SYED MUJAHID HUSSAIN

INTRADAY DYNAMICS OF INTERNATIONAL EQUITY MARKETS
Intraday dynamics of international equity markets

Key words: Intraday; Macroeconomic surprises; intraday seasonality; Flexible Fourier Form; conditional mean; conditional volatility; information spillover; Diurnal Pattern; VAR; EGARCH; Asymmetry; Trading volume; Bid-Ask Spread.

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Syed Mujahid Hussain
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PART II: THE ESSAYS

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1 Introduction

The increased availability of high frequency data sets have led to important new insights in understanding of financial markets’ behavior. The use of high frequency data is interesting and persuasive, since it can reveal new information that cannot be seen in lower data aggregation. However, high frequency observations also pose a number of challenges for the academics and researchers as they are subject to a wide range of idiosyncratic factors such as non-synchronous trading, intra-day seasonal effects, measurement errors due to bid-ask spreads or reporting difficulties, and even conceptual problems, such as defining a ‘return’ during an interval in which no trading occurs [Goodhart and O’ Hara (1997)].

The development of high frequency data bases has allowed for empirical investigations of a wide range of issues in financial markets’ research. Traditionally, most of the studies using high frequency data have either focused on the U.S markets or concentrated on foreign exchange markets. Though, more recently, many studies have emerged exploring the intraday dynamics of stock markets other than the U.S. However, the studies focusing on the European equity markets are still rare. Accordingly, this study investigates intraday dynamics of the major European equity markets using equally spaced 5-minute data.

In this dissertation, we explore some of the many important issues connected with the use, analysis and application of high-frequency data. These include the effects of intra-day seasonals, the behavior of time-varying volatility, and the information content of various market data. We also address the issue of inter-market linkages using high frequency data. Understanding intraday regularities is important for market participants, regulators and researchers. It is also important for policy makers and enforcers to better understand market events, in order to formulate and implement effective regulation.

2 Stylized Facts of High Frequency Data

It is important to recognize the main qualitative features that affect the intraday return process but are absent at daily and lower frequency levels. One stylized feature of financial markets’ volatility that impacts the modelling process is long memory in intraday returns. Recent work using intraday returns has produced evidence of so-called long memory, implying a slow hyperbolic decay in the absolute and squared
return auto-correlation patterns, rather than the faster geometric decay associated with traditional volatility models. This, of course, has important implications for longer-run conditional volatility and return distribution forecasts. Andersen and Bollerslev (2006) argue that the studies applying standard modeling and inference techniques to the newly available intraday data are seriously misspecified as they produce badly downward biased estimates of the degree of volatility persistence.

Figure 1 displays the correlogram of the absolute returns for three international stock market indices, the UK, Germany and the U.S. For all three markets, the series were lagged for 10 trading days. As can be clearly seen, the high autocorrelations are clustered around the opening and closing of each trading day in FT100 and SP500 index, whereas XDAX30 displayed a pattern resembling W. The source for this characteristic was the intraday seasonal volatility pattern depicted in Figure 2, i.e. high volatilities at the opening and closing of the trading day caused the autocorrelation pattern to behave in a cyclical manner. The 10-day correlogram also illustrate the well-known volatility persistence.

The other feature that distinguishes intra-daily from lower-frequency studies of volatility is much stronger intra-day seasonality. Much of this intra-day seasonality in stock markets’ volatility arises from time-of-day phenomena, e.g. market opening and closing and macroeconomic news announcements during the trading day. Adjustments to do so have involved using seasonal dummies [Baillie and Bollerslev(1990a,b)], time-scaling [Dacorogna et al.(1993)], or some type of Fourier transform [Andersen and Bollerslev(1994)].
Figure 1. Autocorrelation pattern of 5-minute absolute index returns.
Notes: The maximum lag length depicted on x-axis is 10 trading days for all markets. The dashed line depicts the autocorrelation coefficients for absolute returns.
Andersen and Bollerslev (1994) and Guillaume et al. (1995) show that, unless the (deterministic) intra-daily affects on volatility are taken into account, GARCH coefficients are likely to be spurious, and, even when they are incorporated, GARCH processes often tend to be unstable and unsatisfactory when used on intra-daily data.

In this dissertation, we explore intraday seasonalities in four major European stock markets of France, U.K, Germany and Switzerland. Figure 2 presents average intraday volatilities for each 5 minute period across the trading day. The return volatilities clearly exhibit intraday periodicities in all four markets. Furthermore, the periodic pattern across all European markets exhibits remarkable similarities. Though, these equity markets did not exhibit a typical diurnal pattern (a reverse J shape) observed in other financial markets. We report a new empirical evidence of intraday periodicities in European stock markets.

Before modeling the return volatility in our dissertation, following Andersen and Bollerslev (1994), the 5-minute returns were filtered from intraday seasonalities using Flexible Fourier Form (FFF) transformation. Our results (shown in Appendix A) confirmed that the Flexible Fourier Form (FFF) representation provided an excellent overall characterization of the intraday periodicity.

Figure 2. Periodic pattern in intraday volatilities.
3 Market Reactions to Macro Announcements

The intraday return data also facilitate the study of market reactions to economic news. As noted by Andersen and Bollerslev (2006), at daily or shorter intervals, it is critical to understand the likely reaction of markets to impending news releases and to control for the intraday pattern in the market activity and return dynamics.

In this dissertation, we examine the role of U.S macroeconomic news announcements in explaining the return and volatility process in the major European stock markets. Our findings suggest that the U.S. macroeconomic surprises exerted an immediate and major impact on both, the European stock markets’ intraday returns and volatilities. Thus, high frequency data appear to be critical for the identification of news that impacts the markets. This research contributes to the existing literature by presenting new evidence of the effect of U.S. macro surprises upon European equity markets in the intraday setting.

4 Spillovers and Cross Market Interactions

We address the issue of cross market linkages using high frequency data. There were fewer studies that have modeled dynamic intraday interactions between equity markets using high-frequency data, owing perhaps to the difficulty, until recently, of obtaining intra-daily time series for other markets than the U.S. Since a shock in a national market may be transmitted to another market within a very short period of time, it is essential to employ high-frequency data in studies of markets that operate concurrently.

Among the earlier papers employing high frequency data, Engle and Susmel (1994) examined the relationship between the New York and London stock markets using concurrent hourly returns. They did not report any significant evidence of volatility spillovers between these two markets. Jeong (1999) employed overlapping high-frequency data (5-minute returns during 2 hours of overlapping trading) to explore the transmission pattern of intraday volatility among the US, Canadian and UK markets. His results provide evidence of strong inter-market dependence in intraday setting.

We investigate the intraday return and volatility interaction between the UK and German equity markets using concurrent 5-minute data. Furthermore, the US effect is explicitly modeled using SP500 and macroeconomic surprises, hence controlling for
any overlapping impact on European markets. We report significant and reciprocal intraday spillovers across two European equity markets. Whereas, in contrast to earlier findings, no significant volatility spillover from the US to European stock markets is observed during the overlapping trading hours. However, the US stock market impact could largely be described as a contemporaneous effect.

5 Market Microstructure Issues

Another issue of interest is the effects of market structure on subsequent return volatility where market participants learn from past trades and use this information to adjust prices in the following period. Since the information about the foreign market movements (trading behavior) becomes available to domestic investors after the trade, it may take time for the market to resolve heterogeneous interpretation of foreign information. As a result, spillovers effects from foreign market to the local market will be observed.

We also explore whether lagged trading activity in one market contributes to the return and volatility process in other market using 5 minute concurrent data from German and the U.K equity markets. Our findings clearly indicate that intraday trading volume contains predictive power for cross border return and volatility processes. Moreover, these volume effects are found to be asymmetric in the sense that impact of positive volume changes is larger on foreign stock market volatility than the impact of negative changes.

6 Intraday Patterns

Voluminous research has documented the existence of intraday periodicities in returns, return volatility, bid-ask spreads and trading volume, in both equity and foreign exchange markets. Among the earlier studies, intraday U-shaped pattern in return variance were demonstrated, for example by McInish, Ord and Wood (1985), McInish and Wood (1990a) and Harris (1986). Jain and Joh (1988), McInish and Wood (1990b) reported intraday U-shaped patters in trading volume. Brock and Kleidon (1992) report that bid-ask spreads tend to be higher at the beginning and the end of the trading day, thus follow a U-shaped pattern during the day.

There are different explanations for intraday regularities observed in key financial markets’ variables. Admati and Pfleiderer (1988) relate the U-shaped (also sometimes
referred as reverse J shaped) pattern in volume and volatility with the private information. They argue that high volume in a particular time segment reveals the presence of asymmetric information as noise traders camouflage the activities of the informed traders, and this gives rise to the volatility. Therefore, volume and volatility move in the same direction. In contrast, Brock and Kleiden (1992) argue that trading halts and different trading strategies at the open and close of the markets form these volume patterns. Since, in their model, high volume is associated with the high liquidity demand at the open and close of the trading day, spreads will also follow a U-shaped pattern during the day.

![Figure 3: Intraday patterns in return volatility, bid-ask spread and trading volume in XDAX-30 index](image)

In this dissertation, we take a fresh empirical look at the intraday patterns in return volatility, trading volume and bid-ask spread using the aggregate data on XDAX30 constituents. Intraday patterns in return volatility, bid-ask spread and trading volume in XDAX-30 index are shown in Figure 3. We display strong intraday seasonal pattern in return volatility, trading volume and bid-ask spread using the aggregate data for the XDAXD 30 index. We report a pattern close to reverse J-shape for intraday bid-ask spreads and return volatility. The aggregate trading volume exhibits L-shaped pattern for the German blue chip index. Furthermore, this study provides additional empirical evidence on the relationship between return volatility, trading activity and market liquidity variables at the aggregate level for the XDAX30 constituents. We also relate the return volatility with informed and uninformed trading by splitting the data into
expected and unexpected component, and also report asymmetry effect of trading volume on return volatility.

7 The Essays

This dissertation *Intraday dynamics of International Equity Markets* consists of four interlinked essays. This section provides the summaries and central findings of these essays.

7.1 Essay 1: Intraday Seasonalities and Macroeconomic News Announcements

In this paper the intraday dynamics of major European stock markets were analyzed using high frequency 5-minute returns. Furthermore, the role of U.S macroeconomic news announcements was examined to explain the return and volatility process in major European stock markets. This research contributes to the existing literature by presenting new evidence of the effect of U.S. macro surprises upon European equity markets in the intraday setting, using carefully constructed 5-minute returns, efficiently filtered for intraday seasonalities.

The main findings are as follows. First, European equity markets did not exhibit a typical diurnal pattern (a reverse J shape) observed in other financial markets. This so-called intraday diurnal pattern was typically affected by two major happenings in the U.S., the scheduled U.S. macroeconomic news announcements at 14.30 and 16.05 CET, and the NYSE cash market opening time at 15.30 CET. Second, the calendar effects were commonly observed in all European equity markets in question, i.e., the intraday seasonalities differed across the weekdays and market openings and closures were apparent as typically noticed in financial markets. Third, empirical findings provided support for the initial indication that the major U.S. macroeconomic news had cross border impact on both European equity returns and volatilities. Furthermore, the major U.S. macroeconomic announcements dominated the picture immediately following their release, thus high frequency data were critical for the identification of news that impacted the markets. The findings also related to a common result in spillover literature in that the U.S. market is the most important producer of information (Eun & Shim, 1989; Ng, 2000; Theodossiou & Lee, 1993).
Overall, the results suggested that the U.S. fundamentals form a subset of European investors’ public information. This implies that equity returns and volatilities are generally sensitive to the news originating in foreign markets. The analysis indicated that two U.S. inflation measures (CPI and PPI), three real macroeconomic variables (retail sales, advanced durable goods and the unemployment rate) and U.S. broad output measure (industrial production) could be considered as potential market risk factors by investors. Moreover, two other variables, ISM indices and Housing starts also had significant impact on volatilities across all four European stock markets. Another important finding is that European stock markets reacted similarly to the information originating in the U.S. One interpretation for such behavior is that news revealed in the U.S. is perceived as informative to fundamentals of stock prices in the Europe, a view that can be attributed to real and economic linkages of international economies.

