focusing on short-term (intra-day) periods, we would like to avoid any bias that might stem from non-trading. For these two reasons combined, we choose to investigate the largest and most liquid stocks in each market.

Despite the advantage of avoiding the above-described biases, there are, of course, disadvantages to this approach. Most importantly, we cannot make strict comparisons across markets, since we do not match our sample stocks according to factors such as the level of the stock prices, the industry they belong to, or the level of leverage they have. Also, we are not able to make firm statements about the universality of our findings for lower liquidity (and market capitalization) stocks beyond the expectation that the price discovery errors would probably be more prominent for them. Clearly, matched sample comparisons and extending our research into lower capitalization stocks are two important venues that merit future research.

We are able to reach several conclusions from this study. First of all, our results show that the complexity of finding the price that best reflects the broad market is particularly magnified during the opening period. In all of the markets that we studied, opening volatility is accentuated, not only compared to the remaining intra-day periods of the trading day; it is also significantly accentuated compared to longer-term, daily or weekly volatility. We also show that the individual stock prices' behavior in the opening period are less correlated with the market compared to later periods during the day. Secondly, the pattern of intra-day volatility is a reverse J-shape with the highest spike at the beginning of the day with another, albeit less pronounced, spike towards the close. This finding is strikingly similar across markets despite the fact that the *level* of volatility varies considerably depending on the stocks included in the study. On the other hand, when we evaluate the level of closing volatility accentuation, we find more mixed results. Despite the fact that volatility picks up as the market close approaches for all the markets, when we compare the level of volatility at the close with longer period volatilities we find that it is highly accentuated only for Nasdaq and the London Stock Exchange, more mildly accentuated for Euronext Paris, and not accentuated for either NYSE or Deutsche Boerse.

One of the central premises of this study is that the quality of a market can best be evaluated during stressful periods. Market openings and closings certainly fit that description. Furthermore, if that stress is linked to the pressures of trading right before or immediately after the non-trading period, we should see that the opening period of a Monday and the closing period of a Friday are even more volatile than the mid-week opening and closing periods.[52] Indeed, we find evidence of this hypothesis since, more often than not, opening volatility appears to be the highest on Mondays and closing volatility appears to be the highest on Fridays. This effect is particularly significant in the London Stock Exchange. An interesting venue to further this analysis would be to investigate the extent to which the pattern of news releases in each of these markets matters.

Another interesting finding is related to the relationship between volume and volatility. Even though the focus of this study is not this relationship, our results show that the pattern of trading volume varies substantially across different markets. For the US markets, the intra-day pattern of volume is a reverse J-shape, very similar to the intra-day pattern of volatility. On the other hand, for all the European markets, volume picks up towards the end of the trading day. The most striking case is the London Stock Exchange, where, at the beginning of the day, the volume is the lowest and the volatility accentuation is the highest, across all markets studied. This area requires further study since academic studies (that generally use domestic data) typically find that the intra-day patterns of volume and volatility are positively correlated. Trading volume is related to liquidity and we know that volatility is higher in less liquid markets. Consequently, we raise the question: Which way does the causal arrow point?

[52] Assuming more information is accumulated over the weekend than mid-week overnight periods.

One more area that is a natural extension of this study is to find whether there are any variations in the volatility patterns of cross-listed stocks. The pattern of volume in the European markets suggests that the opening of trading in the US markets (and the consequent transfer of information) is important in the price formation process for European stocks. Conversely, one would expect the American Depository Receipts to have a unique volatility/volume pattern, as opposed to the domestic stocks, due to the price discovery that carries over from their home market to the US market.

The intra-day pattern of stock price volatility (and volume) indicates a very intricate process of price discovery in equity markets. We are able to make statements about the quality and efficiency of markets through investigating these patterns. All told, an intra-day analysis of volatility (and volume) raises many exciting questions that should lead the way to new and fruitful research.

Appendix A

I) New York Stock Exchange Stocks

Alcoa Inc.
Allegheny Technologies Inc.
American Electric Power
American Express
American Int'l. Group
At&T Corp.
Avon Products
Baker Hughes
Bank Of America Corp.
Bank One Corp.
Baxter International Inc.
Black & Decker Corp.
Boeing Company
Boise Cascade
Bristol-Myers Squibb
Burlington North.Santa Fe Corp.
Campbell Soup
Cigna Corp.
Citigroup Inc.
Coca Cola Co.
Colgate-Palmolive
Computer Sciences Corp.
Delta Air Lines
Dow Chemical
Du Pont (E.I.)
Eastman Kodak
Entergy Corp.
Exxon Mobil Corp.
Fedex Corporation
Ford Motor (New)
General Dynamics
General Electric
General Motors
Halliburton Co.
Harrah's Entertainment
Hartford Financial Svc.Gp.
Hca-The Healthcare Company
Heinz (H.J.)
Hewlett-Packard
Home Depot
Honeywell Int'l. Inc.
International Bus. Machines
International Paper
J.P. Morgan Chase & Co.
Johnson & Johnson
Limited, Inc.
Lucent Technologies
May Dept. Stores
Mcdonald's Corp.
Merck & Co.
Merrill Lynch
Minn. Mining & Mfg.
National Semiconductor
Norfolk Southern Corp.
Nortel Networks Corp. Hldg. Co.
Pepsico Inc.
Procter & Gamble
Radioshack Corp.
Raytheon Co.
Rockwell International
Sara Lee Corp.
Schlumberger Ltd.
Sears, Roebuck & Co.
Southern Co.
Texas Instruments
Toys R Us Hldg. Cos.
U.S. Bancorp
Unisys Corp.
United Technologies
Verizon Communications
Wal-Mart Stores
Walt Disney Co. (The)
Wells Fargo & Co. (New)
Weyerhaeuser Corp.
Williams Cos.
Xerox Corp.

II) Nasdaq Stocks

3Com Corporation
A D C Telecom Inc
Adelphia Comm Corp
Adobe Systems Inc
Altera Corp
Amazon.Com Inc
Amgen Inc
Apple Computer Inc
Applied Materials Inc
Applied Micro Circuits Cp
At Home Corporation
Atmel Corp
Bed Bath & Beyond Inc
Biogen Inc
Biomet Inc
Bmc Software, Inc.
Broadvision, Inc.
C I E N A Corp
Chiron Corp
Cintas Corp
Cisco Systems Inc
Citrix Systems Inc
Cmgi, Inc.
Cnet Networks, Inc.
Comcast Corp
Compuware Corp
Comverse Technology Inc
Concord E F S Inc
Conexant Systems Inc
Costco Wholesale Corporat
Dell Computer Corp
Ebay Inc
Echostar Comm Corp
Electronic Arts Inc
Ericsson L M Tel Co
Fiserv Inc
Gemstar-Tv Guide Intl Inc
Genzyme Corp
I2 Technologies
Immunex Corp
Intel Corp
Intuit Inc
Jds Uniphase Corp
K L A Tencor Corp
Level 3 Communications, Inc.
Linear Technology Corp
Maxim Integrated Prod Inc
Mcleodusa Incorporated
Medimmune Inc
Metromedia Fiber Network, Inc.
Microchip Technology Inc
Microsoft Corp
Molex Inc
Network Appliance Corp
Nextel Comm Inc
Novell, Inc.
Oracle Corp
P M C Sierra Inc
Paccar Inc
Panamsat Corp
Parametric Technology Corporation
Paychex Inc
Peoplesoft Inc
Qlogic Corp
Qualcomm Inc
Realnetworks, Inc.
Rf Micro Devices Inc
Sanmina-Sci Corp
Sdl, Inc.
Siebel Systems Inc
Smurfit Stone Container C
Staples Inc
Starbucks Corp
Sun Microsystems Inc
Tellabs Inc
U S A Networks Inc
Veritas Software Corp De
Vitesse Semiconductr Corp
Voicestream Wireless Corporation
Worldcom Inc-Worldcom Gro
Xilinx Inc
Xo Communications, Inc.
Yahoo! Inc

Appendix B

I) Deutsche Boerse Stocks

Adidas-Salomon Ag
Allianz Ag
Basf Ag
Bay.Hypo-Vereinsbk.
Bay.Motoren Werke Ag St
Bayer Ag
Commerzbank Ag
Daimlerchrysler Ag Na
Degussa-Huels Ag
Deutsche Bank Ag Na
Dresdner Bank Ag Na
Dt.Telekom Ag Na
E.On Ag
Epcos Ag Na
Fresen.Med.Care Ag
Henkel Kgaa Vzo
Karstadt Quelle Ag
Linde Ag
Lufthansa Ag Vna
Man Ag St
Metro Ag St
Muench.Rueckvers.Vna
Preussag Ag
Sap Ag Vzo
Schering Ag
Siemens Ag Na
Thyssenkrupp Ag
Volkswagen Ag St

II) Euronext Paris Stocks

AGF
TF1
Air liquide
Carrefour
Sanofi Synthélabo
Total Fina elf
L'Oréal
Accor
Bouygues
Suez Lyonnaise des Eaux
Lafarge
Axa
Danone
LVMH
Sodexho Alliance
Micheli,
Thales
Vivendi universal
Pinault Printemps
Peugeot
Schneider Electric
Saint Gobain
Cap Gemini
Casino guichard
Alcatel
Lagardere
Valéo
Société Générale
Aventis
Bnp Paribas
Renault
STMicroelectronics
Dassault systèmes
France Télécom
Alstom
Equant
Crédit Lyonnais
Thomson Multimedia
Dexia

III-a) FTSE 100 Stocks, First Period

Abbey National
Alliance & Leicester
Emi Group
Bhp Billiton
Baa
Bank Of Scotland(Governor & Co Of)
Barclays
Boc Group
Boots Co
Amvescap
British Airways
British Telecommunications
British Sky Broadcasting Group
Cable & Wireless
Cgnu
Reuters Group
Diageo
National Grid Group
Six Continents
Gkn
Kingfisher
Bae Systems
British American Tobacco
Carlton Communications
Gus
Misys
Hays
Colt Telecom Group
Imperial Chemical Industries
Anglo American
Hilton Group
Land Securities
Logica
Hsbc Hldgs
Legal & General Group
Marks & Spencer
Centrica
Unilever
Halifax Group
Cadbury Schweppes
International Power
United Utilities
Telewest Communications
Royal & Sun Alliance Insurance Gr
Pearson
Scottish Power
Prudential
Rio Tinto
Vodafone Group
Railtrack Group
Reckitt Benckiser
Reed International
Rentokil Initial
Old Mutual
Rolls-Royce
Royal Bank Of Scotland Group
Sainsbury(J)
Scottish & Southern Energy
Bp
Sage Group
Shell Transport & Trading Co
Invensys
Standard Chartered
Lloyds Tsb Group
Bg Group
Tesco
3i Group
United Business Media
Wpp Group
Astrazeneca
Norwich Union
Blue Circle Industries
Smithkline Beecham
Cmg
Sema
Energis
Allied Zurich
Compass Group(Former)
Glaxo Wellcome
Peninsular & Orient Steam Nav Co
Granada Group
Corus Group
Sun Life & Provincial Hldgs
3i Group
Woolwich

III-b) FTSE 100 Stocks, Second Period

Abbey National
Alliance & Leicester
Emi Group
Dixons Group
Safeway
Bhp Billiton
Arm Hldgs
Baa
Bank Of Scotland(Governor & Co Of)
Barclays
Boc Group
Boots Co
Amvescap
British Airways
British Sky Broadcasting Group
Cable & Wireless
Capita Group
Celltech Group
Cgnu
Reuters Group
Diageo
Schroders
National Grid Group
Six Continents
Gkn
Kingfisher
Bae Systems
Amersham
British American Tobacco
Electrocomponents
Carlton Communications
Gus
Cmg
Misys
Hanson
Hays
Colt Telecom Group
Powergen
Exel
Imperial Tobacco Group
Imperial Chemical Industries
Spirent
Anglo American
Hilton Group
Land Securities
Logica
Hsbc Hldgs
Legal & General Group
Marks & Spencer
Centrica
Unilever
Halifax Group
Cadbury Schweppes
International Power
United Utilities
Telewest Communications
Royal & Sun Alliance Insurance Gr
Pearson
Scottish Power
Prudential
Rio Tinto
Vodafone Group
Railtrack Group
Reckitt Benckiser
Allied Domecq
Reed International
Rentokil Initial
Old Mutual
Rolls-Royce
Royal Bank Of Scotland Group
Sainsbury(J)
Scottish & Southern Energy
Bp
Shire Pharmaceuticals Group
Sage Group
Shell Transport & Trading Co

Invensys
Smiths Group
Standard Chartered
Lloyds Tsb Group
Bg Group
Marconi
Tesco
3i Group
United Business Media
Daily Mail & General Trust
Wpp Group
Astrazeneca

Table 1. Day of the Week Variance Ratios for Opening/Closing Half Hour Periods

Ratio of opening half hour variance on Monday to the opening half hour variance on Wednesday is presented in Column A. Ratio of closing half hour variance on Friday to the closing half hour variance on Wednesday is presented in Column B. The first study period is January-June 2000 for New York Stock Exchange and Nasdaq Stock Market, January-May 2000 for Deutsche Boerse and London Stock Exchange, and January -March 2000 for Euronext Paris. The second study period is July-December 2000 for New York Stock Exchange and Nasdaq Stock Market, June-December 2000 for Deutsche Boerse and London Stock Exchange, and April-December 2000 for Euronext Paris. Deutsche Boerse (1) statistics are calculated using 5:30 pm as the effective closing time and Deutsche Boerse (2) statistics are calculated using the actual 8:00 pm as the closing time during the second study period.