The implication of these findings for investors is a reduced portfolio diversification effect between the European markets and the U.S. due to fundamental linkages and the dominant impact of the U.S market. These results suggested a further investigation of the short-term cross dependencies on stock markets and the economic integration of Europe and U.S. The strong intraday seasonal pattern, exhibited by the European stock markets, has important implications for researchers and investors when modeling the short-term dynamics of the return and volatility behavior.

7.2 Essay 2: Intraday Linkages across International Equity Markets

This paper explores the dynamic first and second moment linkages among international equity markets using 5-minute index returns from the equity markets of the UK, Germany and the US, for the period September, 2001 through August, 2003. The sample was divided into two sub-samples according to time. The first sub-sample consisted of 5-minute return observations from the opening until 15.30 CET for two stock indices, FTSE 100 of the UK and XDAX of Germany, while the second sub-sample reached from 15.35 through 17.30 (CET). This allowed the modeling of intraday dependencies of two major European markets in the absence and presence of the US stock market trading activity.

The main findings are as follows. The two European markets exhibited significant reciprocal return and volatility spillovers. This relationship appeared virtually
unchanged by the presence or absence of the US market. The US stock market impact could largely be described as a contemporaneous effect, i.e. the return correlation among the UK and Germany rose significantly during the afternoon trading following the US stock market opening. In contrast to earlier findings, no significant volatility spillovers from the US to the European stock markets were observed. The concurrent intraday returns were found to be informative as they demonstrated substantial cross correlation among the three equity markets. Furthermore, taking into account the strong intraday seasonalities appeared essential when modeling intraday returns.

While interpreting the lead/lag relationships, the fact that these indices constitute different number of stocks, should be taken into consideration, due to potential influence of non synchronous trading. Further research is needed to investigate the causes of the reciprocal spillovers. In addition, the index constituents’ time varying covariance structure could be investigated for deeper understanding of the observed cross market dependencies on index data.

### 7.3 Essay 3: Intraday Trading Volume and International Spillover Effects

This paper investigated whether lagged trading activity in one market contributes to the return and volatility process in another market using 5 minute concurrent data from German and the U.K equity markets.

The use of trading volume facilitates us to measure information transmission mechanism across two stock markets. This setting allows us to combine the two possible channels of information transmission across markets, with volatility and trading volume providing measures of the significance of the information reflected in other market.

Moreover, this paper also sheds light on market microstructure issues in which traders and market makers learn from watching market data, and it is this learning process that leads to price adjustments.

Overall, we conclude that lagged trading volume plays an important role in explaining international return and volatility transmissions. The examination concerning asymmetries revealed that the impact of positive volume changes is larger on foreign stock market volatility than the impact of negative changes.
These findings shed new light on the application of trading volume in the market integration literature. The availability of trading volume data on smaller intervals has enabled us to measure information transmission mechanism across stock markets. However, it would be worth mentioning in the end that there are certain limitations to our study. The access of high frequency transaction data for other markets such as UK and the U.S would have made it possible to examine the role of trading volume in multi market framework. Another interesting possibility is to test causality in trading volume between FT100 and XDAX30. We look forward to explore these avenues in our future research.

7.4 Essay 4: The Intraday Behavior of Bid-Ask Spreads, Trading Volume and Return Volatility: Evidence from XDAX30

This paper explores the widely observed empirical regularities in intraday return volatility, trading volume and bid-ask spreads using high frequency 5-minute aggregate data on XDAX30 constituents for the period May 5, 2004 through September 29, 2005. Moreover, we also examine the effect of trading activity and liquidity measures as mixing variable on conditional return volatility.

We document a number of regularities in the pattern of intraday return volatility, trading volume and bid-ask spreads. We are able to confirm the reverse J-shaped pattern of intraday bid-ask spreads with the exception of a major bump following the intraday auction at 13:00 CET. We verify that the trading halt during the intraday call auction significantly induces higher bid-ask spread for the subsequent period. The aggregate trading volume exhibits L-shaped pattern for the XDAX30 index, while for individual stocks, we generally find an intraday pattern close to a reverse J shape. The index volatility also displays a somewhat inverted J-shaped pattern with two major humps at 14:30 and the 15:30 CET. These findings are contrary to a U-shaped pattern found in previous studies [e.g., (Wood, McInish, and Ord (1985), McInish and Wood (1990a) and Harris (1986)].

In line with the results of Wang and Yau (2000) and Rahman et al. (2002), our empirical findings suggest a contemporaneous and positive relationship between the intraday return volatility, bid-ask spread and unexpected trading volume. Whereas, the expected trading volume is found to have a negative relationship with conditional
return volatility. We also find that higher trading volume and bid-ask spreads increase subsequent volatility.

In general, these results confirm the role of trading volume and bid-ask spreads as proxies for information arrival in producing the intraday return volatility. However, in contrast with Lamoureux and Lastrapes (1990), GARCH effects remain significant even after the inclusion of contemporaneous and lagged trading volume and bid-ask spreads in the volatility equation. Our results also indicate asymmetry in the effects of volume on conditional volatility.

Overall, our findings suggest that key financial markets’ variables; return volatility, trading volume and bid-ask spreads exhibit intraday seasonalities. We also show that contemporaneous and lagged trading volume and bid-ask spreads have numerically small but statistically significant effect on return volatility. However, inclusion of both measures as proxy for informal arrival in conditional volatility equation does not explain the well known volatility persistence in intraday stock returns. For future research, it would be interesting to incorporate other information variables in the volatility equation to see if they are able to reduce the ARCH effects. Furthermore, the use of contemporaneous variables in the volatility equation could be subject to a specification bias. As pointed out by Fleming et al. (2006), adding volume to the GARCH model implies that volume is treated as exogenous variable, which is contrary to most trading models including MDH. If the volume parameter is endogenous, problems arise in the estimation of the maximum likelihood making it hard to trust the significance of the results. One option for the upcoming research would be to run simultaneous tests including return volatility, trading volume and bid-ask spread.
REFERENCES


Appendix A

Actual and fitted intraday volatility pattern

**FT100**

![Graph of FT100](image)

**XDAX**

![Graph of XDAX](image)

**SP500**

![Graph of SP500](image)

Notes: Actual volatility pattern in solid line is the average absolute return for each 5-minute interval and the dashed line depicts the fitted seasonal component which is the FFF representation of the diurnal pattern.
PART II: The Essays
Intraday Seasonalities and Macroeconomic News Announcements

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Abstract
Using a data set consisting of more than five years of 5-minute intraday stock index returns for major European stock indices and the U.S. macroeconomic surprises, the conditional mean and volatility behaviors in European markets were investigated. The findings suggested that the opening of the U.S market significantly raised the level of volatility in Europe, and that all markets respond in an identical fashion. Furthermore, the U.S. macroeconomic surprises exerted an immediate and major impact on both, the European stock markets' intraday returns and volatilities. Thus, high frequency data appear to be critical for the identification of news that impacted the markets.

Keywords: Macroeconomic surprises; intraday seasonality; Flexible Fourier Form; conditional mean; conditional volatility; information spillover

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1 Introduction

The economic integration among nations (Christie-David et al, 2002) indicates that the investors observe domestic, as well as international information when valuing equities. The Efficient Market Hypothesis assumes that financial markets react immediately to pertinent information. By implication, price changes should reflect the arrival and processing of all relevant news. The purpose of this study is to investigate whether investors in European stock markets consider the U.S. market as an important source of information by examining European high frequency equity returns and volatilities along with contemporaneous U.S. macroeconomic news announcements. As noted by Flannery and Protopapadakis (2002), “the hypothesis that macroeconomic developments exert important effects on equity returns has strong intuitive appeal, but little empirical support.” They also noted that the impact of real macroeconomic variables on aggregate equity returns has been difficult to establish. However, they argued that macroeconomic variables are excellent candidates for extra market risk factors, because macro changes simultaneously affect many firms’ cash flows and may influence the risk-adjusted discount rate. The idea that the pronounced volatility process in financial markets can partly be explained by macroeconomic fundamentals is appealing and persuasive. The impact of information on the volatility of foreign exchange (FOREX) returns has been studied in several papers (Andersen and Bollerslev, 1998, 2003; Cai, Cheung, Lee, and Melvin, 2001; Melvin & Yin, 2000). However, there are fewer papers that have focused on equity markets.

No previous research was found regarding the impact of U.S macroeconomic announcements on European equity markets’ returns and volatilities using high frequency data. This paper takes a step in this direction by providing a comprehensive characterization of the volatility process in major European equity markets based on a large sample of five-minute returns. The analysis of high frequency stock market data was revealing and intriguing. The main findings were as follows: First, European equity markets did not exhibit a typical diurnal pattern (a reverse J shape) observed in other financial markets. This so-called intraday diurnal pattern was typically affected by two major events in the U.S., the scheduled U.S. macroeconomic news announcements at 14.30 and 16.30 CET and the U.S. cash market opening time at 15.30 CET. Second, the calendar effects were commonly observed in all European equity markets in question, i.e., the intraday seasonalities differed across the weekdays and market openings and closures were apparent as typically noticed in financial markets. Third, the empirical findings provided support for the initial indication that the major U.S. macroeconomic announcements have cross-border impact on both European equity returns and volatilities, and that the major U.S. macro surprises dominate the picture immediately following their release. Thus, high frequency data are critical for the identification of the news that impacts the markets. Finally, the Flexible Fourier Form (FFF)
introduced by Gallant (1981, 1982) and proposed by Andersen and Bollerslev (1997, 1998) was found to be an efficient way of determining the seasonal pattern. 

Among previous research, Chan, Karceski and Lakonishok (1998) did not find any empirical relevance of macroeconomic factors to equity returns, while Lamont (2001) attempted to identify priced macro factors by determining whether a portfolio constructed to “track” the future path of the macro series earned positive abnormal returns. He found some support for the effect of three macro variables: industrial production, consumption, and labor income on portfolio return. Flannery and Protopapadakis (2002) found support for the influence of macroeconomic variables on the realized stock returns and their conditional volatilities. Errunza and Hogan (1998) estimated VAR models for European stock returns for the period 1959-1993. Their main findings suggested that Money supply Granger caused equity volatility in Germany and France, and that the volatility of industrial production Granger caused equity volatility in Italy and the Netherlands. Nikkinen and Sahlström (2004) tested the effect of scheduled domestic and US macroeconomic news announcements on two European markets, the German and Finnish equity markets. Their results indicated that the US macroeconomic news announcements were viewed as a valuable source of information in European stock markets, while domestic news releases seemed to be unimportant. However, all the above-mentioned studies have relied on daily data. 

This paper contributes to the existing literature in several ways. First, it attempts to explore the intraday dynamics of major European equity markets using high frequency 5-minute data. Second, this study sets out to combine the phenomena that have mostly been studied in isolation; pronounced volatility patterns, the calendar effects, and macroeconomic announcements, thus presenting new evidence. As noted by Andersen and Bollerslev (1998), “a full account of the process governing price variability must also confront the pronounced volatility clustering, or ARCH effects, that are evident at the interday level.” The intraday seasonal patterns in the volatility of foreign exchange markets have been largely documented in academic literature. These seasonalities have important implications for modeling the volatility of high frequency data. Andersen and Bollerslev (1997, 1998) argued that standard time series models of volatility failed to capture strong intraday seasonalities when applied to high frequency return data. Finally, this paper contributes to the existing spillover literature by showing that stock markets respond to valuable information originating in foreign markets. 

The strategy for this study was twofold. First, an analysis was conducted of the intraday dynamics of major European equity markets drawing on the methodology proposed by Andersen and Bollerslev (1997, 1998) to take into account strong intraday seasonal patterns. Second, a determination was made regarding the extent to which these seasonalities could be explained by
the U.S. macroeconomic surprises. The rest of the paper is structured as follows: The data are described in section two. A descriptive framework is developed in section three that outlines the seasonalties in intraday stock returns. A robust regression procedure for the estimation of the calendar and announcement effects is presented in section four. The major empirical findings are reported in section five and a summary and conclusion of the paper are in section six.

2 Data

The primary data set consisted of 5-minute price quotes on four major equity indices from September 1, 2000 through March 31, 2006, totaling 5 years and seven months. The four European stock markets; Germany, France, Switzerland and the U.K share the same time for opening auction, i.e. 9.00 CET, whereas the closing times vary. Continuous trading ends at 17.20 on the Swiss market, followed ten minutes later by the other markets. After filtering the data for outliers and other anomalies, more specifically the 11th and 12th of September 2001, and observations influenced by brief lapses in Reuters data feed, the continuously compounded returns were calculated as \( R_{i,t} = 100 \times \log \left( \frac{P_{i,t}}{P_{i,t-1}} \right) \) where \( P_{i,t} \) represents the price level on market \( i \) at time \( t \). \(^1\) Summary statistics for 5-minute intraday returns are presented in Table1. Mean returns for all markets, which were virtually zero, were dwarfed by their standard deviations, the most volatile market being CAC40 exhibiting nearly two times greater standard deviation than FT100. When judged by auxiliary statistics, such as the sample minimum and maximum of –6.462 and 4.505 (in the case of CAC40), the existence of jumps became evident. These minimum and maximum measures were 25-50 times greater than their respective standard deviations. Assuming normality, the probability of coming across such extreme values was practically zero.

\(^1\) The time-series also included the opening returns of the trading that typically exhibit high volatility.
The French equity market index displayed evidence of significant negative first order autocorrelation (-0.144), attributed typically to market microstructure effects. The UK market exhibited a small positive first order autocorrelation implying that stale prices may have entered the calculation of the index. The high first order autocorrelation coefficient of the absolute returns implies that the volatility of 5-minute returns exhibited volatility clustering.

2.1. The U.S. announcements

The U.S. news announcements consist of monthly and quarterly published data on expected and realized macroeconomic fundamentals, defining news as the difference between expectations and realizations. The news coefficient or surprise should therefore more efficiently capture the new information revealed to market participants. Only those announcements that occurred during European stock markets trading were selected. The thirteen U.S. economic indicators are presented in Appendix A. Out of 826 announcements, only 77 (9%) were made on Mondays, whereas the majority, 256 (31%) were released on Fridays. The remaining 60% were almost equally distributed over the rest of the weekdays. U.S. announcement dates are known in advance and typically follow a regular timing within the day. Since the U.S. enters the Daylight Saving Time (DST) one week later than their European counterparts, the announcement timings were accounted for during these five weeks in our sample.

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*The U.S. announcement data were provided by Haver Analytics. They also provided the median market expectation of economic indicators based on regularly conducted surveys. More information and other details about how the surveys are conducted can be found at www.haver.com.*
Because units of measurements differ across economic variables, following Balduzzi, Elton and Green (2001), we use standardized news. That is, we divide the surprise by its sample standard deviation to facilitate interpretation. The standardized news associated with indicator \( k \) at time \( t \) is

\[
S_{k,t} = \frac{A_{k,t} - E_{k,t}}{\hat{\sigma}_k}
\]

where \( A_{k,t} \) is the announced value of indicator \( k \), \( E_{k,t} \) is the market expected value of indicator \( k \) and \( \hat{\sigma}_k \) is the sample standard deviation of \( A_{k,t} - E_{k,t} \). The use of standardized news facilitates meaningful comparisons of responses of different indices to different pieces of news. The standardization affects neither the statistical significance nor the fit of the regression, because \( \hat{\sigma}_k \) is constant for any indicator \( k \), and we estimate responses by regressing stock returns on news.

### 3 Seasonal patterns in intraday stock returns

The ability to access and analyze high frequency data provides enormous potential for furthering our understanding of financial markets. The use of high frequency data is interesting and persuasive, since it can reveal new information that cannot be seen in lower data aggregations, though it does pose new challenges. The intraday periodic return patterns along with 5% confidence bands are depicted in Appendix B. The average returns were dispersed unpredictably over the trading day and hardly any systematic violations of zero mean occurred, except a small positive return at the end of the German trading day. Harris (1986a) reported that average positive returns in the equity markets tended to occur over the first 45 minutes of the trading day. The data from the four European markets investigated in this study did not support these findings. Nonetheless, the return effects are dwarfed by the systematic movements in the return volatility, documented in Figure 1.3

We proxied the return volatility utilizing absolute returns, then the intraday seasonal was calculated as the average absolute return of approximately 1360 observations for each time unit along the trading day. The pattern is comparable even if squared returns were used, though squared returns accentuate sizable shocks typical in intraday data. The periodic pattern across all European markets exhibits remarkable similarities. This calendar effect can hardly be described as a typical J-shaped pattern of volatility, documented by Wood and McInish (1985) and Harris

\[\text{Footnote:} \quad 3 \text{ The first two 5-minute opening returns were excluded from Figure 1 due to scaling problems caused by a strikingly high opening level of volatility. The volatilities at the opening are depicted in Appendix C.}\]
(1986a). Rather, all four markets exhibited a decaying pattern of volatility until 14.30. At 14.35 all four European stock markets’ return volatilities demonstrated a considerable increase. This implies that the increase could be associated with some common factor regularly present at 14.30 CET. An examination revealed that European macroeconomic announcements or other potentially influential information related to the European markets was not regularly released at this time, nor could the Japanese market explain this behavior since it was closed. Potentially, this volatility spike could be explained by at least two Non-European factors; (1) the opening of the NYSE futures exchange market and (2) announcements of the U.S. macroeconomic indicators. To our knowledge, no previous research has examined this feature on European markets.

One hour later, at 15.35 the return volatilities escalated once again and stayed on a relatively high level until market closure. To our knowledge, there was no European related explanation for the rising level of volatility. A plausible explanation for the return volatility boost at 15.35 could be the opening of the NYSE at 15.30 CET. A third spike in volatilities is depicted at 16.05, once more all four European stock markets responded in a similar fashion. Overall, an intriguing feature emerging from the intraday pattern depicted in Figure 1 was that volatilities in all four European stock markets behaved in a similar fashion, albeit SMI and FT100 showed lower absolute levels in comparison with those seen in CAC40 and XDAX30.

To gain a more thorough insight into this seasonal volatility behavior, the average absolute returns by trading time and weekday were classified. The results are reported in Appendix C. The intraday periodicity depicted in Figure 1 was unchanged, with one common exception. On Mondays, the seasonal pattern revealed no volatility increase at 14.35 in any of the four European market indices. The common factor mentioned above was either not present or, at least, had a considerably smaller impact on Mondays. Intuitively this was consistent with the low percentage (7%) of U.S. macroeconomic indicators announced on Mondays and contradicts the suggestion that the NYSE futures market opening caused the volatility spike in Europe. Obviously, the NYSE futures markets should cause a notable volatility spike during every weekday.

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4 We also checked the contemporaneous correlation among all four European stock markets’ volatilities. The average correlation coefficient amounted to 0.60 which indicates a higher degree of co-movement among these markets.
Table 2 reports another interesting feature when splitting the trading day into three separate periods i.e. from 9.00 to 14.30, 14.35 to 15.30, and 15.35 to close, and calculating the average 5-minute volatility for the period. The values were defined as a percentage increase or decrease in volatility for each weekday period in comparison to the respective period on Monday, i.e. the Monday period was the base for comparison. It can be seen that the overall 5-minute volatility was lowest on Mondays in all markets. For example, the Tuesday overall volatility in the French stock market averaged 9% higher than on Mondays. In fact, this volatility raise could be noticed in all markets when comparing the period 9.00 to 17.30 CET. The first morning period volatility level seemed to be relatively stable throughout the week, increasing on average approximately 5%. The opposite was true during the second period, i.e. 14.35 to 15.30 CET. All four European markets exhibited a considerable increase in volatility from Tuesday to Friday. In the case of CAC40, the volatilities increased about 21% to 60%; for the FT100, 15% to 49%; for SMI, 12% to 30%; and for the XDAX, 19% to 61%. Even the last period, i.e. 15.35 to closure, displayed a volatility increase, albeit moderate. Major increases in weekday volatilities seemed to have occurred in European markets during the afternoon trading.

Figure 1. Periodic pattern in intraday volatilities.

Trading continues until 17.30 CET for XDAX30, CAC40 and FT100 while for SMI, the last observation was at 17.20 CET.
This descriptive analysis suggested that the announcements of U.S. macroeconomic indicators and the opening of the NYSE stock exchange affected the European stock markets by raising the level of volatility. To investigate whether this could be the case, an examination was conducted to determine if U.S. macro announcements triggered the seasonal volatility spike seen at 14.35 and 16.05 CET. The volatility data were split according to whether or not U.S. news has been released during the European trading day.

**Table 2**

Changes in seasonal volatilities during weekdays

The values represent a percentage (%) increase or decrease in average volatility for each period and weekday in comparison to the respective period on Monday. The return volatility for the indices was defined as absolute average 5-minute return for the respective period. The mean was calculated from Tuesday to Friday for the respective period.

<table>
<thead>
<tr>
<th>Period</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
<th>Mean</th>
</tr>
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<tr>
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<td></td>
<td></td>
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<tr>
<td>9.00-14.30</td>
<td>-</td>
<td>4</td>
<td>12</td>
<td>11</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>14.35-15.30</td>
<td>-</td>
<td>21</td>
<td>37</td>
<td>53</td>
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<td>15.35-17.20</td>
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<td>19</td>
<td>21</td>
<td>23</td>
<td>22</td>
<td>21</td>
</tr>
<tr>
<td>9.00-17.20</td>
<td>-</td>
<td>9</td>
<td>16</td>
<td>18</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>FT100</td>
<td></td>
<td></td>
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<td></td>
<td></td>
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<td>7</td>
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<td>15.35-17.20</td>
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<td>9</td>
<td>14</td>
<td>14</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>9.00-17.20</td>
<td>-</td>
<td>4</td>
<td>9</td>
<td>12</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>SMI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.00-14.30</td>
<td>-</td>
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<td>6</td>
<td>-2</td>
<td>3</td>
</tr>
<tr>
<td>14.35-15.30</td>
<td>-</td>
<td>12</td>
<td>19</td>
<td>31</td>
<td>30</td>
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<td>15.35-17.20</td>
<td>-</td>
<td>5</td>
<td>12</td>
<td>7</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>9.00-17.20</td>
<td>-</td>
<td>3</td>
<td>9</td>
<td>8</td>
<td>4</td>
<td>6</td>
</tr>
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<td>XDAX</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>9.00-14.30</td>
<td>-</td>
<td>0</td>
<td>8</td>
<td>7</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>14.35-15.30</td>
<td>-</td>
<td>19</td>
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<td>15</td>
<td>18</td>
<td>15</td>
</tr>
<tr>
<td>9.00-17.20</td>
<td>-</td>
<td>4</td>
<td>12</td>
<td>12</td>
<td>11</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 2 displays the 5-minute average absolute returns for respective European markets. On average, 50% of the European trading days were associated with U.S. macroeconomic announcements, naturally with respect to those 13 U.S. announcements selected for this study. As seen in Figure 2a and 2b, the volatilities of the two separate groups followed an almost identical pattern during the whole trading day, except at 14.35 CET and 16.05 CET. This raise in volatility continued 10 to 15 minutes thereafter. The dashed line plots the seasonal volatility on those days.
Figure 2a. Intraday average absolute returns on days containing U.S. macroeconomic news at 14.30 CET (dashed line) and days with no U.S. announcements (solid line).
Figure 2b. Intraday average absolute returns on days containing U.S. macroeconomic news at 16.00 CET (dashed line) and days with no U.S. announcements (solid line).
when the U.S. news was released, and the solid line shows the days when no macro announcements were made in the U.S.

In order to verify the above hypothesis that the U.S. surprises at 14.30 CET and 16.00 CET have significant impact on European markets' volatilities, two separate tests were conducted for the null hypothesis of equal average absolute returns on U.S. release days vs. days with no U.S. news release. Since the distribution of average absolute return was not evident, an independent sample T-test was conducted along with a nonparametric Mann-Whitney U-test. Using a one percent significance level the null hypothesis of equal means was rejected for all four markets at 14.35 and 16.05 by both test methodologies. Consequently it seemed that for all four markets, the volatilities at 14.35 and 16.05 were considerably lower on those days when no U.S. news was released. This strongly supported the initial speculation that U.S. macroeconomic news releases have a significant impact on the volatilities of the four European markets.