	A **Monday Opening HH / Wednesday Opening HH**	**B** **Friday Closing HH / Wednesday Closing HH**
First Study Period		
New York Stock Exchange	1.164	1.043
Nasdaq Stock Market	***1.440***	0.793
London Stock Exchange	***1.582***	1.159
Euronext Paris	0.797	1.102
Deutsche Boerse	0.902	0.933
Second Study Period		
New York Stock Exchange	1.017	1.139
Nasdaq Stock Market	**0.710**	1.154
London Stock Exchange	***1.515***	***1.416***
Euronext Paris	1.221	1.155
Deutsche Boerse (1)	1.072	1.199
Deutsche Boerse (2)	1.072	***1.625***

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 2. Longer-Term Variance Ratio Tests

Variance ratios are presented for longer period differencing intervals. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance. and TW is the scaled two-week variance. The first study period is January-June 2000 for New York Stock Exchange and Nasdaq Stock Market. January-May 2000 for Deutsche Boerse and London Stock Exchange. and January -March 2000 for Euronext Paris. The second study period is July-December 2000 for New York Stock Exchange and Nasdaq Stock Market. June-December 2000 for Deutsche Boerse and London Stock Exchange. and April-December 2000 for Euronext Paris.

First Study Period	OC / TW	OO/TW	CC / TW	OW / TW
New York Stock Exchange	0.998	1.183	1.209	1.035
Nasdaq Stock Market	1.073	1.230	1.221	1.028
London Stock Exchange	**1.306**	**1.293**	1.212	1.118
Euronext Paris	1.009	**1.336**	1.235	1.072
Deutsche Boerse	1.100	**1.320**	**1.265**	1.048
Second Study Period	**OC / TW**	**OO/TW**	**CC / TW**	**OW / TW**
New York Stock Exchange	**0.729**	0.993	0.992	1.094
Nasdaq Stock Market	1.009	**1.301**	1.223	1.108
London Stock Exchange	**1.367**	**1.246**	**1.290**	1.048
Euronext Paris	1.201	***1.591***	**1.279**	1.098
Deutsche Boerse	1.068	1.199	1.188	1.016

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 3. Percentage of Stocks with Variance Ratios Greater Than Unity

Percentages of stocks with variance ratios greater than unity are presented for each market and study period. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance. and TW is the scaled two-week variance. The first study period is January-June 2000 for New York Stock Exchange and Nasdaq Stock Market. January-May 2000 for Deutsche Boerse and London Stock Exchange. and January -March 2000 for Euronext Paris. The second study period is July-December 2000 for New York Stock Exchange and Nasdaq Stock Market. June-December 2000 for Deutsche Boerse and London Stock Exchange. and April-December 2000 for Euronext Paris.

First Study Period	**OC / TW**	**OO/TW**	**CC / TW**	**OW / TW**
New York Stock Exchange	54.17%	61.11%	69.44%	48.61%
Nasdaq Stock Market	62.82%	76.92%	76.92%	67.95%
London Stock Exchange	74.12%	50.59%	70.59%	67.06%
Euronext Paris	56.41%	69.23%	61.54%	58.97%
Deutsche Boerse	60.71%	89.29%	75.00%	57.14%
Second Study Period	**OC / TW**	**OO/TW**	**CC / TW**	**OW / TW**
New York Stock Exchange	36.11%	61.11%	55.56%	56.94%
Nasdaq Stock Market	56.41%	80.77%	67.95%	60.26%
London Stock Exchange	80.00%	52.27%	76.14%	55.29%
Euronext Paris	82.05%	92.31%	82.05%	69.23%
Deutsche Boerse	67.86%	75.00%	67.86%	67.86%