3.1 The U.S. market effect

To study whether the NYSE cash market opening could be the underlying cause for the increased level of volatility in European markets from 15.30 onwards, an emphasis was placed on those days when the U.S. stock market was closed. The sample contained 34 days when the French market was open but the U.S. was closed, 30 days in the case of the UK, 34 days for SMI, and 37 days for the German market. Figure 3 compares the intraday seasonal volatility pattern of all four markets for the days when the U.S market was closed (solid line) with those when the U.S. market was operating (dashed line). Interestingly, on those days when the U.S. market was closed, the European markets tended to exhibit a somewhat typical reverse J-shaped intraday volatility pattern. Moreover, the observed volatility spike at 14.35 and 16.05 disappeared. While the clear level shift at 15.35 also vanished. A null hypothesis was tested of the equality of standardized average absolute returns parametrically, based on central limit theorem, and by a nonparametric Mann-Whitney U-test. Using a five percent significance level, generally both tests rejected the null hypothesis for all the four markets. The results suggested that the opening of the U.S. market exerted a significant impact on European markets, i.e. it generated a structural shift in average volatility level.

6 The detailed results for each market and at each time point are available upon request.
Figure 3. Intraday average absolute returns on days when the U.S. stock market is closed (solid line) and when the U.S. market is open (dashed line).
4 Methodology

Our methodology to test the impact of the U.S macro economics news on both the conditional mean and the conditional variances of the European stock indices is closely based on the time series models for high frequency data proposed by Andersen et al. (2003). The following models allowed us to determine whether high frequency movements in European stock markets are linked to the U.S fundamentals.

4.1 Return Generating Model

A time series model was specified to investigate the impact of the U.S. news releases on the European stock index returns. The return-generating model isolated the impact on stock market index returns of foreign economic surprises and their own ARMA terms. Thus, for each market the 5-minute stock index return $R_t$, was modeled as an ARMA($p,q$) process and $J$ lags of news on each of $K$ fundamentals:

$$R_t = \Phi(L)R_t + \Theta(L)\varepsilon_t + \sum_{k=1}^{K} \sum_{j=0}^{J} \beta_{k,j} S_{k,t-j} + \varepsilon_t, \quad t = 1, \ldots, T \quad (2)$$

Where $\Phi(L)$ and $\Theta(L)$ are polynomial lag operators for the $AR(p)$ and $MA(q)$ process respectively. $S_{k,t}$ is standardized news associated with indicator $k$ at time $t$. There are 13 major U.S. macro announcements, $k = 1, \ldots, 13$ and $T$ is the total number of return observations that differed across countries. A significant $\beta_{k,j}$ coefficient would imply that European markets responded to the U.S. macroeconomic surprises, while the use of standardized news facilitated meaningful comparisons of surprise response coefficients. The number of lagged values in (2) was based on the Schwarz information criteria, resulting in ARMA (1,1) and $T = 1$ for CAC40, the FT100 and XDAX, while ARMA (1,1) and $J = 0$ for SMI. Contemporaneous response, i.e. $J = 0$, refers to the same 5-minutes return period within which the news was released.

4.2 Volatility Response Model

The disturbance volatility was approximated using the following model (3):

$$|\varepsilon_t| = \Phi(L)|\varepsilon_t| + \Theta(L)\mu_t + \frac{\theta_{d(t)}}{\sqrt{N}} + \sum_{k=1}^{K} \sum_{j=0}^{J} \beta_{k,j} |S_{k,t-j}| + \left( \sum_{x=1}^{X} \delta_{x} \cos \left( \frac{x2\pi t}{N} \right) + j_{x} \sin \left( \frac{x2\pi t}{N} \right) \right) + \sum_{m=1}^{M} \gamma_{m} D_{m} + \mu_t$$

The left hand side variable $|\varepsilon_t|$, is the absolute value of the residual of equation (2), which proxies for the volatility in the 5-minute interval $t$. The right-hand side of the equation (3) follows that the 5-minute volatility is driven partly by its own ARMA terms, partly by the average volatility over the
trading day containing the 5-minute interval in respective market $\hat{d}_{d(t)}/\sqrt{N}$, partly by the news, $S_{k,t}$ and partly by the seasonal pattern exhibited in Figure 1. $N$ is the number of intraday intervals within a trading day. The seasonal component was split into two parts. The first is a Flexible Fourier Form (FFF) with trigonometric terms that obey the strict periodicity of one day. To obtain strictly periodical data, the few missing observations were replaced by linear interpolation. The second is a set of dummy variables $D_{m,t}$ capturing the European markets’ opening and closing times, as well as the U.S. market opening time.

The ARMA terms in equation (3) are included to capture the short run volatility dynamics or volatility clustering effect within the intraday data, while $\hat{d}_{d(t)}$ is intended to capture the “average” level of volatility on day $d(t)$. It is interesting to note that this setting facilitated modeling the impact of foreign economic surprises on stock market return volatility by taking into account the strong intraday seasonalities, distortions that arise from the distinct periods, and its own time varying volatility behavior.

Our estimation procedure involved the determination of a daily volatility factor $\hat{d}_{d(t)}$. The daily volatility, which is a one-day ahead forecast for the day, $d(t)$ from the daily ARMA(1,1)-GARCH(1,1) model was computed using the intradaily stock returns calculated over the sample period for each market. As noted by Andersen and Bollerslev (1997), given the relative success of the daily GARCH models in explaining the aggregation results for the intradaily frequencies in financial markets, the use of ARMA(1,1)-GARCH(1,1) appeared to be a natural choice. In order to estimate the contemporaneous volatility response to each news surprise $S_{k,t}$, we regressed the absolute residuals on each fundamental $k = 1, \ldots, 13$ at time $t$. Next, the Flexible Fourier Form, as proposed by Gallant (1981, 1982) and advocated by Andersen et al. (1997), was employed to account for the strong intraday periodicity. As noted by Andersen et al. (2003), the truncation lag for the Fourier expansion, $x$ must be determined. The Schwarz information criteria chose $x = 7$ for CAC40, the FT100 and SMI, and $x = 5$ for XDAX.

As seen in Appendix C, the volatility profile for the first five to ten minutes and the last ten to fifteen minutes showed an abrupt change from the overall smooth intraday pattern, while the spike at 15:30 and 15:35 CET in the European markets at the U.S. market opening time was also apparent. The set of dummy variables, $D_{m,t}$ is included to minimize the distortions that may otherwise arise from these distinct periods. It was evident from the resulting fit in Appendix D,

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7 The number of interpolated observations was France, 335, FT100 132, SMI 1733, and XDAX 226.
that this representation provided an excellent overall characterization of the average intraday periodicity in all the stock markets in question.

It is noteworthy that models, (2) and (3) offered flexibility and could be estimated using standard time-series techniques. Both models were estimated using a Newey-West standard errors and covariance consistent estimators that were robust in the presence of both heteroskedasticity and autocorrelation of unknown form.

5 Empirical Findings

Models (2) and (3) provided a good approximation of both conditional mean and conditional volatility dynamics, as shown by the residual statistics⁸ and the resulting fit of the intraday seasonalities. Many U.S. indicators have generally statistically significant influence across all markets, including real variables (unemployment rate and advanced durable goods), U.S. output measure (industrial production) and aggregate economic indicators such as retail sales. Some fundamentals seemed only to have a significant impact on the conditional volatility, not on the return.

5.1 Contemporaneous return responses

Estimation results are provided in the upper panel of Table 3. As shown in the Table, at least seven of the thirteen contemporaneous return response coefficients were generally sizeable and statistically significant across all markets. The unemployment rate coefficient, consistent with earlier findings, was negative and significantly affected three of the four European stock returns, indicating that the higher than anticipated U.S. unemployment depressed equity values in European markets. At the same time the advance durable goods coefficient was positive and statistically significant across all markets, explaining that the higher than expected U.S. value of orders received by manufacturers of durable goods positively affected the European stocks’ return levels. These two factors have the most sizeable effect on European equity returns. The impact of a one standard deviation news surprise was normally 2 to 3 times bigger in comparison to the rest of the significant fundamentals.

⁸ The $Q$-statistic for the null hypothesis that there is no autocorrelation in residuals is shown in table 3. The resulting autocorrelations are significant almost across all the European indices. However, the coefficients are generally so small that they likely will have no practical impact on the estimation results.
The conditional mean model (2), \( R_t = \Phi(L)R_t + \Theta(L)\varepsilon_t + \sum_{k=1}^{K} \phi_k \varepsilon_{t-k} + \varepsilon_t \) and the conditional disturbance volatility model (3),

\[
|\varepsilon_t| = \Phi(L)|\varepsilon_t| + \Theta(L)\mu_t + \Psi_{d(t)} + \sum_{j=1}^{J} \beta_j \varepsilon_{t-j} + \left( \sum_{i=1}^{M} \delta_i \cos \left( \frac{2\pi t}{N} \right) + j_0 \sin \left( \frac{2\pi t}{N} \right) \right) + \sum_{m=1}^{M} \gamma_m D_m + \mu_t
\]

for four European stock indices, namely France (CAC40), the UK (FT100), Switzerland (SMI) and Germany (XDAX) was estimated. We report the estimates and p-values for \( H_0: \beta_{k,t} = 0 \) of the contemporaneous equity markets' return and volatility response to standardized U.S macroeconomic news. Contemporaneous response, \( \beta_{k,0} \), refers to the same 5-minute period within which the news was released. Significant coefficients are denoted with **, * on 5 % and 10 % significance level respectively. The residual autocorrelation coefficients, and their respective Ljung-Box Q statistics are reported.

<table>
<thead>
<tr>
<th>Announcements</th>
<th>CAC40</th>
<th>FT100</th>
<th>SMI</th>
<th>XDAX</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta_{k,0} )</td>
<td>t-value</td>
<td>( \beta_{k,0} )</td>
<td>t-value</td>
</tr>
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<td><strong>Panel A: Contemporaneous return response</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advance Durable Goods</td>
<td>0.171**</td>
<td>3.194</td>
<td>0.119**</td>
<td>2.882</td>
</tr>
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<td>Consumer Price Index</td>
<td>0.002</td>
<td>0.029</td>
<td>-0.026</td>
<td>-1.359</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>0.019</td>
<td>1.135</td>
<td>0.025**</td>
<td>2.393</td>
</tr>
<tr>
<td>Index of Leading Indicators</td>
<td>0.068**</td>
<td>3.242</td>
<td>0.045**</td>
<td>3.022</td>
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<tr>
<td>Industrial Production</td>
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<td>4.014</td>
<td>0.060**</td>
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</tr>
<tr>
<td>ISM Index</td>
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<td>4.736</td>
<td>0.095**</td>
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</tr>
<tr>
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<tr>
<td>Producer Price Index</td>
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<td>-1.597</td>
<td>-0.022</td>
<td>-1.311</td>
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<tr>
<td>Real GDP</td>
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<td>1.268</td>
<td>0.029</td>
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<tr>
<td>Retail Sales</td>
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<td>5.110</td>
<td>0.065**</td>
<td>3.718</td>
</tr>
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<td>-0.083**</td>
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<td>0.005</td>
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<td>AC</td>
<td>Q-stat</td>
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<td></td>
<td>-0.003</td>
<td>1.114</td>
<td>0.021**</td>
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<td><strong>Panel B: Contemporaneous volatility response</strong></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>( \beta_{k,0} )</td>
<td>t-value</td>
<td>( \beta_{k,0} )</td>
<td>t-value</td>
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</tr>
<tr>
<td>Housing Starts</td>
<td>0.018**</td>
<td>2.070</td>
<td>0.006**</td>
<td>2.985</td>
</tr>
<tr>
<td>Index of Leading Indicators</td>
<td>0.009</td>
<td>0.627</td>
<td>0.006</td>
<td>0.805</td>
</tr>
<tr>
<td>Industrial Production</td>
<td>0.085**</td>
<td>4.645</td>
<td>0.026**</td>
<td>2.280</td>
</tr>
<tr>
<td>ISM Index</td>
<td>0.046</td>
<td>1.594</td>
<td>0.052**</td>
<td>3.355</td>
</tr>
<tr>
<td>ISM Services</td>
<td>0.035*</td>
<td>1.776</td>
<td>0.041**</td>
<td>3.013</td>
</tr>
<tr>
<td>Personal Income</td>
<td>0.028**</td>
<td>2.646</td>
<td>0.007</td>
<td>1.605</td>
</tr>
<tr>
<td>Producer Price Index</td>
<td>0.082**</td>
<td>2.993</td>
<td>0.034**</td>
<td>3.358</td>
</tr>
<tr>
<td>Real GDP</td>
<td>0.014</td>
<td>1.244</td>
<td>0.017**</td>
<td>2.168</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>0.055**</td>
<td>2.676</td>
<td>0.038**</td>
<td>3.709</td>
</tr>
<tr>
<td>Trade Balance</td>
<td>0.033*</td>
<td>1.922</td>
<td>0.007</td>
<td>1.161</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>0.173**</td>
<td>6.368</td>
<td>0.105**</td>
<td>4.828</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.303</td>
<td>0.328</td>
<td>0.340</td>
<td>0.332</td>
</tr>
<tr>
<td>Residual diagnostics</td>
<td>AC</td>
<td>Q-stat</td>
<td>AC</td>
<td>Q-stat</td>
</tr>
<tr>
<td></td>
<td>-0.032**</td>
<td>1983.100</td>
<td>-0.008**</td>
<td>120.310</td>
</tr>
</tbody>
</table>
Other macroeconomic variables, the index of leading indicators, trade balance, ISM index, industrial production, and retail sales generally exerted influence on European stock returns. All these coefficients were positive, explaining that positive U.S. surprises enlivened the stock prices in European markets. The forward-looking measure, housing starts, significantly affected three of the European stock index returns, namely France, the UK, and Germany. The other U.S. macro announcements, including personal income, producer price index, and real GDP, had no significant effect on European stock returns. An interesting feature is that the common pattern was one of the very quick stock return conditional mean adjustments, indicating that the stock returns adjusted to news immediately and the response faded away swiftly thereafter. Only very few of the lagged return coefficients were found to be significant, i.e. the impact on European index returns occurred within five minutes from the U.S. news release.9

5.2 Volatility response to macro surprises

The contemporaneous volatility response to macro variable surprises is reported in the lower panel of Table 3. The conditional variance equation (3) included eight macro variable surprises with significant coefficients. The volatility coefficients on the advanced durable goods, consumer price index, industrial production, producer price index, retail sales, housing starts, ISM index and unemployment rate were statistically significant across all markets. It is also interesting to note that the coefficients on the unemployment rate and advanced durable goods were also economically large, meaning that a one standard deviation surprise had a simultaneous and sizeable effect on conditional volatility across all markets. The two nominal series (CPI and PPI) had been previously identified as important for equities, bonds, and foreign exchange rates. The findings suggested that in contrast to the conditional return equation (2), the two nominal series (CPI and PPI) were found to be significant for the conditional volatility equation (3). This implied that nominal news triggered a price adjustment process, but the direction of the adjustment was not consistent probably because the information contained in these two nominal indices might be nuanced. The monthly U.S. broad output measure, i.e., industrial production affected both conditional stock returns and volatility across all European markets, contradicting Flannery and Protopapadakis (2002). Another important finding was that the contemporaneous volatility response coefficients, although statistically significant, were smaller than their counterparts reported in the mean equation. However, stock return volatilities adjust relatively gradually, with

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9 The contemporaneous coefficient values for the first and second moment are reported in the article. Full results are available upon request
complete adjustment occurring usually after two 5-minute periods as the response of volatility was clearly seen in the first lag, in contrast to the return equation.

Two announcement pairs were evaluated that frequently occurred simultaneously (PPI with Unemployment rate and CPI with Housing starts). It was possible that the insignificance of their individual surprise coefficient in model (2)-(3) reflected a correlation between their surprises. However, the robustness check suggested that apparently the series individual insignificance reflected irrelevance rather than high correlation. Finally, the relatively small number of individual macroeconomic announcements, especially concerning real GDP, may have affected the significance of the estimators.

5.3 Response asymmetry

A stylized fact in the stock markets is that downward movements are followed by higher volatility. There are competing hypothesis that have attempted to explain the reasons for well known return and volatility asymmetries in financial markets. For example, Black (1976) and Christie (1982) have attributed this to leverage effect where the stock price declines increase the financial leverage, and consequently, the degree of volatility. Whereas, Koutmos et al. (2008) showed that the dynamic market factor is capable of explaining asymmetry in the conditional variance of individual portfolios. Moreover, Koutmos (1998) argued that the asymmetries in the conditional variance could be linked to asymmetries in the conditional variance because the faster adjustment of prices to bad news cause higher volatility during down markets.

In line with the earlier research, it was investigated whether this was the case concerning macroeconomic news announcements. We measure the combined asymmetric effect of all significant macro announcements presented in Table 3. We examined the return and volatility asymmetry using equation (2) and (3), where a dummy variable was included to capture the asymmetric effect. The dummy variable took the value 1 when the news was considered to have a negative effect on the equity returns, i.e. positive figures in case of consumer price index, whereas producer price index and unemployment rate were assumed negative news. This assumption was a necessary simplification concerning consumer- and producer-price indices. As shown in the upper panel of Table 3, the coefficient values for CPI and PPI tend to be negative, but not significant. This methodology, utilizing a dummy variable to capture the average effect of all significant announcements, required that the size of the asymmetric response not be dependent on the type of macroeconomic news.

After dropping the insignificant news variables in the return- and volatility equations and including the dummy variable, new regressions were conducted. The asymmetry coefficient in the return
equation was expected to be negative, whereas in the volatility equation it was expected to be positive. The results revealed that both the returns and the volatilities on all four markets responded in an asymmetric fashion to the U.S. news. The asymmetry coefficient values for the return equations, followed by the coefficient values for the volatility asymmetry within parenthesis, were for CAC40, -0.079 (0.049); FT100, -0.053 (0.038); SMI, -0.049 (0.023); and XDAX, -0.095 (0.037). All coefficients were found to be significant using a five percent significance level, except the volatility coefficient of asymmetry for SMI, which was significant at a ten percent level. Overall, the European stock markets were shown not only to respond to U.S. macroeconomic surprises, moreover, they responded in an asymmetric way.

6 Summary

In this paper the intraday dynamics of major European stock markets were analyzed using high frequency 5-minute returns. Furthermore, the role of U.S macroeconomic news announcements was examined to explain the return and volatility process in major European stock markets. This research contributes to the existing literature by presenting new evidence of the effect of U.S. macro surprises upon European equity markets in the intraday setting, using carefully constructed 5-minute returns, efficiently filtered for intraday seasonalities.

The main findings are as follows. First, European equity markets did not exhibit a typical diurnal pattern (a reverse J shape) observed in other financial markets. This so-called intraday diurnal pattern was typically affected by two major happenings in the U.S., the scheduled U.S. macroeconomic news announcements at 14.30 and 16.05 CET, and the NYSE cash market opening time at 15.30 CET. Second, the calendar effects were commonly observed in all European equity markets in question, i.e., the intraday seasonalities differed across the weekdays and market openings and closures were apparent as typically noticed in financial markets. Third, empirical findings provided support for the initial indication that the major U.S. macroeconomic news had cross border impact on both European equity returns and volatilities. Furthermore, the major U.S. macroeconomic announcements dominated the picture immediately following their release, thus high frequency data were critical for the identification of news that impacted the markets. The findings also related to a common result in spillover literature in that the U.S. market is the most important producer of information (Eun & Shim, 1989; Ng, 2000; Theodossiou & Lee, 1993).

Overall, the results suggested that the U.S. fundamentals form a subset of European investors’ public information. This implies that equity returns and volatilities are generally sensitive to the news originating in foreign markets. The analysis indicated that two U.S. inflation measures (CPI and PPI), three real macroeconomic variables (retail sales, advanced durable goods and the unemployment rate) and U.S. broad output measure (industrial production) could be considered as
potential market risk factors by investors. Moreover, two other variables, ISM indices and Housing starts also had significant impact on volatilities across all four European stock markets. Another important finding is that European stock markets reacted similarly to the information originating in the U.S. One interpretation for such behavior is that news revealed in the U.S. is perceived as informative to fundamentals of stock prices in the Europe, a view that can be attributed to real and economic linkages of international economies.

The implication of these findings for investors is a reduced portfolio diversification effect between the European markets and the U.S. due to fundamental linkages and the dominant impact of the U.S market. These results suggested a further investigation of the short-term cross dependencies on stock markets and the economic integration of Europe and U.S. The strong intraday seasonal pattern, exhibited by the European stock markets, has important implications for researchers and investors when modeling the short-term dynamics of the return and volatility behavior.
References:


### Appendix A

The U.S. announcement times are reported in Central European Time (CET). Obs. is the number of observations followed by announcements per weekday.

<table>
<thead>
<tr>
<th>Announcement</th>
<th>Time</th>
<th>Obs.</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advance Durable Goods</td>
<td>14.30</td>
<td>68</td>
<td>0</td>
<td>12</td>
<td>23</td>
<td>19</td>
<td>14</td>
</tr>
<tr>
<td>Composite Index of Leading Indicators</td>
<td>16.00</td>
<td>68</td>
<td>19</td>
<td>4</td>
<td>5</td>
<td>40</td>
<td>0</td>
</tr>
<tr>
<td>Consumer Price Index</td>
<td>14.30</td>
<td>68</td>
<td>0</td>
<td>14</td>
<td>25</td>
<td>11</td>
<td>18</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>14.30</td>
<td>68</td>
<td>1</td>
<td>25</td>
<td>21</td>
<td>14</td>
<td>7</td>
</tr>
<tr>
<td>Industrial Production</td>
<td>15.15</td>
<td>68</td>
<td>3</td>
<td>18</td>
<td>14</td>
<td>7</td>
<td>26</td>
</tr>
<tr>
<td>ISM Index: Manufacturing</td>
<td>16.00</td>
<td>62</td>
<td>21</td>
<td>13</td>
<td>9</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>ISM Services Non-Manufacturing Index</td>
<td>16.00</td>
<td>62</td>
<td>8</td>
<td>9</td>
<td>20</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td>Personal Income</td>
<td>14.30</td>
<td>68</td>
<td>21</td>
<td>6</td>
<td>4</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td>Producer Price Index</td>
<td>14.30</td>
<td>68</td>
<td>0</td>
<td>10</td>
<td>4</td>
<td>17</td>
<td>37</td>
</tr>
<tr>
<td>Real GDP</td>
<td>14.30</td>
<td>23</td>
<td>0</td>
<td>1</td>
<td>5</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td>Retail Sales</td>
<td>14.30</td>
<td>68</td>
<td>2</td>
<td>18</td>
<td>11</td>
<td>19</td>
<td>18</td>
</tr>
<tr>
<td>Trade Balance: Goods &amp; Services</td>
<td>14.30</td>
<td>68</td>
<td>1</td>
<td>12</td>
<td>18</td>
<td>16</td>
<td>21</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>14.30</td>
<td>67</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>65</td>
<td></td>
</tr>
<tr>
<td><strong>Totally</strong></td>
<td></td>
<td>826</td>
<td>77</td>
<td>142</td>
<td>159</td>
<td>192</td>
<td>256</td>
</tr>
</tbody>
</table>
Appendix B
Average intraday 5-minute returns

Notes: Average 5-minute returns shown by solid line and a five percent confidence band by the dashed lines
Appendix C

Average absolute returns classified by weekday and time

CAC40

FT100
Appendix C continued

Average absolute returns classified by weekday and time
Appendix D
Actual (solid line) and fitted (dashed line) intraday volatility pattern

CAC40

FT100

SMI

XDAX
Intraday Linkages across International Equity Markets

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Abstract

Utilizing concurrent 5-minute returns, the intraday dynamics and inter-market dependencies in international equity markets were investigated. A strong intraday cyclical autocorrelation structure in the volatility process was observed to be caused by the diurnal pattern. A major rise in contemporaneous cross correlation among European stock markets was also noticed to follow the opening of the New York Stock Exchange. Furthermore, the results indicated that the returns for UK and Germany responded to each other’s innovations, both in terms of the first and second moment dependencies. In contrast to earlier research, the US stock market did not cause significant volatility spillover to the European markets.