Table 4. Intra-Day Variance Ratio Tests, New York Stock Exchange (First Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The first study period is January-June 2000 for New York Stock Exchange.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
10:00	***2.444***	***2.061***	***2.018***	***2.356***	***2.439***
	99%	93%	93%	97%	99%
10:30	***1.596***	**1.346**	***1.318***	***1.539***	***1.593***
	82%	67%	64%	79%	82%
11:00	1.043	0.880	0.861	1.006	1.041
	51%	24%	19%	50%	51%
11:30	**0.800**	***0.675***	***0.661***	**0.772**	**0.799**
	21%	14%	11%	18%	21%
12:00	**0.748**	***0.631***	***0.617***	**0.721**	**0.746**
	17%	11%	11%	17%	17%
12:30	***0.631***	***0.532***	***0.521***	***0.608***	***0.630***
	13%	6%	3%	11%	13%
1:00	***0.609***	***0.513***	***0.503***	***0.587***	***0.608***
	10%	4%	3%	7%	10%
1:30	***0.542***	***0.457***	***0.448***	***0.523***	***0.541***
	6%	3%	3%	6%	6%
2:00	***0.547***	***0.461***	***0.451***	***0.527***	***0.546***
	7%	4%	4%	4%	7%
2:30	***0.680***	***0.573***	***0.561***	***0.656***	***0.678***
	13%	7%	6%	11%	13%
3:00	***0.682***	***0.575***	***0.563***	***0.658***	***0.681***
	11%	7%	6%	11%	11%
3:30	0.904	**0.763**	**0.747**	0.872	0.903
	21%	15%	14%	21%	21%
4:00	1.095	0.924	0.904	1.056	1.093
	39%	25%	25%	35%	39%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 5. Intra-Day Variance Ratio Tests, New York Stock Exchange (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is July-December 2000 for New York Stock Exchange.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
10:00	***3.474***	***2.550***	***2.551***	***2.314***	***2.531***
	100%	94%	94%	94%	94%
10:30	***1.839***	**1.350**	**1.351**	1.225	**1.340**
	92%	63%	63%	54%	63%
11:00	**1.362**	1.000	1.000	0.907	0.992
	47%	28%	28%	26%	28%
11:30	0.962	***0.706***	***0.706***	***0.641***	***0.701***
	32%	13%	13%	8%	13%
12:00	0.824	***0.605***	***0.605***	***0.549***	***0.600***
	24%	10%	10%	8%	10%
12:30	***0.655***	***0.481***	***0.481***	***0.437***	***0.477***
	10%	6%	6%	6%	6%
1:00	***0.568***	***0.417***	***0.417***	***0.378***	***0.414***
	8%	6%	6%	4%	6%
1:30	***0.555***	***0.407***	***0.408***	***0.370***	***0.404***
	8%	4%	4%	4%	4%
2:00	***0.596***	***0.437***	***0.438***	***0.397***	***0.434***
	11%	6%	6%	3%	6%
2:30	***0.639***	***0.469***	***0.469***	***0.426***	***0.466***
	13%	10%	10%	10%	10%
3:00	**0.727**	***0.534***	***0.534***	***0.484***	***0.530***
	14%	8%	8%	7%	8%
3:30	0.818	***0.601***	***0.601***	***0.545***	***0.596***
	21%	8%	8%	8%	8%
4:00	1.017	**0.747**	**0.747**	***0.678***	**0.741**
	33%	17%	17%	13%	17%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 6. Intra-Day Variance Ratio Tests, Nasdaq Stock Market (First Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The first study period is January-June 2000 for Nasdaq Stock Market.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
10:00	***2.794***	***2.438***	***2.455***	***2.915***	***2.998***
	94%	94%	94%	94%	94%
10:30	***1.485***	**1.296**	**1.305**	***1.549***	***1.593***
	69%	67%	67%	69%	72%
11:00	0.929	0.811	0.817	0.970	0.997
	37%	26%	27%	42%	44%
11:30	***0.704***	***0.614***	***0.619***	**0.735**	**0.755**
	15%	8%	10%	21%	22%
12:00	0.836	**0.730**	**0.735**	0.872	0.897
	33%	22%	22%	33%	33%
12:30	***0.568***	***0.496***	***0.499***	***0.593***	***0.609***
	6%	4%	4%	6%	6%
1:00	***0.550***	***0.480***	***0.483***	***0.573***	***0.590***
	6%	3%	3%	10%	13%
1:30	***0.493***	***0.430***	***0.433***	***0.514***	***0.529***
	4%	3%	3%	4%	4%
2:00	***0.661***	***0.577***	***0.581***	***0.690***	***0.709***
	15%	12%	12%	15%	17%
2:30	**0.788**	***0.688***	***0.693***	0.822	0.846
	19%	17%	17%	23%	26%
3:00	0.899	**0.785**	**0.790**	0.938	0.965
	35%	26%	28%	37%	40%
3:30	1.019	0.889	0.895	1.063	1.093
	47%	29%	29%	51%	51%
4:00	***1.932***	***1.686***	***1.697***	***2.015***	***2.073***
	82%	76%	76%	83%	85%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 7. Intra-Day Variance Ratio Tests, Nasdaq Stock Market (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is July-December 2000 for Nasdaq Stock Market.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
10:00	***2.868***	***2.222***	***2.365***	***2.609***	***2.892***
	99%	90%	92%	95%	99%
10:30	***1.590***	1.232	**1.311**	***1.447***	***1.604***
	73%	55%	60%	68%	73%
11:00	**1.286**	0.996	1.060	1.170	**1.297**
	64%	44%	49%	56%	64%
11:30	0.830	***0.643***	***0.684***	**0.755**	0.837
	26%	13%	18%	21%	26%
12:00	***0.712***	***0.551***	***0.587***	***0.648***	***0.718***
	18%	6%	8%	14%	18%
12:30	***0.584***	***0.453***	***0.482***	***0.531***	***0.589***
	10%	4%	4%	5%	10%
1:00	***0.479***	***0.371***	***0.395***	***0.436***	***0.483***
	3%	3%	3%	3%	3%
1:30	***0.523***	***0.405***	***0.431***	***0.476***	***0.528***
	4%	1%	1%	3%	5%
2:00	***0.590***	***0.457***	***0.487***	***0.537***	***0.595***
	12%	3%	4%	8%	13%
2:30	***0.671***	***0.520***	***0.554***	***0.611***	***0.677***
	15%	4%	5%	10%	15%
3:00	**0.773**	***0.599***	***0.637***	***0.703***	**0.779**
	26%	12%	15%	21%	26%
3:30	0.932	**0.722**	**0.769**	0.848	0.940
	38%	21%	23%	33%	40%
4:00	**1.367**	1.059	1.127	1.244	**1.378**
	68%	50%	59%	62%	68%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 8. Intra-Day Variance Ratio Tests, London Stock Exchange (First Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The first study period is January-May 2000 for London Stock Exchange.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
8:30	***8.836***	***8.924***	***9.524***	***10.318***	***11.539***
	98%	98%	99%	99%	100%
9:00	***2.356***	***2.379***	***2.539***	***2.751***	***3.076***
	87%	88%	91%	92%	94%
9:30	***1.556***	***1.572***	***1.678***	***1.817***	***2.032***
	72%	72%	74%	78%	84%
10:00	1.175	1.186	**1.266**	**1.371**	***1.534***
	52%	52%	60%	64%	68%
10:30	1.022	1.032	1.101	1.193	**1.334**
	39%	40%	47%	51%	61%
11:00	0.915	0.924	0.986	1.068	1.194
	34%	34%	36%	42%	52%
11:30	***0.698***	***0.704***	**0.752**	0.814	0.911
	24%	24%	32%	33%	45%
12:00	***0.699***	***0.706***	**0.754**	0.817	0.913
	21%	21%	26%	29%	35%
12:30	***0.658***	***0.665***	***0.710***	***0.769***	0.860
	14%	14%	16%	19%	32%
1:00	***0.538***	***0.543***	***0.579***	***0.628***	***0.702***
	8%	8%	9%	12%	20%
1:30	***0.486***	***0.490***	***0.523***	***0.567***	***0.634***
	8%	8%	11%	12%	18%
2:00	***0.609***	***0.615***	***0.656***	***0.711***	0.795
	13%	13%	21%	25%	29%
2:30	***0.613***	***0.619***	***0.660***	***0.715***	0.800
	13%	15%	15%	18%	26%
3:00	**0.775**	**0.783**	0.835	0.905	1.012
	22%	22%	31%	38%	48%
3:30	0.814	0.822	0.878	0.951	1.063
	32%	32%	38%	45%	51%
4:00	0.941	0.951	1.014	1.099	1.229
	42%	42%	51%	56%	62%
4:30	***2.364***	***2.388***	***2.548***	***2.760***	***3.087***
	92%	92%	92%	93%	96%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 9. Intra-Day Variance Ratio Tests, London Stock Exchange (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance. and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is June-December 2000 for London Stock Exchange.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
8:30	***9.374***	***10.427***	***10.074***	***12.314***	***12.992***
	98%	99%	99%	99%	99%
9:00	***2.196***	***2.442***	***2.360***	***2.884***	***3.043***
	82%	86%	85%	90%	91%
9:30	***1.531***	***1.703***	***1.645***	***2.011***	***2.121***
	75%	80%	80%	86%	89%
10:00	1.135	**1.262**	1.219	***1.491***	***1.573***
	52%	59%	56%	73%	77%
10:30	1.040	1.157	1.117	**1.366**	***1.441***
	40%	45%	43%	59%	64%
11:00	0.947	1.054	1.018	1.244	**1.313**
	31%	41%	36%	58%	61%
11:30	**0.754**	0.839	0.810	0.990	1.045
	22%	28%	24%	35%	38%
12:00	***0.688***	**0.765**	**0.739**	0.904	0.953
	22%	24%	23%	35%	39%
12:30	***0.644***	***0.717***	***0.692***	0.846	0.893
	20%	23%	20%	32%	36%
1:00	***0.612***	***0.681***	***0.658***	0.805	0.849
	11%	17%	14%	23%	27%
1:30	***0.572***	***0.636***	***0.614***	**0.751**	0.792
	13%	17%	17%	24%	24%
2:00	***0.603***	***0.671***	***0.648***	0.792	0.835
	13%	16%	13%	24%	25%
2:30	***0.629***	***0.700***	***0.676***	0.827	0.872
	15%	17%	16%	27%	31%
3:00	0.951	1.058	1.022	1.249	**1.318**
	34%	36%	36%	45%	50%
3:30	0.884	0.983	0.950	1.161	1.225
	28%	33%	31%	45%	52%
4:00	1.029	1.145	1.106	**1.352**	***1.427***
	36%	47%	45%	61%	65%
4:30	***2.052***	***2.283***	***2.205***	***2.696***	***2.844***
	91%	92%	91%	97%	97%
Closing Call	***2.193***	***2.440***	***2.357***	***2.881***	***3.040***
	89%	91%	91%	98%	98%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 10. Intra-Day Variance Ratio Tests, Euronext Paris (First Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance, OO is the scaled open-to-open variance. CC is the scaled close-to-close variance, OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The first study period is January-March 2000 for Euronext Paris.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
9:30	***2.475***	***1.869***	***2.022***	***2.329***	***2.497***
	97%	85%	85%	92%	97%
10:00	**1.370**	1.034	1.119	**1.289**	**1.382**
	59%	44%	46%	54%	59%
10:30	1.174	0.887	0.959	1.105	1.185
	59%	33%	36%	51%	59%
11:00	1.004	**0.758**	0.821	0.945	1.013
	44%	21%	28%	36%	44%
11:30	0.878	**0.663**	**0.717**	0.826	0.886
	26%	15%	23%	23%	28%
12:00	0.794	***0.600***	***0.649***	**0.747**	0.801
	31%	10%	18%	26%	33%
12:30	***0.668***	***0.504***	***0.546***	***0.628***	***0.674***
	21%	8%	13%	18%	21%
1:00	***0.622***	***0.470***	***0.509***	***0.586***	***0.628***
	10%	3%	8%	10%	10%
1:30	***0.537***	***0.406***	***0.439***	***0.506***	***0.542***
	8%	5%	5%	8%	10%
2:00	***0.527***	***0.398***	***0.430***	***0.496***	***0.531***
	13%	5%	10%	10%	13%
2:30	***0.622***	***0.469***	***0.508***	***0.585***	***0.627***
	10%	10%	10%	10%	10%
3:00	0.779	***0.589***	***0.637***	**0.733**	0.786
	26%	13%	15%	26%	26%
3:30	**0.725**	***0.547***	***0.592***	***0.682***	**0.731**
	23%	13%	18%	23%	26%
4:00	0.968	**0.731**	0.791	0.910	0.976
	41%	28%	28%	33%	44%
4:30	1.087	0.821	0.888	1.023	1.097
	44%	28%	33%	36%	44%
5:00	***1.714***	**1.294**	***1.400***	***1.613***	***1.729***
	77%	59%	62%	72%	77%
Closing Call	1.024	**0.774**	0.837	0.964	1.034
	36%	26%	28%	33%	38%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 11. Intra-Day Variance Ratio Tests, Euronext Paris (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is April-December 2000 for Euronext Paris.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
9:30	***2.855***	***2.155***	***2.681***	***3.122***	***3.429***
	97%	97%	97%	100%	100%
10:00	***1.559***	***1.176***	***1.463***	***1.704***	***1.872***
	77%	56%	72%	90%	90%
10:30	1.176	0.888	1.104	**1.286**	***1.412***
	62%	36%	59%	64%	69%
11:00	1.046	0.790	0.982	1.144	**1.256**
	51%	38%	49%	56%	64%
11:30	0.889	***0.671***	0.835	0.972	1.067
	41%	23%	33%	56%	64%
12:00	0.861	***0.650***	0.809	0.942	1.034
	41%	21%	33%	44%	54%
12:30	**0.745**	***0.562***	***0.700***	0.815	0.895
	33%	10%	28%	33%	38%
1:00	***0.702***	***0.530***	***0.659***	**0.767**	0.843
	28%	8%	28%	31%	36%
1:30	***0.627***	***0.473***	***0.588***	***0.685***	**0.752**
	18%	10%	15%	23%	28%
2:00	***0.644***	***0.486***	***0.605***	***0.704***	**0.774**
	21%	10%	15%	26%	31%
2:30	***0.637***	***0.481***	***0.598***	***0.697***	**0.765**
	21%	3%	18%	23%	26%
3:00	0.973	**0.734**	0.913	1.064	1.168
	36%	31%	33%	41%	46%
3:30	**0.780**	***0.589***	**0.732**	0.853	0.937
	31%	10%	21%	33%	36%
4:00	1.114	0.841	1.046	1.218	**1.338**
	54%	31%	49%	62%	64%
4:30	1.143	0.862	1.073	1.250	**1.372**
	54%	33%	49%	62%	67%
5:00	1.173	0.885	1.101	**1.282**	***1.408***
	54%	36%	49%	56%	77%
5:30	***1.552***	1.171	***1.457***	***1.697***	***1.863***
	79%	64%	77%	85%	87%
Closing Call	0.924	***0.697***	0.867	1.010	1.109
	41%	15%	31%	51%	56%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 12. Intra-Day Variance Ratio Tests, Deutsche Boerse (First Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The first study period is January-May 2000 for Deutsche Boerse.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
9:30	***2.714***	***2.261***	***2.359***	***2.847***	***2.985***
	100%	96%	96%	100%	100%
10:00	***1.475***	**1.229**	**1.282**	***1.548***	***1.623***
	75%	46%	57%	89%	89%
10:30	**1.342**	1.118	1.166	***1.408***	***1.476***
	64%	50%	54%	71%	82%
11:00	0.987	0.822	0.858	1.036	1.086
	54%	25%	32%	54%	57%
11:30	0.896	**0.747**	**0.779**	0.940	0.986
	29%	21%	21%	29%	29%
12:00	0.857	***0.714***	**0.745**	0.899	0.942
	29%	18%	18%	36%	36%
12:30	0.803	***0.669***	***0.698***	0.843	0.883
	25%	14%	21%	29%	39%
1:00	***0.646***	***0.538***	***0.562***	***0.678***	***0.711***
	14%	7%	7%	18%	18%
1:30	***0.596***	***0.496***	***0.518***	***0.625***	***0.655***
	11%	7%	7%	11%	11%
2:00	***0.599***	***0.499***	***0.521***	***0.628***	***0.659***
	11%	4%	11%	11%	14%
2:30	***0.589***	***0.491***	***0.512***	***0.618***	***0.648***
	7%	0%	0%	14%	14%
3:00	0.868	**0.723**	**0.755**	0.911	0.955
	29%	14%	18%	32%	36%
3:30	***0.658***	***0.548***	***0.572***	***0.690***	**0.724**
	7%	4%	4%	11%	11%
4:00	1.035	0.862	0.900	1.086	1.138
	39%	25%	25%	54%	57%
4:30	0.997	0.830	0.866	1.046	1.096
	39%	29%	32%	43%	50%
5:00	1.097	0.914	0.953	1.151	1.206
	50%	25%	25%	54%	54%
5:30	1.187	0.988	1.032	1.245	**1.305**
	64%	39%	39%	64%	71%
Closing Call	**0.739**	***0.616***	***0.643***	**0.776**	0.813
	29%	11%	11%	39%	39%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 13.a Intra-Day Variance Ratio Tests, Deutsche Boerse (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is June-December 2000 for Deutsche Boerse.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
9:30	***3.359***	***2.991***	***3.019***	***3.529***	***3.587***
	100%	100%	100%	100%	100%
10:00	***1.537***	**1.369**	**1.382**	***1.615***	***1.642***
	79%	71%	71%	86%	93%
10:30	1.196	1.065	1.075	**1.257**	**1.277**
	54%	39%	39%	68%	75%
11:00	0.974	0.867	0.876	1.023	1.040
	43%	36%	36%	54%	57%
11:30	0.858	**0.764**	**0.771**	0.902	0.916
	36%	21%	21%	39%	39%
12:00	0.791	***0.704***	***0.711***	0.831	0.844
	32%	18%	18%	36%	36%
12:30	**0.775**	***0.690***	***0.696***	0.814	0.827
	21%	18%	18%	25%	25%
1:00	***0.657***	***0.585***	***0.590***	***0.690***	***0.701***
	14%	7%	7%	14%	18%
1:30	***0.691***	***0.615***	***0.621***	**0.726**	**0.738**
	11%	11%	11%	11%	11%
2:00	***0.688***	***0.612***	***0.618***	**0.723**	**0.735**
	18%	14%	14%	18%	18%
2:30	***0.650***	***0.579***	***0.584***	***0.683***	***0.694***
	14%	11%	11%	18%	18%
3:00	**0.753**	***0.671***	***0.677***	**0.792**	0.805
	21%	18%	18%	25%	25%
3:30	***0.663***	***0.590***	***0.596***	***0.697***	***0.708***
	14%	7%	7%	21%	21%
4:00	0.995	0.886	0.894	1.045	1.063
	39%	18%	18%	43%	43%
4:30	1.002	0.892	0.900	1.053	1.070
	46%	36%	39%	46%	46%
5:00	1.070	0.952	0.962	1.124	1.142
	57%	39%	39%	57%	57%
5:30	1.145	1.019	1.029	1.203	1.222
	57%	39%	39%	75%	79%
Closing Call	***0.369***	***0.329***	***0.332***	***0.388***	***0.394***
	4%	4%	4%	4%	4%

Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 13.b Intra-Day Variance Ratio Tests, Deutsche Boerse (Second Period)

Intra-day variance ratios are presented for each half hour period during the trading day. INT is the scaled intra-day half hour variance. OC is the scaled open-to-close variance. OO is the scaled open-to-open variance. CC is the scaled close-to-close variance. OW is the scaled one-week variance, and TW is the scaled two-week variance. The percentages of stocks with variance ratios greater then unity are also presented below the market variance ratios. The second study period is June-December 2000 for Deutsche Boerse.

INT Ending	INT/OC	INT/OO	INT/CC	INT/OW	INT/TW
9:30	***3.516***	***2.991***	***3.019***	***3.457***	***3.118***
	100%	100%	100%	100%	100%
10:00	***1.609***	**1.369**	**1.382**	***1.582***	***1.427***
	100%	96%	96%	100%	100%
10:30	1.252	1.065	1.075	1.231	1.110
	89%	79%	79%	89%	82%
11:00	1.020	0.867	0.876	1.003	0.904
	79%	61%	61%	79%	71%
11:30	0.898	**0.764**	**0.771**	0.883	0.797
	61%	43%	43%	57%	43%
12:00	0.828	***0.704***	***0.711***	0.814	**0.734**
	46%	39%	39%	46%	43%
12:30	0.811	***0.690***	***0.696***	0.797	**0.719**
	57%	32%	43%	54%	43%
1:00	***0.687***	***0.585***	***0.590***	***0.676***	***0.610***
	36%	18%	18%	32%	25%
1:30	**0.723**	***0.615***	***0.621***	***0.711***	***0.641***
	32%	18%	18%	29%	18%
2:00	**0.720**	***0.612***	***0.618***	***0.708***	***0.639***
	43%	25%	25%	39%	25%
2:30	***0.681***	***0.579***	***0.584***	***0.669***	***0.604***
	29%	21%	21%	29%	25%
3:00	**0.789**	***0.671***	***0.677***	**0.776**	***0.699***
	46%	29%	29%	46%	39%
3:30	***0.694***	***0.590***	***0.596***	***0.683***	***0.616***
	36%	25%	25%	36%	25%
4:00	1.042	0.886	0.894	1.024	0.924
	68%	46%	46%	68%	54%
4:30	1.049	0.892	0.900	1.031	0.930
	68%	54%	57%	68%	64%
5:00	1.120	0.952	0.962	1.101	0.993
	71%	64%	68%	71%	68%
5:30	1.198	1.019	1.029	1.178	1.063
	82%	79%	79%	82%	79%
6:00	**0.780**	***0.663***	***0.670***	**0.767**	***0.692***
	54%	43%	43%	54%	43%

6:30	***0.481*** 7%	***0.409*** 4%	***0.413*** 4%	***0.473*** 7%	***0.427*** 7%
7:00	***0.360*** 0%	***0.306*** 0%	***0.309*** 0%	***0.354*** 0%	***0.319*** 0%
7:30	***0.375*** 7%	***0.319*** 0%	***0.322*** 0%	***0.368*** 7%	***0.332*** 0%
8:00	***0.535*** 14%	***0.455*** 4%	***0.460*** 4%	***0.526*** 14%	***0.475*** 7%
Closing Call	1.131 61%	0.962 54%	0.971 54%	1.112 61%	1.003 54%

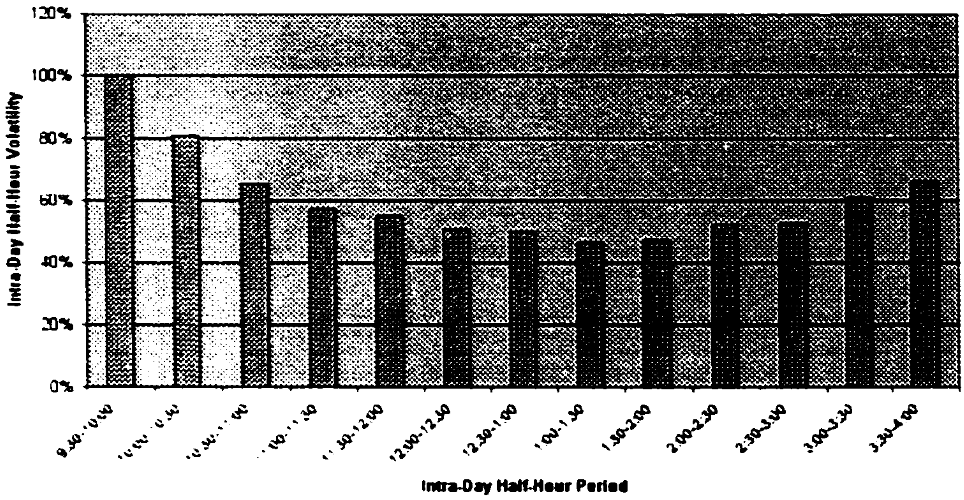
Bold entries indicate significantly different than unity at the 5% confidence level.
Bold and italic entries indicate significantly different than unity at the 1% confidence level.

Table 14. Ratios of Average Market Model R-Squares

	A Open / Mid	B Close / Mid	C Call / Mid
First Study Period			
New York Stock Exchange	0.710	1.068	NA
Nasdaq Stock Market	0.752	1.002	NA
London Stock Exchange	0.439	0.683	NA
Euronext Paris	1.142	1.063	0.507
Deutsche Bourse	1.177	0.938	0.795
Second Study Period			
New York Stock Exchange	0.911	1.063	NA
Nasdaq Stock Market	0.587	0.906	NA
London Stock Exchange	0.657	0.582	1.015
Euronext Paris	1.195	1.063	0.470
Deutsche Bourse (1)	1.246	1.038	NA
Deutsche Bourse (2)	1.272	1.126	1.561

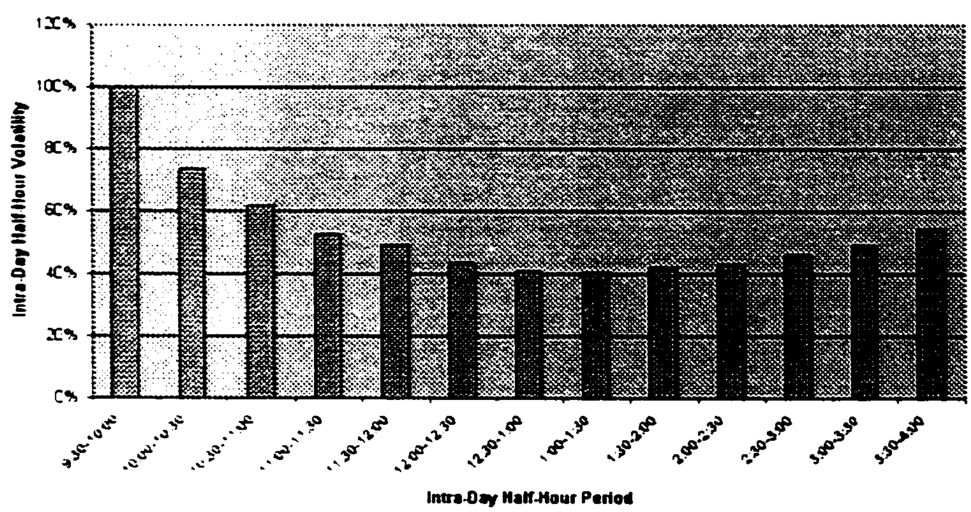
Opening R-squares (Open) are calculated as the average R-square of all stocks in the market during the opening half-hour period. Closing R-squares (Close) are calculated as the average R-square of all stocks in the market during the closing half-hour period. Closing call R-squares (Call) are calculated as the average R-square of all stocks in the market during the period from the closing of the continuous market to the closing call auction. Mid-day market model R-squares (Mid) are calculated as the average across all stocks in a market of all intra-day period market model R-squares for the periods excluding the opening half-hour, closing half-hour, and the closing call (if applicable). Deutsche Boerse (1) statistics are calculated using 5:30 pm as the effective closing time and Deutsche Boerse (2) statistics are calculated using the actual 8:00 pm as the closing time during the second study period.

Figure 1. Intra-Day Volatility, New York Stock Exchange, First Study Period



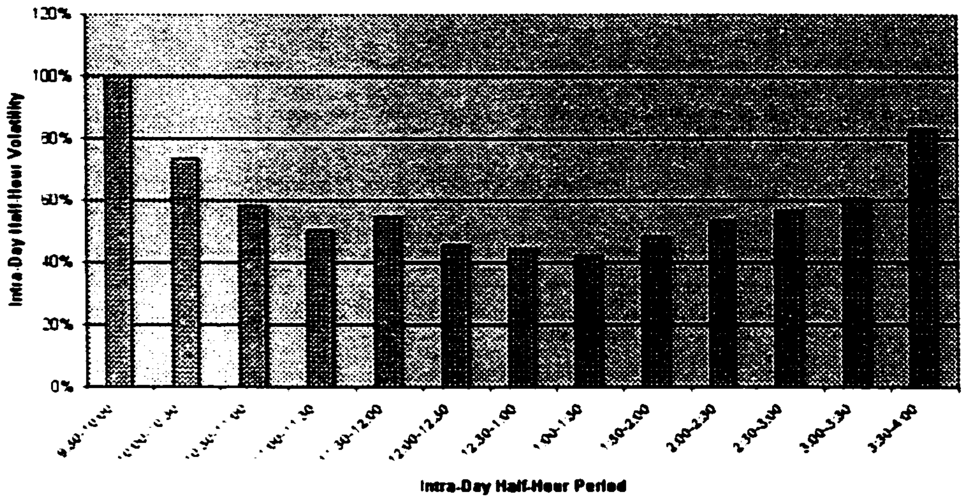
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 2. Intra-Day Volatility, New York Stock Exchange, Second Study Period



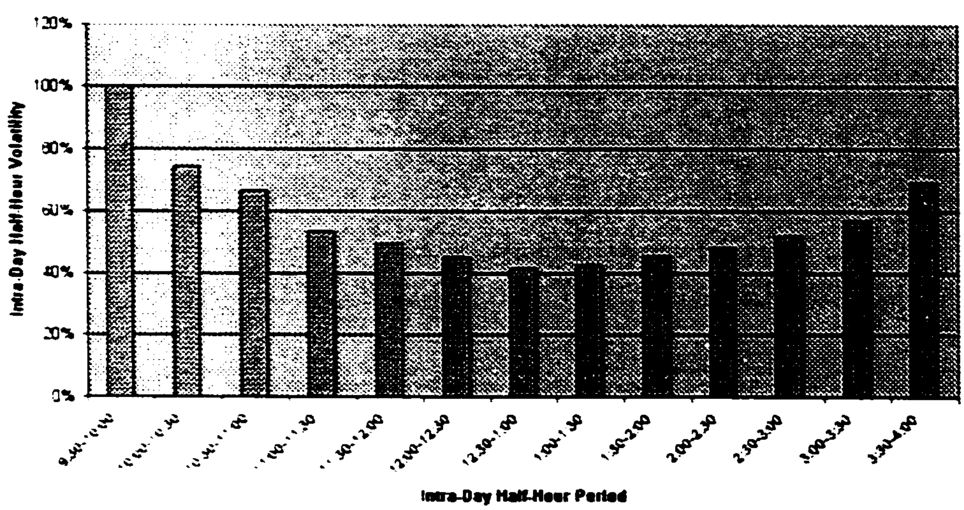
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 3. Intra-Day Volatility, Nasdaq Stock Market, First Study Period



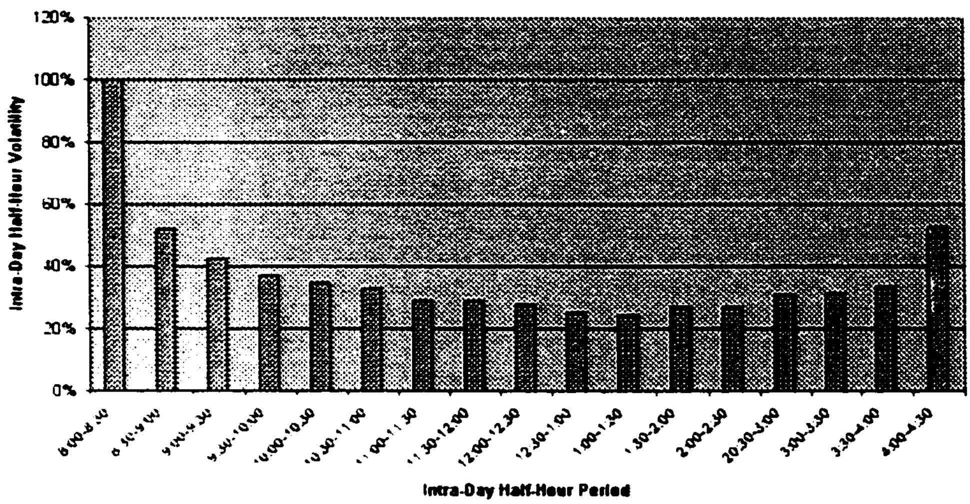
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 4. Intra-Day Volatility, Nasdaq Stock Market, Second Study Period



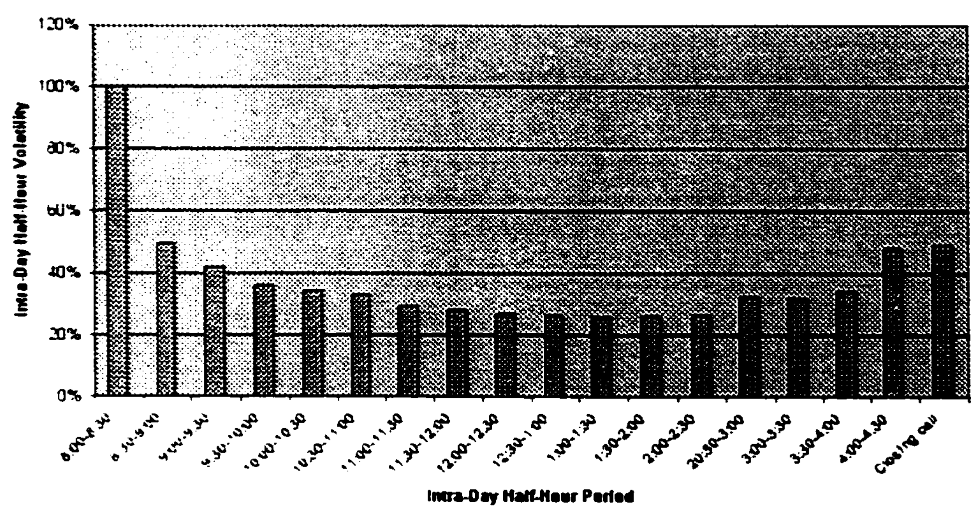
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 5. Intra-Day Volatility, London Stock Exchange, First Study Period



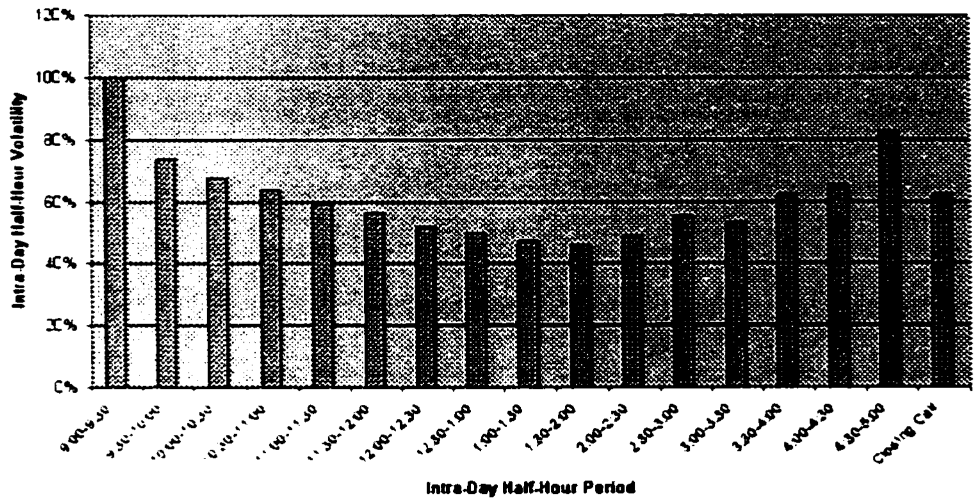
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 6. Intra-Day Volatility, London Stock Exchange, Second Study Period