Key words: Intraday; diurnal pattern; conditional mean; volatility spillovers; Flexible Fourier Form; VAR; EGARCH; asymmetry

JEL classifications: G14, G15

*Corresponding author.

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1 Introduction

An understanding of inter-market volatility is important for the pricing of securities within and across the markets, for international diversification strategies, for hedging strategies and for regulatory policy. The crash of October 1987 triggered the phenomenon of information spillovers across national markets. Since then volatility spillovers across markets have been reported in many studies. Most of these studies fall mainly into three categories. One strand of this literature investigated inter-market dependencies using daily open-to-close or close-to-open returns due to the sequential trading caused by different time zones. For example, Hamao et al. (1990) and Koutmos and Booth (1995), focused on spillovers across New York, London and Tokyo. Their findings suggested that stock markets are generally sensitive to news originating in other markets. Knif et al. (1999) investigated lead-lag relationships between international stock markets by taking account of the different trading hours of stock exchanges. Their findings showed that New York is evidently the most influential market affecting all other stock exchanges in Europe and in the Asian-Pacific. A second group of papers is concerned with the lead-lag relations between two or more markets that trade simultaneously. Koutmos (1996) and Kanas (1998) documented significant volatility transmissions across major European markets. They also reported that in most instances the volatility transmission mechanism was asymmetric, i.e. negative innovations in a given market increase volatility in the next market to trade considerably more than positive innovations. Finally, some studies have explored the role of information flow and other microstructure variables as determinants of intraday return volatility [e.g. Andersen et al. (2002)].

This paper investigates the intraday return and volatility interaction between three international equity markets using carefully constructed 5-minute intraday returns from September 2000 to August 2003. The question whether return and volatility in one market predicts the return and volatility in the other market during contemporaneous trading hours is analyzed. The stock markets of UK and Germany operate concurrently for at least eight hours during every trading day, whereas the US market shares at least two hours of concurrent trading with these European markets. This fact enables modeling the dynamic first and second moment behavior among the European markets in the presence and absence of the US market’s operation. Two major European equity markets, Frankfurt and London, share the same trading hours and are closely linked

1 See the survey by Roll (1989).
through economic fundamentals. Furthermore, earlier research has shown that the US macroeconomic announcements significantly affected the return and volatility process in European equity markets [Harju and Hussain (2006), Nikkinen et al (2004)]. These findings indicate that significant spillovers among these three national stock markets may be attributed to a high degree of interdependence.

Since a shock in a national market may be transmitted to another market within a very short period of time, it is essential to employ high-frequency data. There were fewer studies that have modeled dynamic intraday interactions between equity markets using high-frequency data. Engle and Susmel (1994) examined the relationship between the New York and London stock markets using concurrent hourly returns. They did not report any significant evidence of volatility spillovers between both markets. Jeong (1999) employed overlapping high-frequency data (5-minute returns during 2 hours of overlapping trading) to explore the transmission pattern of intraday volatility among the US, Canadian and UK markets. His results showed that there existed a strong inter-market dependence, implying that the information produced in any market is affecting other cross-border markets. Both of these articles have utilized the ARCH methodology. However, Jeong (1999) did not take into account the diurnal pattern, which could have led into spurious dependencies.

There are several plausible explanations mentioned in financial literature for the interdependence between the returns and the volatilities of two equity markets. Market contagion implies that enthusiasm for stocks in one market brings about enthusiasm for stocks in other markets, regardless of the evolution of the market fundamentals. Another possible explanation is financial market integration. One interpretation of financial market integration is that shocks are propagated through real economic linkages between countries, such as trade [see for example Connolly and Wang (1998)]. However, investigating the specific factor driving potential spillovers during concurrent trading hours was beyond the scope of this paper.

The main findings are as follows: First, the New York Stock Exchange (NYSE) typically affected the diurnal pattern in two major European markets. This potential effect of the US market’s opening pointed to constant volatility shift and a significant rise in correlations structure within European markets. Second, significant and reciprocal intraday spillovers are reported across two European

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\[^{2}\] For a detailed discussion see Forbes and Rigobon (2002).
equity markets. Finally, the US stock market impact could largely be described as a contemporaneous effect, i.e. the return correlation among the UK and Germany rose significantly during the afternoon trading following the US stock market opening. In contrast to earlier findings no significant volatility spillover from the US to European stock markets is observed. The concurrent intraday returns are found to be informative as they demonstrated significant cross correlation among the three equity markets.

This paper contributes to the existing literature in mainly two aspects. First, it demonstrates high level of contemporaneous interdependence among intraday returns. The correlation coefficients reported are comparable to those found on lower data aggregations. This interdependence increased significantly following the opening of the New York stock exchange. Thus, this article extends the work by Koutmos (1996) and Kanas (1998) by presenting new evidence of the high frequency interdependence among the major European equity markets. Second, it takes into account strong intraday seasonalities observed in intraday data. Finally, the US effect is explicitly modeled using SP500 and macroeconomic surprises, hence controlling for any overlapping impact on European markets.

The rest of the paper is organized as follows. The data are described in section two. Some stylized facts of intraday data are presented in section three. Cross correlations are discussed in section four. The methodological framework is outlined in section five. The major empirical findings are reported in section six and a summary and conclusion of the paper are in section seven.

2 Data

The primary dataset consisted of 5-minute price quotes on three major equity indices from September 1, 2000 through August 29, 2003, totaling three years.³ The indices are XDAX of Germany, FT100 of the UK, and SP500 of the US. These indices were selected since they offer comparability to earlier research. The two European markets share the same opening time, i.e. 9.00 CET⁴, whereas the closing times vary. Typically, concurrent trading continues until 17.30, a total of eight and half hours per day. The New York Stock Exchange (NYSE) opens at 15.30 CET, sharing at least two hours of concurrent trading with the European counterparts. The continuously

³ The data were obtained from Olsen Data, Switzerland.

⁴ Hereafter all trading times are given in Central European Time, CET.
compounded returns were calculated as $R_{i,t} = 100 \times \log\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$, where $R_{i,t}$ and $P_{i,t}$, are the return and price level on index $i$ at time $t$ respectively. The data were filtered for outliers and other anomalies, more specifically September 11 effect and observations influenced by brief lapses in Reuters data feed. Very occasionally, linear interpolation was used to replace solitary 5-minute price quotes to obtain strictly periodical data required by the filtration technique discussed in the next section. Finally, the total number of observations summed up to 56 160 (702 days) for SP500 stock index, 73 851 (717 days) for FT100 stock index, and 99 225 (735 days) for XDAX.

### 2.1 Stylized facts of high frequency data

The usage of high frequency data is interesting and persuasive since it may reveal new information that is not observable in lower data aggregations. However it poses new challenges too. The analyses of these data are complicated by irregular temporal spacing, price discreteness, diurnal pattern and complex, long-lived dependence [e.g. Engle and Russel (2002)]. It has been widely documented that return volatilities vary systematically over the trading day, exhibiting typically a U-shaped pattern of volatility. Among the first to document this diurnal pattern were Wood et al. (1985) and Harris (1986a). The pronounced periodic structure in the return volatility has a strong impact on the dynamic properties of high frequency returns. Andersen and Bollerslev (1997) showed that standard time series methods applied to high frequency returns may give rise to erroneous inference about the return volatility dynamics. The existence of pronounced intraday patterns has been shown in average volatility over the trading day across the stock markets. Moreover, correcting for the pronounced periodic pattern is a critical issue in examining lead-lag relations between equity markets that trade simultaneously.

As seen in Table 1, the average returns during this three-year period were slightly negative for all markets. Retrospectively, this period could well be characterized as a bear market. The 5-minute mean return was practically zero for all markets and dwarfed by its standard deviation. In contrast, the minimum and maximum returns were sizeable, especially when associated with the substantial change of total market value within such a short time period. If pure geometric Brownian motion would be the underlying return generating process, the minimums and maximums would be expected to diminish in size, as the frequencies become higher. In comparison to lower data aggregations, no considerable reduction in extreme values was observed. Several different intervals were investigated, although not reported in this study. The minimum 5-minute return for XDAX was 7.27%, which is 40 times greater than its respective standard deviation. The existence of jumps and discontinuities in high frequency data is therefore evident. The first order autocorrelation, $AC(1)$, was slightly positive for all markets, implying some evidence of stale prices. The positive
autocorrelation of the squared returns indicates presence of volatility clustering. The augmented Dickey-Fuller test rejected the null hypothesis of nonstationarity for all three return series.

Table 1
Summary statistics for 5-minute stock index returns

<table>
<thead>
<tr>
<th></th>
<th>FT100</th>
<th>XDAX</th>
<th>SP500</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.0006</td>
<td>-0.0007</td>
<td>-0.0007</td>
</tr>
<tr>
<td>Maximum</td>
<td>3.65</td>
<td>4.68</td>
<td>3.51</td>
</tr>
<tr>
<td>Minimum</td>
<td>-3.74</td>
<td>-7.27</td>
<td>-5.14</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.13</td>
<td>0.18</td>
<td>0.14</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.44</td>
<td>-0.55</td>
<td>-0.83</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>68.81</td>
<td>58.78</td>
<td>71.26</td>
</tr>
<tr>
<td>Return autocorrelation (lag 1)</td>
<td>0.051</td>
<td>0.018</td>
<td>0.071</td>
</tr>
<tr>
<td>Return autocorrelation (lag 2)</td>
<td>0.001</td>
<td>-0.019</td>
<td>0.005</td>
</tr>
<tr>
<td>Squared return autocorrelation (lag 1)</td>
<td>0.194</td>
<td>0.065</td>
<td>0.04</td>
</tr>
<tr>
<td>Squared return autocorrelation (lag 2)</td>
<td>0.062</td>
<td>0.035</td>
<td>0.018</td>
</tr>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-151</td>
<td>-225</td>
<td>-221</td>
</tr>
<tr>
<td>Number of observations</td>
<td>73851</td>
<td>99225</td>
<td>56160</td>
</tr>
<tr>
<td>Percentage of zero returns</td>
<td>1.17</td>
<td>1.00</td>
<td>2.37</td>
</tr>
</tbody>
</table>

The intraday seasonalities in average absolute returns are depicted in Figure 1. The calendar effects were obvious in all three markets, while another noticeable feature in Figure 1 was the apparent co movement of these equity markets. Furthermore, in line with Andersen and Bollerslev (1997), the autocorrelation pattern of absolute average returns and squared returns were analyzed. The correlograms of the absolute and the squared returns are presented in Figures A1 and A2 in Appendix A, respectively. For each stock market the series was lagged for 10 trading days. This operation revealed an intriguing intraday dependence. The high autocorrelations were clustered around the opening and closing of each trading day, except for XDAX that displayed a pattern resembling a W. The source for this characteristic was the intraday seasonal volatility pattern depicted in Figure 1, i.e. high volatilities at the opening and closing of the trading day caused the autocorrelation pattern to behave in a cyclical manner. This dependence structure was particularly exposed in the absolute returns since it contained more serial correlation than the squared return.

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5 For detailed discussion on the diurnal pattern see Harju and Hussain (2006).
This phenomenon was dubbed “Taylor effect” as Taylor (1986) found that absolute returns of speculative assets have significant serial correlation over long horizons. The 10-day correlogram also illustrated the well-known volatility persistence. These distinct systematic fluctuations provided an initial indication that direct ARCH type modeling of the intraday return volatility would be problematic. As noted by Andersen and Bollerslev (1997), “standard ARCH models imply a geometric decay in the return autocorrelation structure and simply cannot accommodate strong regular cyclical patterns”. To avoid potential biases further in the study, the seasonal component was filtered from the returns. The next section introduces the routine of deseasonalizing intraday returns.