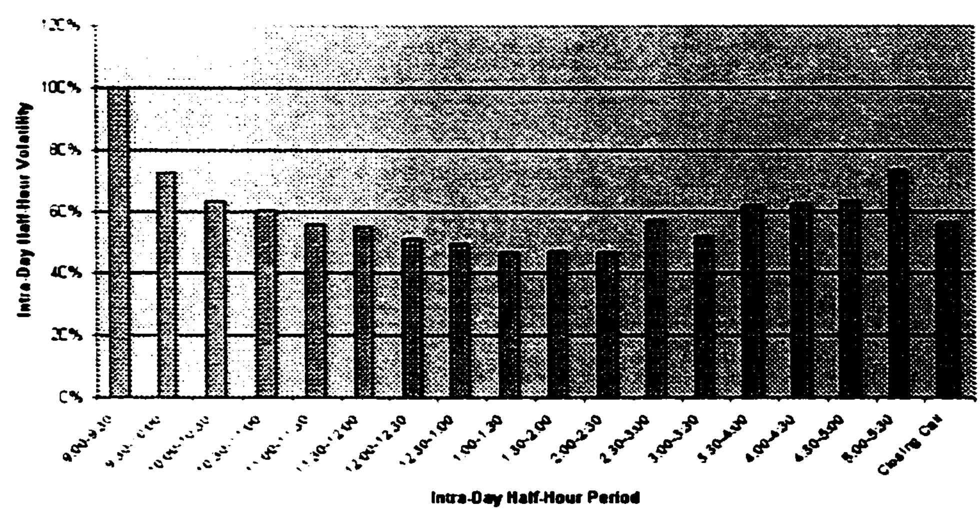
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 7. Intra-Day Volatility, Euronext Paris, First Study Period



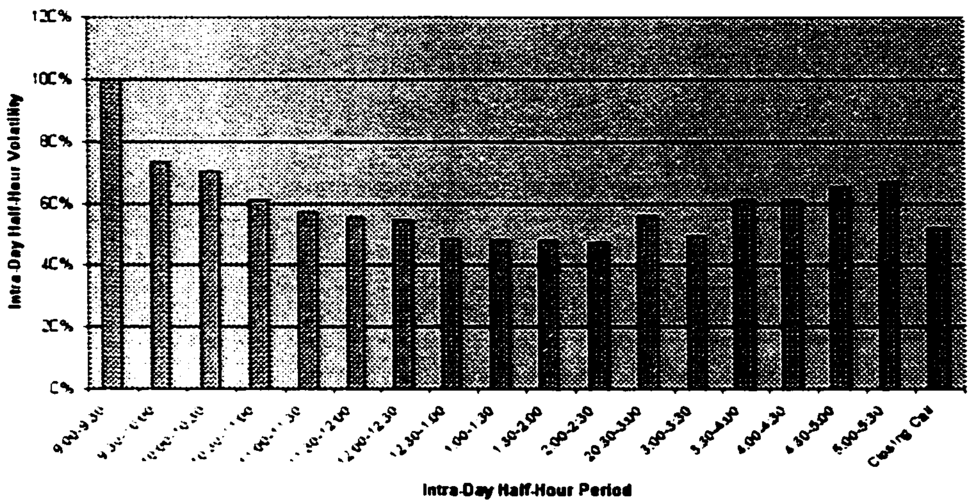
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 8. Intra-Day Volatility, Euronext Paris, Second Study Period



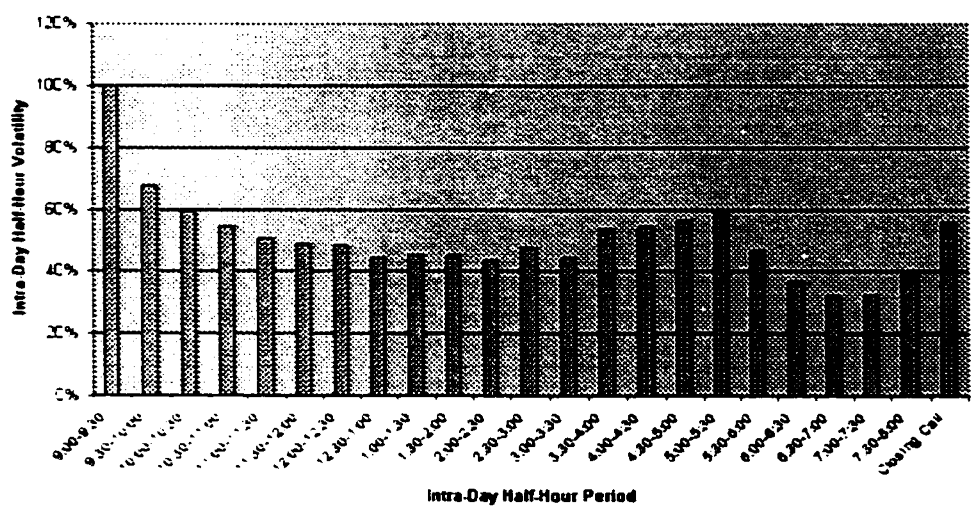
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 9. Intra-Day Volatility, Deutsche Boerse, First Study Period



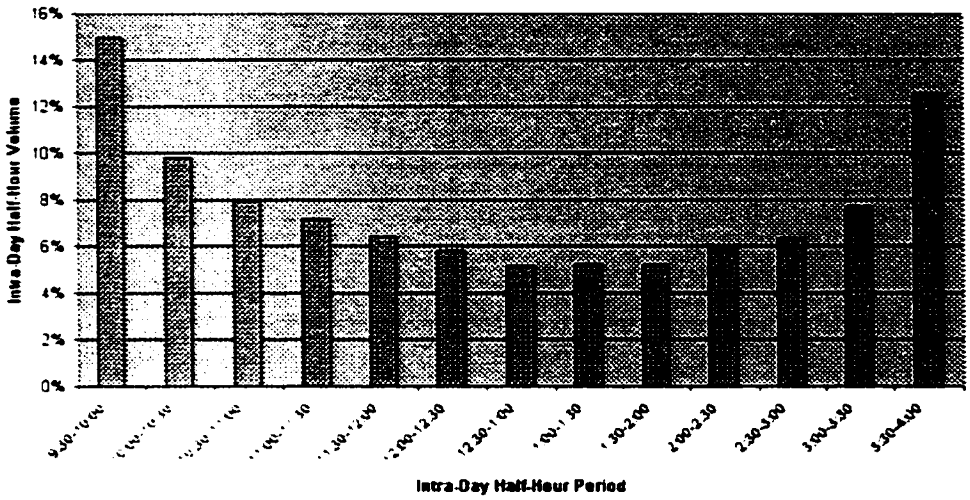
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 10. Intra-Day Volatility, Deutsche Boerse, Second Study Period



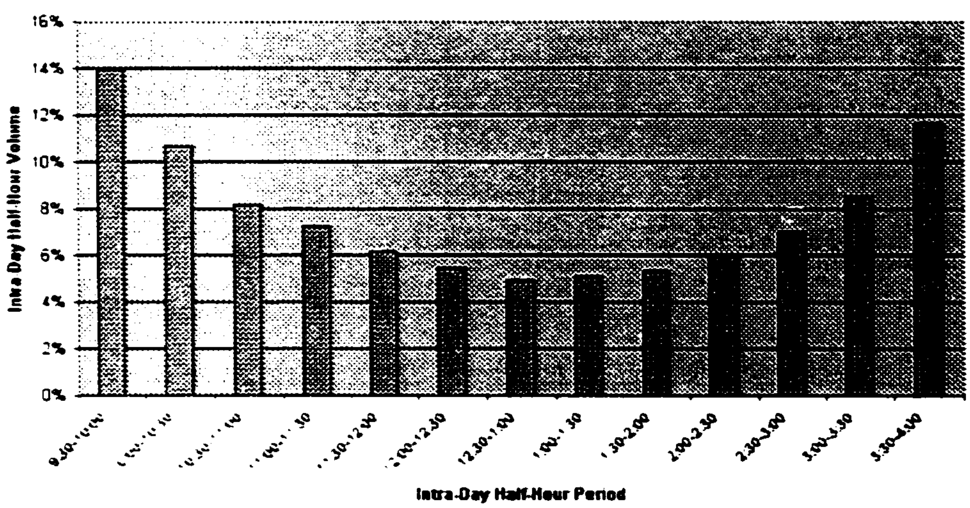
Intra-day half hour volatility is presented as a percentage of opening half-hour volatility for each of the half-hour periods. Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 11. Intra-Day Volume, New York Stock Exchange



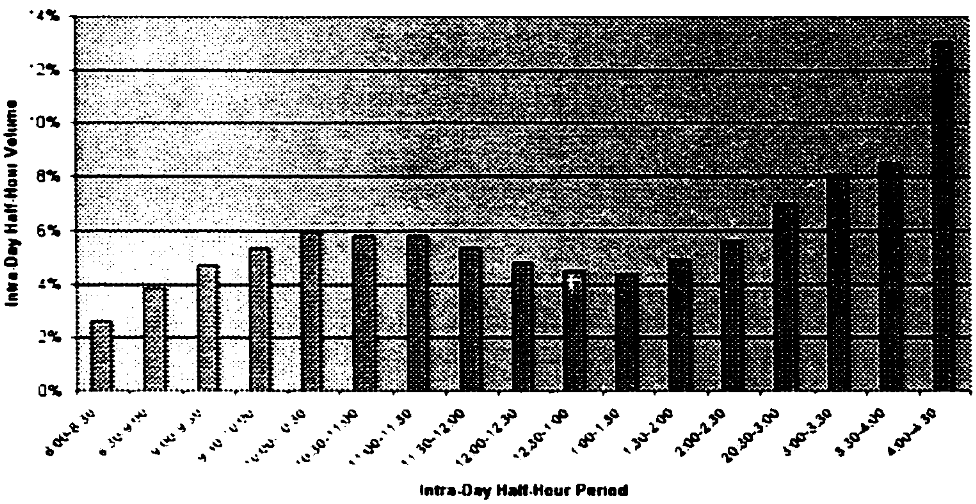
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The study period is January-February 2000.

Figure 12. Intra-Day Volume, Nasdaq Stock Market



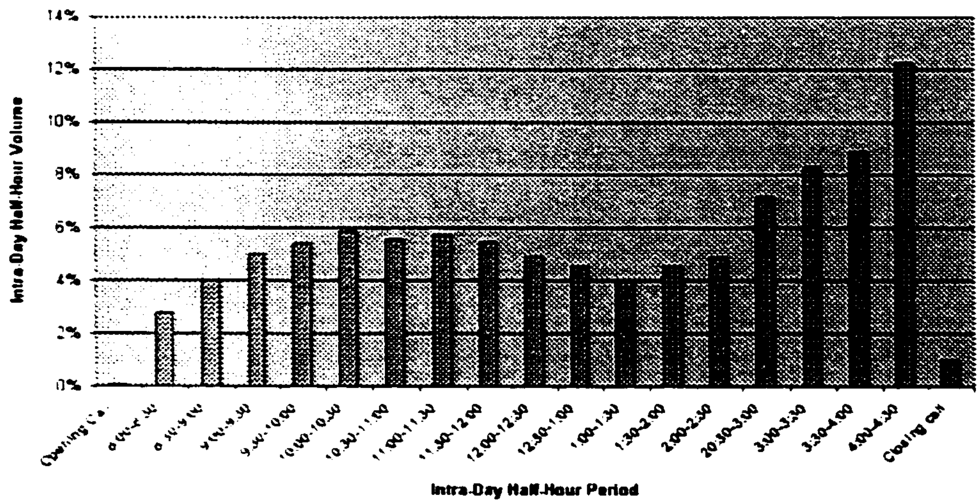
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The study period is January-February 2000.

Figure 13. Intra-Day Volume, London Stock Exchange, First Study Period



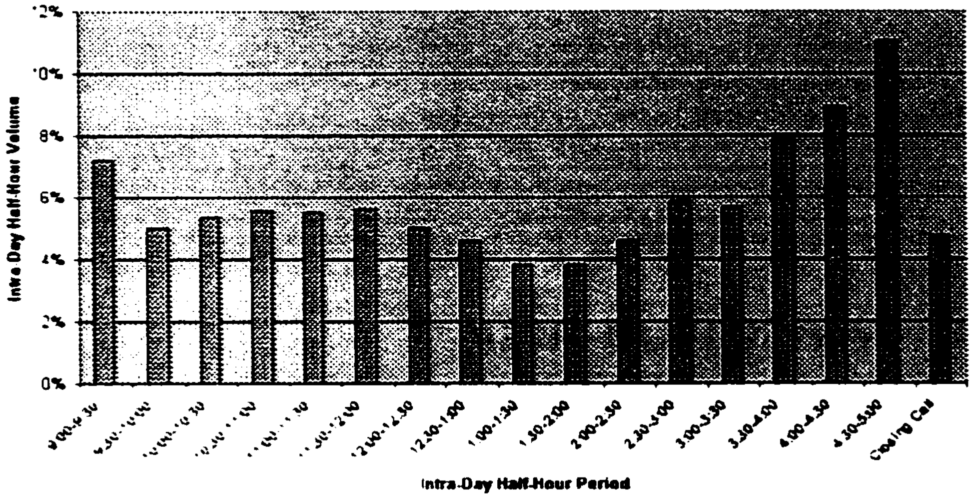
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-May 2000 and the second study period is June-December 2000

Figure 14. Intra-Day Volume, London Stock Exchange, Second Study Period



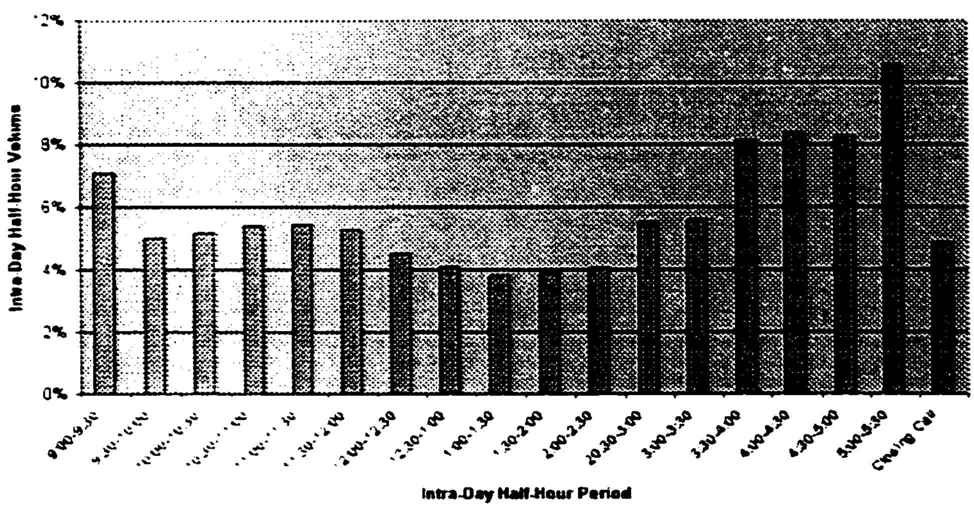
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-May 2000 and the second study period is June-December 2000

Figure 15. Intra-Day Volume, Euronext Paris, First Study Period



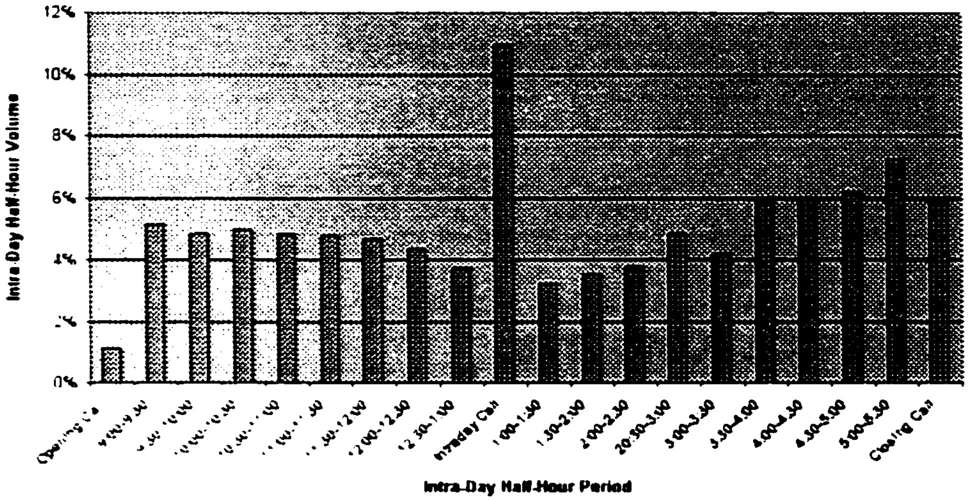
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 16. Intra-Day Volume, Euronext Paris, Second Study Period



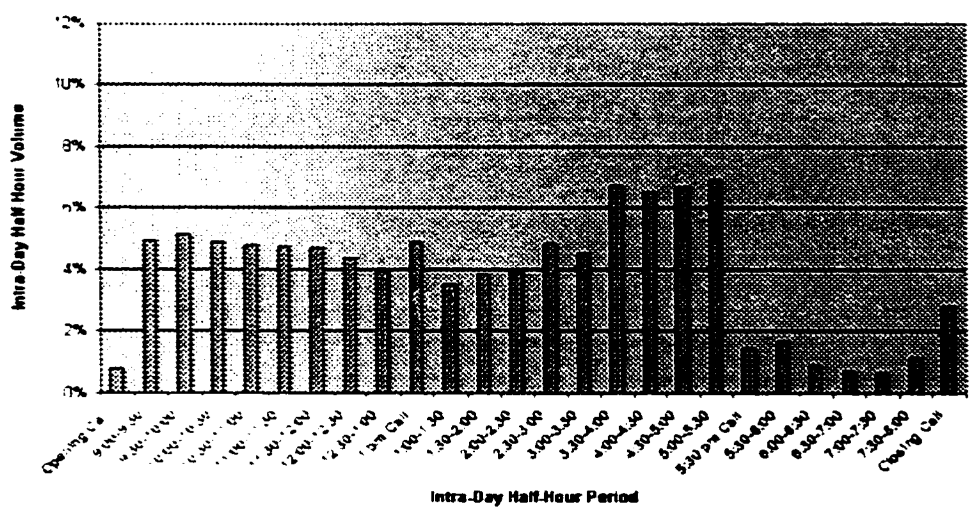
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 17. Intra-Day Volume, Deutsche Boerse, First Study Period



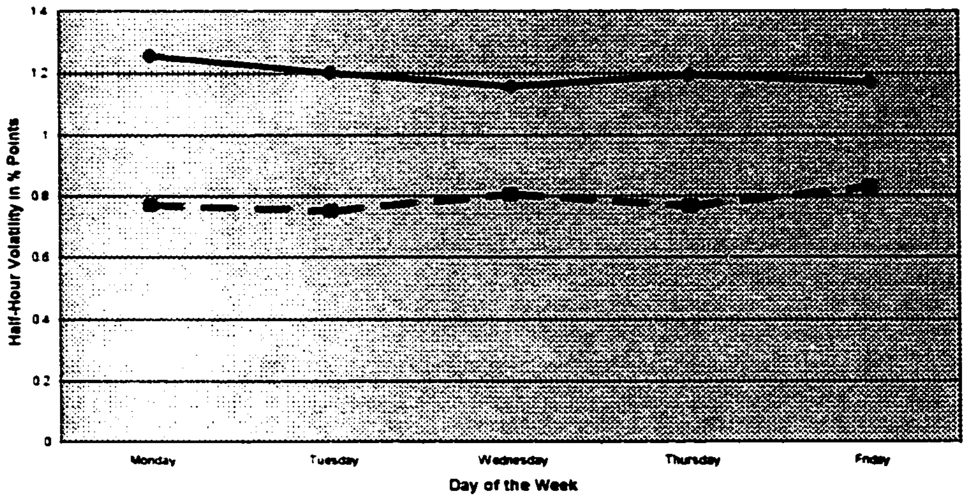
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 18. Intra-Day Volume, Deutsche Boerse, Second Study Period



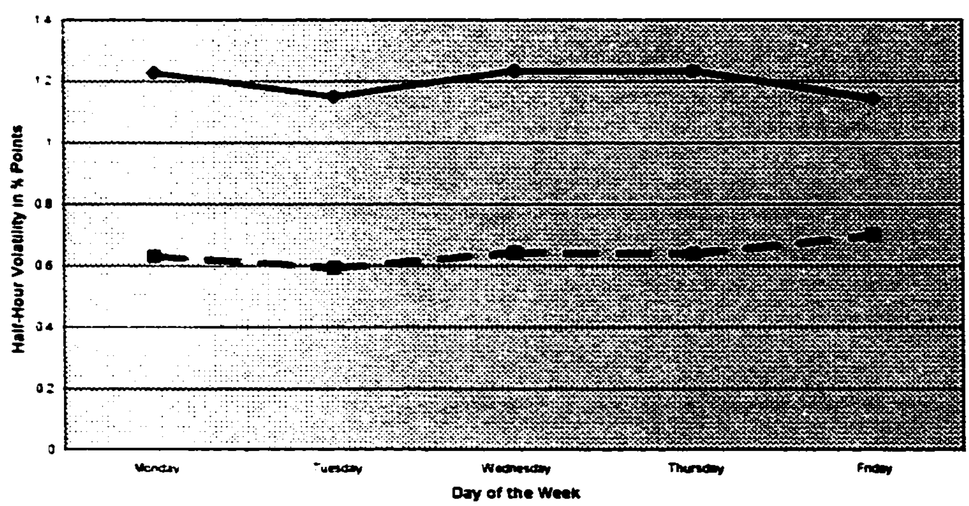
Intra-day half hour volume is presented as the cumulative volume traded during that half-hour period as a percentage of total daily volume traded. Volume is calculated as the cumulative volume across all the stocks in the sample for each of the half hour periods during the trading day. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 19. Day of the Week Volatility, New York Stock Exchange, First Study Period



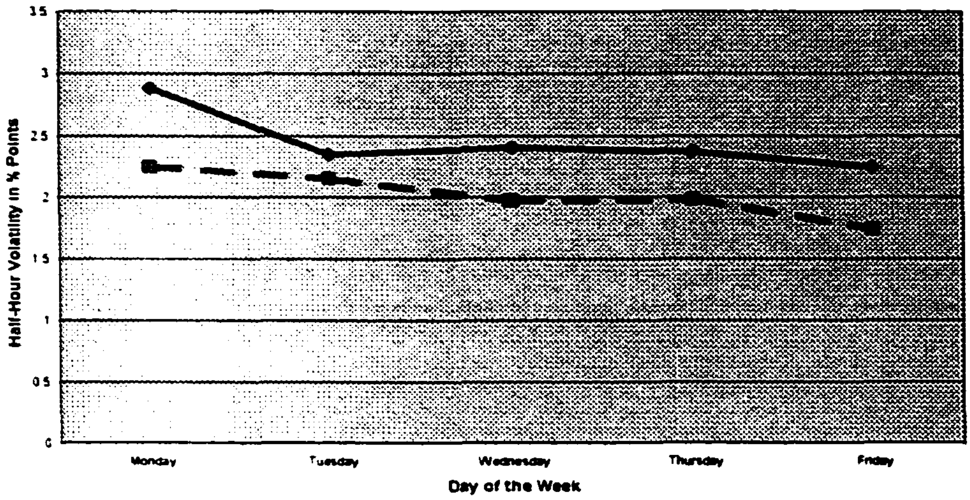
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 20. Day of the Week Volatility, New York Stock Exchange, Second Study Period



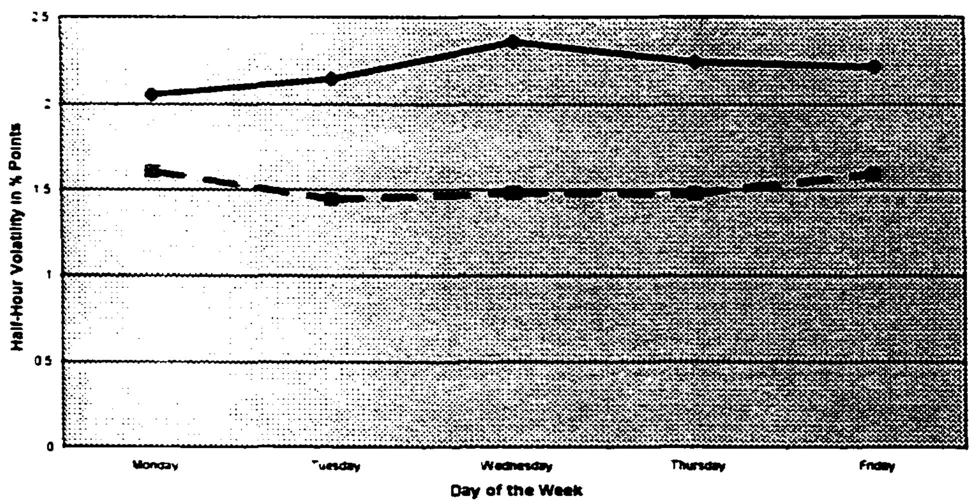
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 21. Day of the Week Volatility, Nasdaq Stock Market, First Study Period



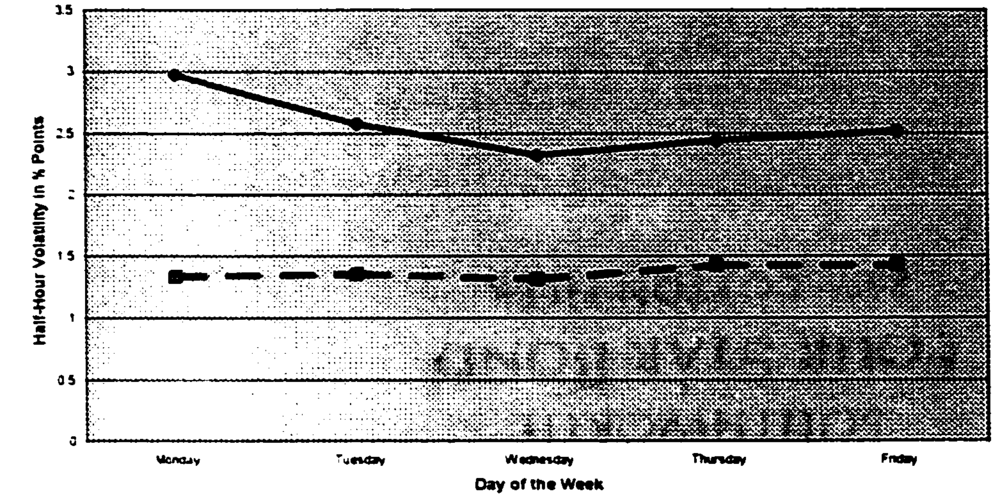
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 22. Day of the Week Volatility, Nasdaq Stock Market, Second Study Period