3 Flexible Fourier Form of seasonal volatility

The intraday seasonal patterns in the volatility of financial markets have important implications for modeling the volatility of high frequency returns. The patterns were so distinctive that there was a strong need for taking them into account before attempting to model the dynamics of intraday volatility. Andersen and Bollerslev (1997, 1998) note that standard time series models of volatility have proven inadequate when applied to high-frequency returns data, and that the reason for this is simply the systematic pattern in average volatility across the trading day. They also suggest a practical method for the estimation of the intraday seasonal pattern. The seasonal could be estimated either by simply averaging the volatility over the number of trading days for each intraday period in line with Taylor and Xu (1997), or by using the Flexible Fourier form (FFF) proposed by Gallant (1981, 1982) and advocated by Andersen and Bollerslev (1997, 1998).
Following Andersen and Bollerslev (1997, 1998), the following decomposition of the intraday returns was considered, 6

\[ R_{t,n} = E(R_{t,n}) + \frac{\sigma_t}{N^{1/2}} S_{t,n} Z_{t,n} \]  

(1)

According to the above equation, the volatility of the intraday return process \( R_{t,n} \) can be divided into three components: the daily volatility component \( \frac{\sigma_t}{N^{1/2}} \), the intraday seasonal component \( S_{t,n} \), and the random error term \( Z_{t,n} \). Whereas \( E(R_{t,n}) \) is the expected 5-minute return and \( N \) refers to the number of return intervals per day, i.e., 102 for 5-minute intervals in one trading day.

The expected return \( E(R_{t,n}) \) is then replaced by the mean return \( \bar{R} \), and the absolute demeaned returns are used as the measure of volatility \( |R_{t,n} - \bar{R}| \). The daily volatility component \( \sigma_t \) in equation (2) is obtained by \( \frac{\tilde{\sigma}_t}{N^{1/2}} \), where \( \tilde{\sigma}_t \) is an estimate from a daily-realized volatility.

By squaring and taking logs of both sides in equation (1), \( X_{t,n} \) is then defined as

\[ X_{t,n} = 2 \left( \ln |R_{t,n} - \bar{R}| \right) - \ln(\sigma_t^2) + \ln(N) = \ln(S_{t,n}^2) + \ln(Z_{t,n}^2) \]  

(2)

The seasonal pattern was estimated by using ordinary least square estimation (OLS).

\[ \tilde{X}_{t,n} = f(\theta; t, n) + (\mu_{t,n}) \]  

(3)

\[ f(\theta; t, n) = \sum_{j=0}^{I} \alpha_j \left[ (\mu_{0,j}) + \mu_{1,j} \left( \frac{n}{N_2} \right) + \mu_{2,j} \left( \frac{n^2}{N_2} \right) + \sum_{i=1}^{I} \lambda_{i,j} I_{t,n} \sum_{i=1}^{P} \left[ y_{i,j} \cos \left( \frac{2\pi i n}{N} \right) + \delta_{i,j} \sin \left( \frac{2\pi i n}{N} \right) \right] \right] \]  

(4)

Where \( N_1 = (N + 1)/2 \) and \( N_2 = \frac{(N+1)(N+2)}{6} \) are normalizing constants. Based on the Schwartz criterion, the model for equity market returns sets \( j = 1 \) and \( p = 2 \). This specification allows the shape of the periodic pattern in the market to also depend on the overall level of the volatility. Also the combination of trigonometric functions and polynomial terms are likely to result in better approximation properties when estimating regularly recurring cycles. For the information variables \( I_{t,n} \), major US macroeconomic news announcements were used to control for likely volatility spikes

\[ \text{51} \]

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6 Detailed discussion on Flexible Fourier Form (FFF) is found in Andersen and Bollerslev (1997, 1998).
in the European equity markets. These announcements consist of monthly and quarterly published data on expected and realized macroeconomic fundamentals, defining news as the difference between expectations and realizations. Furthermore, three time specific dummy variables were generally included to minimize the distortion that may otherwise arise from the distinct volatility periods shown in Figure 1. The intraday seasonal volatility pattern was then determined by using

\[ S_{t,n} = \exp \left( \frac{f_{t,n}}{2} \right) \]  

The deseasonalized intraday returns were then obtained simply by \[ \hat{R}_{t,n} = \frac{R_{t,n}}{S_{t,n}} \], while the standardized intraday returns were generated by \[ \hat{R}_{t,n} = \frac{R_{t,n}}{\hat{\sigma}_{t,n}} \].

The resulting fit of the estimated seasonal component \( \hat{S}_{t,n} \) in equation 6 is depicted in Figure B1 in Appendix B. Clearly, the Flexible Fourier Form representation provided an excellent overall characterization of the intraday periodicity. To observe how the filtration method affected the serial correlation, the return series was reinvestigated. The correlograms of deseasonalized and standardized absolute and squared returns are presented in Figure A1 and A2 in Appendix A. The autocorrelation pattern confirmed that the FFF has reduced the cyclical behavior considerably, although the long-lived persistence became even more apparent. This is particularly seen in the deseasonalized absolute returns which exhibited a long lived dependence structure, whereas the standardized squared returns displayed a clear decay in serial correlation. Based on these auxiliary measures, utilizing the standardized returns appeared more feasible, thus reducing the risk of spurious causality among the intraday stock returns.

4 Stock market correlations

Once the diurnal pattern had been filtered from the returns, all observations were combined to obtain contemporaneous 5-minute deseasonalized and standardized returns. Prior to modeling the first and second moment dependencies, the data were analyzed using simple measures to facilitate additional understanding. Table 2 provides a matrix of contemporaneous and lagged correlations between the three markets. The contemporaneous correlations between the stock markets

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7 The eleven US macroeconomic announcements are Advance Durable Goods, Index of Leading Indicators, Consumer Price Index, Housing Starts, Industrial Production, Personal Income, Producer Price Index, Gross Domestic Product, Retail Sales, Trade Balance, and Unemployment Rate.
demonstrated strong relationships, varying between 0.5 and 0.7. The high cross correlation coefficients suggested that intraday 5-minute index returns contained information, not able to be detected by means of univariate time series analysis. Thus, financial markets appeared to be highly integrated even on intraday level and individual stock markets seemed to adopt new information rapidly.

To capture the potential impact of US presence or absence on European stock markets, the trading day was divided into two different sub-samples, the first one reaching from 9.00 to 15.30 (US absence) and the second one from 15.35 to 17.30 (US presence). The contemporaneous 5-minute deseasonalized return correlation between FT100 and XDAX was 0.54 in the first sub-sample, while correlation rose to 0.7 in the second sample. To test whether correlation coefficient had changed significantly, the equality of the correlations coefficients was checked by using the Fisher’s z-transform. The resulting z value was 30.40, which gave formal support for the suggestion that the dependence between FT100 and XDAX had increased significantly following 15.30 CET.

Table 2. Cross-correlogram of deseasonalized and standardized returns

<table>
<thead>
<tr>
<th></th>
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<th>XDAX</th>
<th>FT100</th>
<th>XDAX</th>
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<tbody>
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<td>1</td>
<td>0.54</td>
<td>1</td>
<td>0.50</td>
</tr>
<tr>
<td>XDAX</td>
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<td>1</td>
<td>XDAX</td>
<td>0.50 1.00</td>
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<tr>
<td>FT100_{t-1}</td>
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<tr>
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<td>XDAX_{t-1}</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Panel A. From 9.00 to 15.30 CET

<table>
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<th>SP500</th>
<th>FT100</th>
<th>XDAX</th>
<th>SP500</th>
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</thead>
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<td></td>
<td></td>
<td>FT100</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>XDAX</td>
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<td>1</td>
<td></td>
<td>XDAX</td>
<td>0.66</td>
<td>1</td>
</tr>
<tr>
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<td>0.60</td>
<td>0.65</td>
<td>1</td>
<td>SP500</td>
<td>0.59</td>
<td>0.66 1</td>
</tr>
<tr>
<td>FT100_{t-1}</td>
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<td>0.06</td>
<td>FT100_{t-1}</td>
<td>0.04</td>
<td>-0.02</td>
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<tr>
<td>XDAX_{t-1}</td>
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<td>-0.05</td>
<td>0.09</td>
<td>XDAX_{t-1}</td>
<td>0.14</td>
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<tr>
<td>SP500_{t-1}</td>
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<td>0.06</td>
<td>SP500_{t-1}</td>
<td>0.10</td>
<td>-0.01</td>
</tr>
</tbody>
</table>

Panel B. From 15:35 to 17.30 CET

Notes: Subscript t-1 denotes a lag of 5 minutes.

Both the increased return dependence and the sudden rise in European stock index volatilities occurring exactly at 15.30 suggested an existence of a common factor. Harju and Hussain (2006)
demonstrate that the volatilities on major European equity markets were significantly affected by the opening of the NYSE. Building on the notion that the US market was the most important producer of information [Eun and Shim (1989); Theodossiou and Lee (1993); Ng (2000)], it seems reasonable to presume that the US market, proxied by SP500, caused the structural break in European equity markets.

The cross-autocorrelations indicate an asymmetry of lead/lag relationship between two European markets. XDAX seem to predict clearly more of the FT100 returns than vice versa. This relationship remained unaffected by the change in the sub-sample.

5 Research methodology

Simultaneous effects of price and volatility spillovers were estimated by the bivariate VAR-EGARCH model. We use bivariate setting as it offers parsimony over multivariate EGARCH models particularly when applied to intraday data. The Exponential GARCH model, introduced by Nelson (1990c), allows for asymmetric volatility impact on past standardized innovations, a feature often attributed to the behavior of stock market prices. Unlike the linear GARCH, there are no restrictions on the \( \alpha_t \) and \( \gamma_t \) parameters to ensure non-negativity of the conditional variances. Moreover, this model allows for a simultaneous estimation of both the first and the second moment interdependencies. Let \( R_{it}, i = 1, ..., n \); (i.e., 1 = UK, 2 = Germany, 3 = US) be the return for the market \( i \) at time \( t \), where the return was calculated as \( R_{it} = 100 \times \ln (P_{it}/P_{it-1}) \) and \( P_{it} \) being the stock price of index \( i \) at time \( t \). A VAR-EGARCH model depicting price and volatility spillovers may be formulated as:

\[
R_{it} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{jt-1} + \varepsilon_{it}, \text{ for } i, j = 1, ..., n \text{ and } \varepsilon_{it} | \Psi_{t-1} \sim \text{MNV}(0, \Sigma_t) \quad (6)
\]

\[
\sigma_{it}^2 = \exp \{ \alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} f_j (Z_{jt-1}) + \gamma_{i} \ln (\sigma_{jt-1}^2) \}, \text{ for } i, j = 1, ..., n \quad (7)
\]

\[
f_j (Z_{jt-1}) = (|z_{jt-1}| - E(|z_{jt-1}|) + \delta_j z_{jt-1}), \text{ for } j = 1, ..., n; \quad (8)
\]

\[
\sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t}, \text{ for } i, j = 1, ..., n \text{ and } i \neq j. \quad (9)
\]

Where \( \varepsilon_{it} \) represents the error term conditional on the past information set \( \Psi_{t-1} \) and the standardized innovation \( z_{jt} \) is defined as \( \varepsilon_{jt}/\sigma_{jt} \). \( \mu_{it}, \sigma_j^2 \) and \( \sigma_{i,j,t} \) are the conditional mean, conditional variance and conditional covariance, respectively.

Equation (6) describes the returns of the three markets as a vector autoregression (VAR), where the conditional mean in each market is a function of past own returns as well as cross-market past
returns. Lead/lag relationships are captured by coefficients $\beta_{i,j}$ for $i \neq j$. A significant $\beta_{i,j}$ coefficient would imply that market $j$ leads market $i$ or, equivalently, current returns could be used to predict future returns in market $i$.