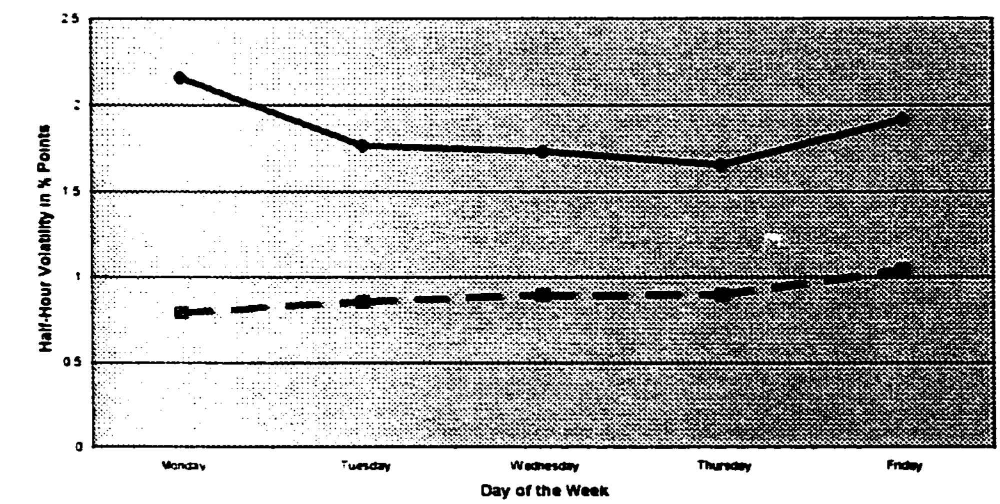
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 23. Day of the Week Volatility, London Stock Exchange, First Study Period



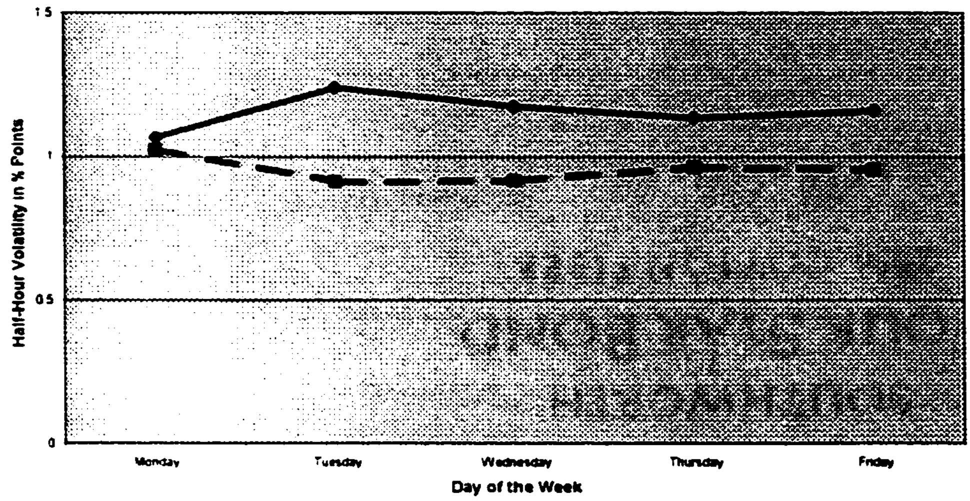
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 24. Day of the Week Volatility, London Stock Exchange, Second Study Period



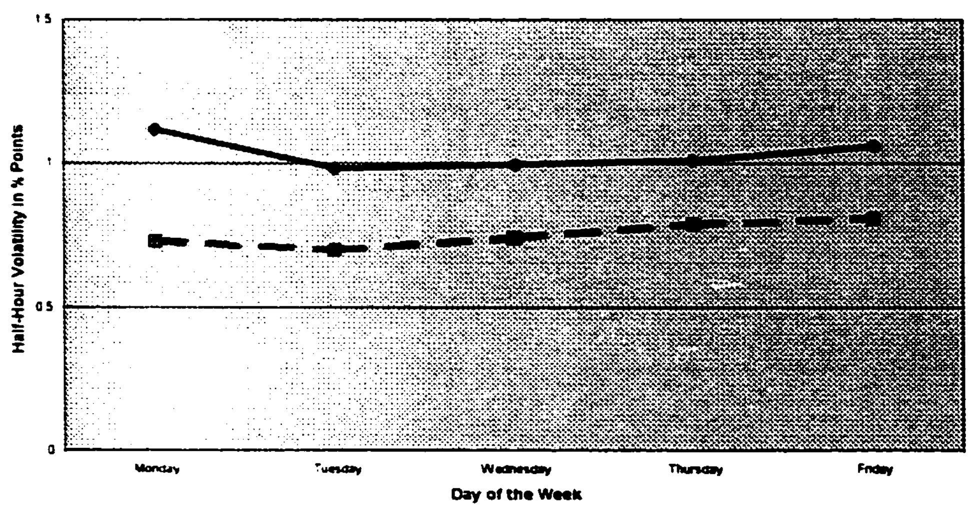
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 25. Day of the Week Volatility, Euronext Paris, First Study Period



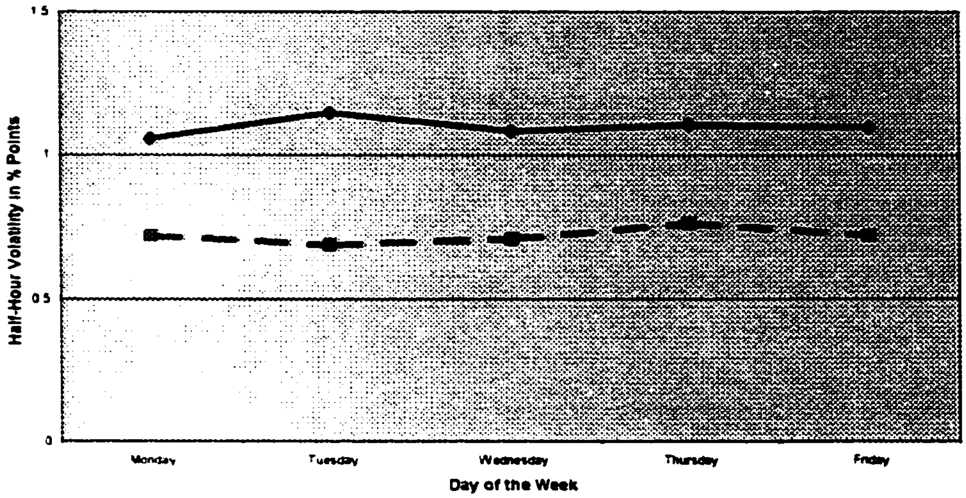
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 26. Day of the Week Volatility, Euronext Paris, Second Study Period



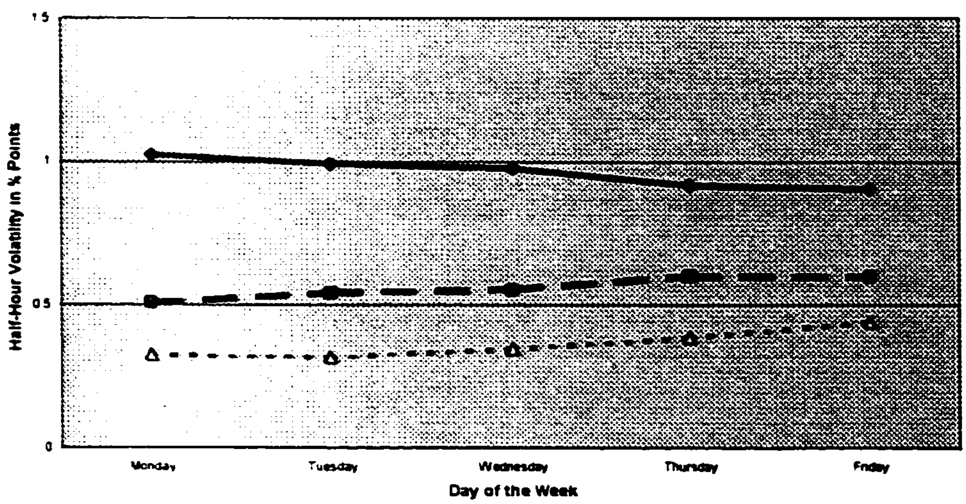
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 27. Day of the Week Volatility, Deutsche Boerse, First Study Period



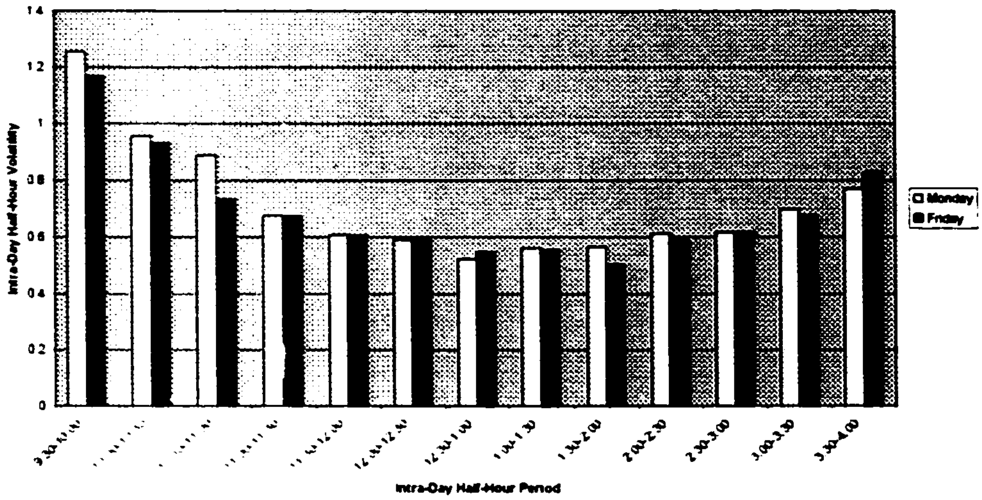
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility and the broken (bottom) line represents the closing half hour volatility. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 28. Day of the Week Volatility, Deutsche Boerse, Second Study Period



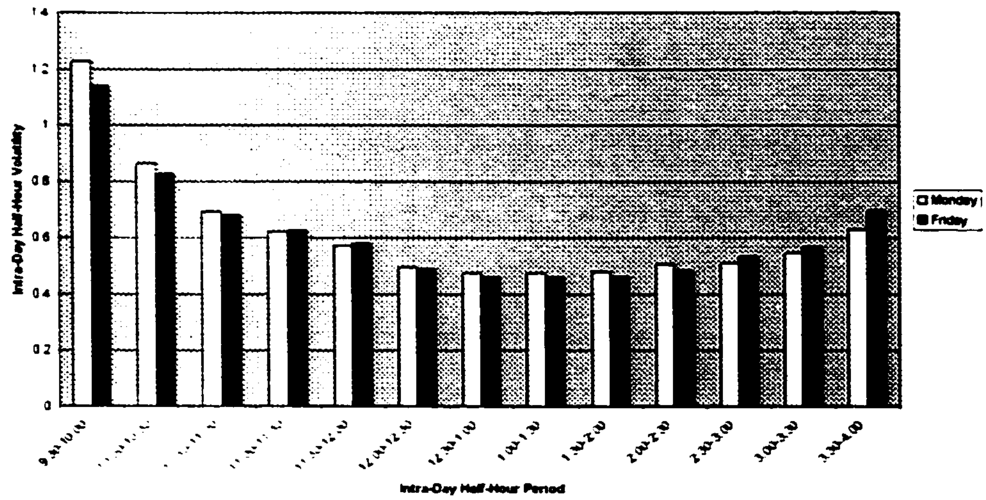
Opening half hour volatility and closing half hour volatility are calculated for each day of the week separately. The unbroken (top) line represents the opening half hour volatility. The broken (middle) line represents the closing half hour volatility for the effective 5:30 pm close, and the dotted (bottom) line represents the closing half hour volatility for the actual 8:00 pm close. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 29. Monday/Friday Intra-Day Volatility, New York Stock Exchange, First Study Period



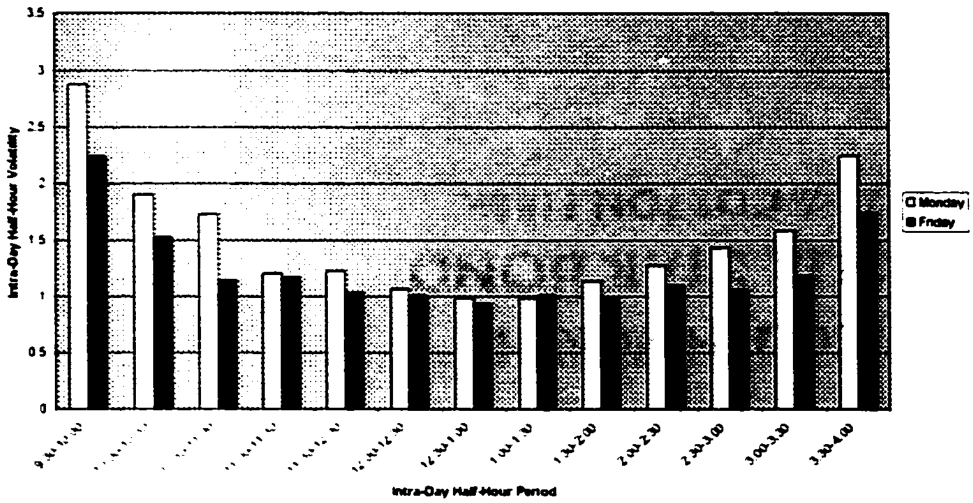
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 30. Monday/Friday Intra-Day Volatility, New York Stock Exchange, Second Study Period



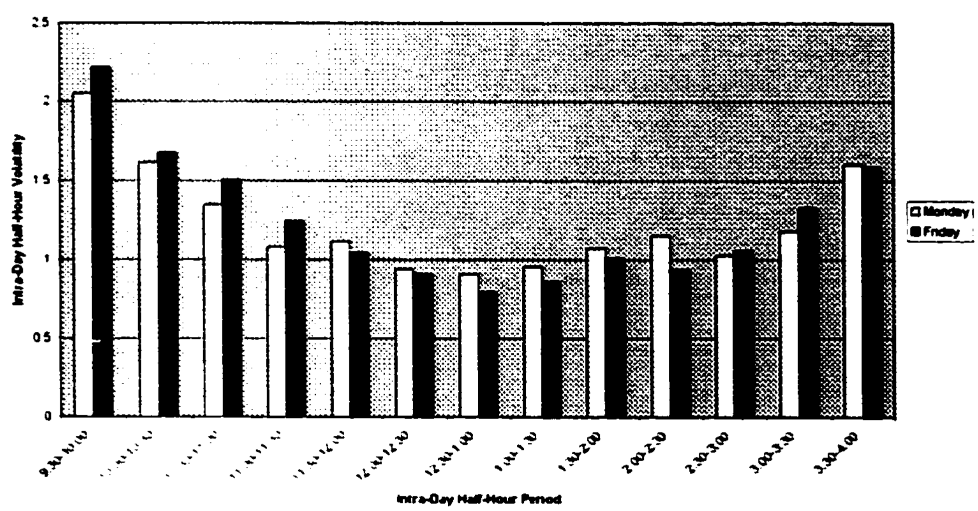
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 31. Monday/Friday Intra-Day Volatility, Nasdaq Stock Market, First Study Period



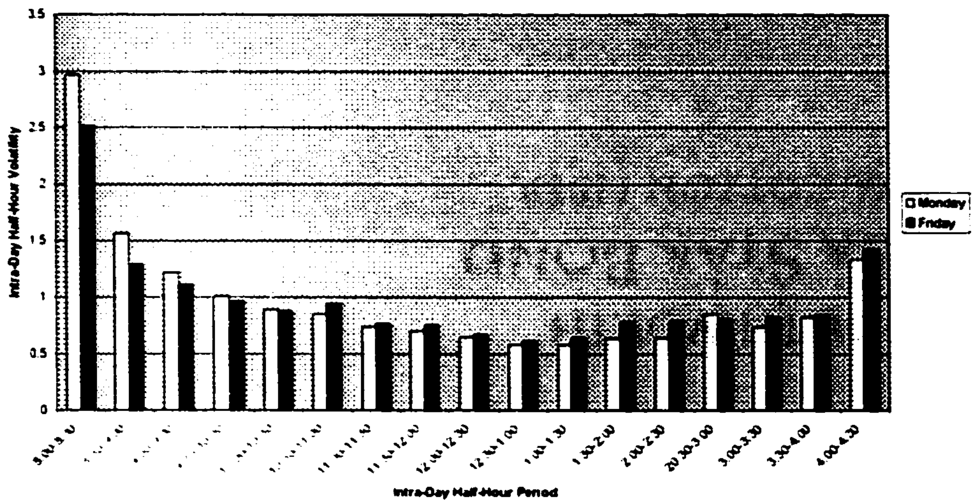
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 32. Monday/Friday Intra-Day Volatility, Nasdaq Stock Market, Second Study Period



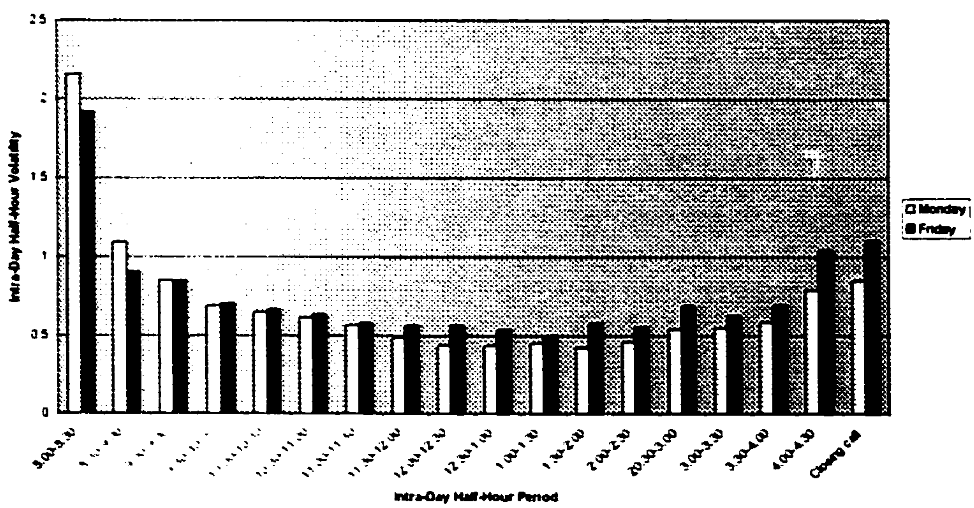
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 33. Monday/Friday Intra-Day Volatility, London Stock Exchange, First Study Period



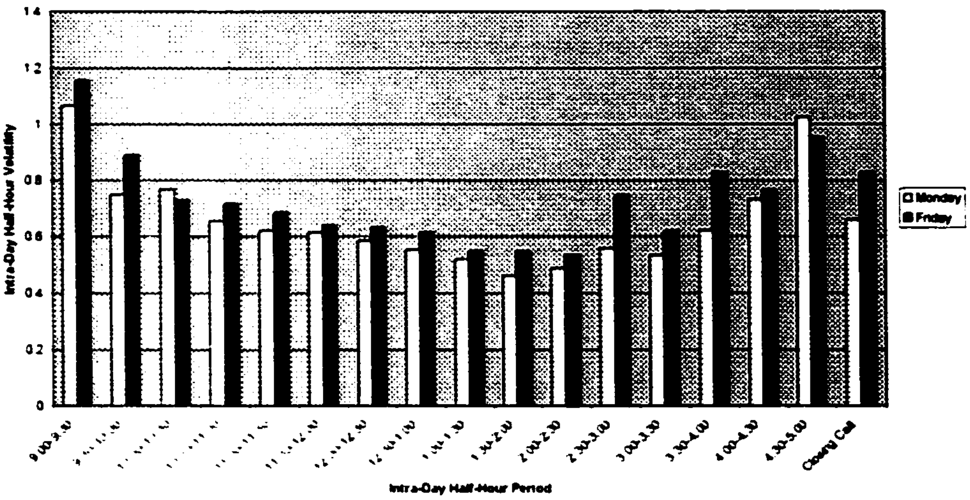
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 34. Monday/Friday Intra-Day Volatility, London Stock Exchange, Second Study Period



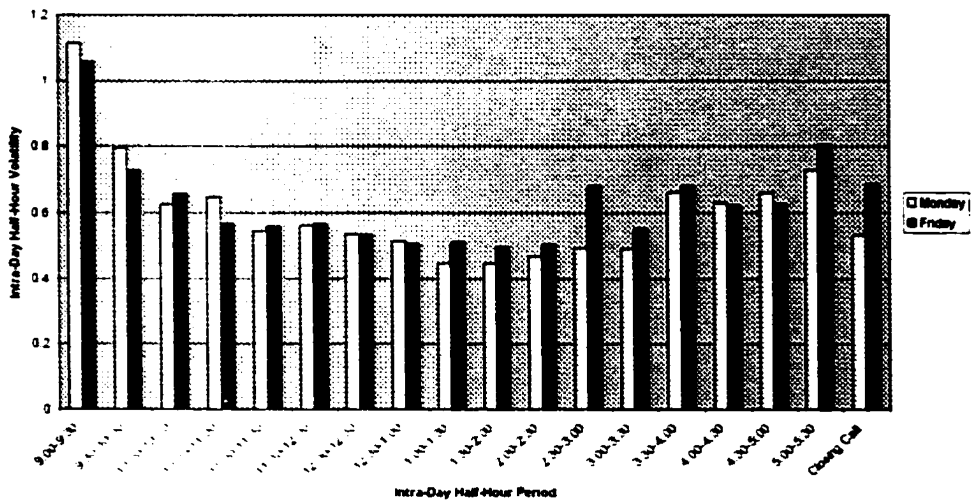
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 35. Monday/Friday Intra-Day Volatility, Euronext Paris, First Study Period



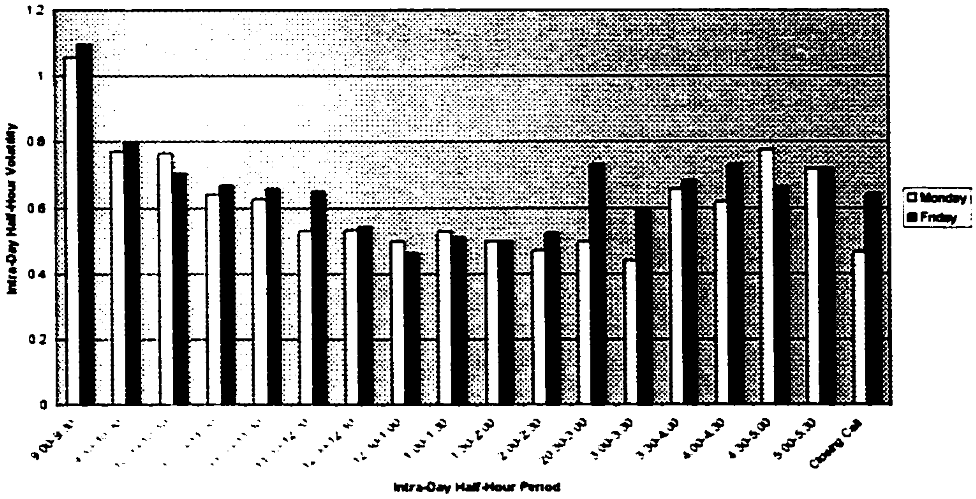
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-March 2000 and the second study period is April-December 2000.

Figure 36. Monday/Friday Intra-Day Volatility, Euronext Paris, Second Study Period



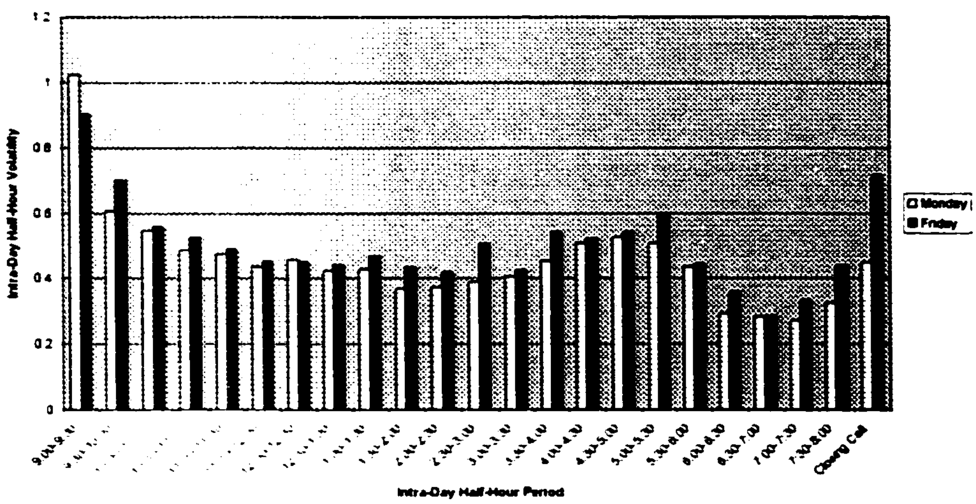
Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-May 2000 and the second study period is June-December 2000.

Figure 37. Monday/Friday Intra-Day Volatility, Deutsche Boerse, First Study Period



Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

Figure 38. Monday/Friday Intra-Day Volatility, Deutsche Boerse, Second Study Period



Volatility is calculated as the average standard deviation across all the stocks in the sample for each of the half hour periods during the trading day. The lighter colored bars denote the Monday intra-day volatilities and the darker colored bars denote the Friday intra-day volatilities. Opening half-hour period does not contain the over-night price changes. The first study period is January-June 2000 and the second study period is July-December 2000.

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