The variance function in equation (7) allows its own (local) standardized innovations as well as regional standardized innovations to exert an asymmetric impact on the volatility of market $i$. Asymmetry was modeled by equation (10) and would be present if $\delta_j < 0$ and statistically significant. The term $|z_{j,t-1} - E(|z_{j,t-1}|)$ measures the size effect and $\delta_j z_{j,t}$ measures the asymmetric or sign effect, also attributed as leverage effect. If $\delta_j$ is significantly negative, a negative $z_{j,t}$ will reinforce the size effect. The ratio $|1 + \delta_j|/|1 + \delta_j|$ measures the leverage effect. Volatility spillover in our model is measured by $\alpha_{i,j}$ for $i,j = 1, \ldots, n$ and $i \neq j$. A significant $\alpha_{i,j}$ implies volatility spillovers. If the $\delta_j$ is at the same time significantly negative this implies that negative innovations on market $j$ will have higher impact on the volatility of market $i$ than positive innovations, i.e. the volatility spillover is asymmetric. The correlation in (9) is assumed to be time-invariant, an assumption that reduces the number of parameters to be estimated. $\Sigma t$ is the conditional $2 \times 2$ variance-covariance matrix.

6 Empirical Findings

The maximum likelihood estimates of the bivariate VAR-EGARCH model for standardized returns are reported separately for different sub-samples in Table 3 panel A and B. In addition, the results obtained using desasonalized returns are reported in Table C1 in Appendix C. The results obtained using deseasonalized returns showed high degree of volatility persistence, the $\gamma$ coefficient indicated a very long or nearly integrated memory process. This finding has been discussed widely in financial literature using high-frequency data that points to a slow hyperbolic rate of decay in the autocorrelation structure of the volatility process (see for example Andersen and Bollerslev, 1997). Furthermore, the Ljung-Box statistics provide some evidence of remaining arch-effect in the residuals. In comparison, the standardized returns exhibited lower persistence parameters ranging from 0.888 to 0.947 and the LB residual statistics in Table 3 confirmed the improved fit of the bivariate model.

Due to the apparent long memory process of desasonalized absolute and squared returns exhibited also in Appendix A, a test was conducted in the following way. The first 20 trading days of the UK return series were removed. A bivariate VAR-EGARCH estimation was then performed on the UK and German return series, treating the returns as contemporaneous
observations, to investigate whether volatility spillovers could be observed. The hypothesis was that no intraday spillovers should appear with a 20-days delay. The results revealed that the desasonalized returns still exhibited a significant volatility spillover, whereas for standardized returns no volatility spillovers were observed. Similar results were found when additional trading days were removed from either the UK or the German stock market returns. In order to avoid spurious spillovers resulting from the nearly integrated volatility processes, results using standardized returns are considered to provide more reliable estimates of the cross-market dependencies.

The bivariate model considered both price and volatility spillovers for the UK and Germany for concurrent trading hours between 9.00 and 15.30. The results presented in the upper panel A of Table 3 indicated significant return spillovers in both directions. The $\beta_{1,2}$ coefficient, estimating return spillovers from Germany to UK, was 0.218. This suggested that roughly 22% of the German return innovations were transferred to the British stock market whereas only 3.3% of the British return innovations were on average spilled over to the German market. The return correlation was 0.502, slightly less than the contemporaneous presented in Table 2. Concerning the second moment interdependencies, in addition to own past innovations (ARCH-effects), the volatility spillovers were clearly noticed in both directions. Thus the conditional variance in each market was affected by innovations coming from the other market. In line with earlier findings [e.g., Kuotmos (1996) and Kanas (1998)], the volatility transmission mechanism was asymmetric in both markets, confirming that both the size and the sign of the innovations are important determinants of the volatility transmission mechanism. The degree of asymmetry, on the basis of the estimated $\delta_j$ coefficients, is highest for Germany. Negative innovations increased the volatility approximately 1.47 times more than positive innovations.

Turning to the bivariate VAR-EGARCH estimates for two hours of concurrent afternoon trading between the UK, Germany and the US, it was important to note that after the opening of the SP500 at 15.30 CET, the correlation between the UK and German market rose significantly from 0.502 to 0.69. It was asserted that the opening of the NYSE induced greater contemporaneous interdependence between the two major European equity markets. The results presented in the panel B of Table 3 indicate significant price spillovers from both Germany and the US to the UK, whereas returns in the German equity market seemed generally unaffected (at 5% significance level) by past returns in any of the two markets. The US market’s returns were influenced by the return process in the German equity market, while the UK market did not seem to have any significant influence on US returns.
Table 3. Maximum likelihood estimates of the VAR-EGARCH for standardized returns

The maximum likelihood estimates were obtained using following bivariate VAR-EGARCH model for 5-minute standardized simultaneous returns. The intercepts are omitted here for convenience, however, may be obtained from authors upon request. The estimation was done assuming multivariate t-distribution with 5 degrees of freedom. $LB^2(n)$ and $AC^2(n)$ are the Ljung-Box statistics and autocorrelation coefficient for squared residuals respectively.

$$R_{it} = \beta_{1,0} + \sum_{j=1}^{n} \beta_{1,j} R_{j, t-1} + \epsilon_i, \text{ for } i, j = 1, ..., n \text{ and } \sigma^2_{j,j} = \exp\{\alpha_{1,0} + \sum_{j=1}^{n} \alpha_{1,j} f_j(z_{j,t-1}) + \gamma_1 \ln(\sigma^2_{j,j-1})\}, \text{ for } i, j = 1, ..., n$$

Panel A. Estimates for UK and Germany for concurrent trading hours between 9.00 and 15.30 (CET) for the period September 1, 2000 through August 1, 2003.

Panel B. Estimates for UK, Germany and the US for concurrent trading hours between 15.30 and 17.30 (CET) for the period September 1, 2000 through August 1, 2003.

<table>
<thead>
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<th>Germany</th>
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</thead>
<tbody>
<tr>
<td><strong>Panel A. Maximum likelihood estimates of bivariate VAR-EGARCH</strong></td>
<td></td>
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<tr>
<td>Coefficient</td>
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<table>
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<td><strong>Panel B. Maximum likelihood estimates of bivariate VAR-EGARCH</strong></td>
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<td>Coefficient</td>
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<table>
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<td><strong>Panel B. Maximum likelihood estimates of bivariate VAR-EGARCH</strong></td>
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<tr>
<td>Coefficient</td>
<td>T-Stat</td>
<td>Coefficient</td>
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</table>
Focusing on the parameters describing the conditional volatility in each market, the volatility spillovers between two European markets, the UK and Germany, were found to be significant, virtually unchanged from the upper panel of Table 3. In contrast to earlier findings [Jeong (1999)], the US market did not seem to have any significant predictive power on European stock market volatilities. Whereas, both European markets predicted the next period volatility in the US stock market.

The leverage effect, or asymmetric impact of past innovations on current volatility is significant in all instances, again lending support to the notion that volatility interactions across national stock markets may also be asymmetric. The degree of asymmetry varied from 1.18 to 1.77.

A robustness check was performed by dividing the full dataset into sub samples of 2000 consecutive observations and estimating the same model on each sub sample. The examination revealed that the parameters were consistent both in terms of magnitude and sign. Furthermore, the significance of the parameters was virtually unchanged.

7 Summary

This paper explores the dynamic first and second moment linkages among international equity markets using 5-minute index returns from the equity markets of the UK, Germany and the US, for the period September, 2001 through August, 2003. The sample was divided into two sub-samples according to time. The first sub-sample consisted of 5-minute return observations from the opening until 15.30 CET for two stock indices, FTSE 100 of the UK and XDAX of Germany, while the second sub-sample reached from 15.35 through 17.30 (CET). This allowed the modeling of intraday dependencies of two major European markets in the absence and presence of the US stock market trading activity.

The main findings are as follows. The two European markets exhibited significant reciprocal return and volatility spillovers. This relationship appeared virtually unchanged by the presence or absence of the US market. The US stock market impact could largely be described as a contemporaneous effect, i.e. the return correlation among the UK and Germany rose significantly during the afternoon trading following the US stock market opening. In contrast to earlier findings, no significant volatility spillovers from the US to the European stock markets were observed. The concurrent intraday returns were found to be informative as they demonstrated substantial cross correlation among the three equity markets. Furthermore, taking into account the strong intraday seasonalities appeared essential when modeling intraday returns.
While interpreting the lead/lag relationships, the fact that these indices constitute different number of stocks, should be taken into consideration, due to potential influence of non synchronous trading. Further research is needed to investigate the causes of the reciprocal spillovers. In addition, the index constituents’ time varying covariance structure could be investigated for deeper understanding of the observed cross market dependencies on index data.
References:


Figure A1. Autocorrelation pattern of 5-minute absolute, deseasonalized and standardized index returns
Notes: The maximum lag length depicted on x-axis is 10 trading days for all markets. The dashed line depicts the autocorrelation coefficients for absolute returns, the gray line deseasonalized absolute returns and the solid line standardized returns.
Figure A2. Autocorrelation pattern of 5-minute raw, deseasonalized and standardized squared index returns
Notes: The maximum lag length depicted on x-axis is 10 trading days for all markets. The dashed line depicts the autocorrelation coefficients for squared returns, the gray line deseasonalized squared returns and the solid line standardized squared returns.
Appendix B

Figure B1. Actual and fitted intraday volatility pattern
Notes: Actual volatility pattern in solid line is the average absolute return for each 5-minute interval and the dashed line depicts the fitted seasonal component $S_{t,n}$, which is the FFF representation of the diurnal pattern.
Appendix C

Table C1. Maximum likelihood estimates of the VAR-EGARCH for deseasonalized returns

The maximum likelihood estimates were obtained using following bivariate VAR-EGARCH model for 5-minute deseasonalized simultaneous returns. The intercepts are omitted here for convenience, however, may be obtained from authors upon request. The estimation was done assuming multivariate t-distribution with 5 degrees of freedom. $LB^2(n)$ and $AC^2(n)$ are the Ljung-Box statistics and autocorrelation coefficient for squared residuals respectively.

\[ R_n = \beta_{i,0} + \sum_{j=1}^{i-1} \beta_{i,j} R_{j-1} + \epsilon_{i,1}, \text{for } i,j = 1,...,n \] and

\[ \sigma^2_{t,j} = \exp \{ \alpha_{i,0} + \sum_{j=1}^{i-1} \alpha_{i,j} f_j (\epsilon_{j-1}) + \gamma_{i} \ln(\sigma^2_{t-1,j}) \}, \text{for } i,j = 1,...,n \]

Panel A. Estimates for UK and Germany for concurrent trading hours between 9.00 and 15.30 (CET) for the period September 1, 2000 through August 1, 2003.

Panel B. Estimates for UK, Germany and the US for concurrent trading hours between 15.30 and 17.30 (CET) for the period September 1, 2000 through August 1, 2003.

<table>
<thead>
<tr>
<th>UK</th>
<th>Germany</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Maximum likelihood estimates of bivariate VAR-EGARCH</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>$\beta_{1,0}$</td>
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</tr>
<tr>
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</tr>
<tr>
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<tr>
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</tr>
<tr>
<td>$\alpha_{1,2}$</td>
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</tr>
<tr>
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<tr>
<td>$\gamma_{1}$</td>
<td>0.984</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>UK-Germany (Market 1,2)</th>
<th>UK-US (Market 1,3)</th>
<th>Germany-US (Market 2,3)</th>
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<tbody>
<tr>
<td><strong>Panel B. Maximum likelihood estimates of bivariate VAR-EGARCH</strong></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Coefficient</td>
<td>T-Stat</td>
</tr>
<tr>
<td>$\beta_{1,1}$</td>
<td>-0.088</td>
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<tr>
<td>$\beta_{1,2}$</td>
<td>0.034</td>
<td>7.305</td>
</tr>
<tr>
<td>$\alpha_{1,1}$</td>
<td>0.108</td>
<td>27.494</td>
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<tr>
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<td>5.626</td>
</tr>
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<td>$\delta_{1}$</td>
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<tr>
<td>$\delta_{1}$</td>
<td>-0.100</td>
<td>-5.854</td>
</tr>
<tr>
<td>$\gamma_{1}$</td>
<td>0.982</td>
<td>1011.007</td>
</tr>
<tr>
<td>$\gamma_{2}$</td>
<td>0.981</td>
<td>993.837</td>
</tr>
</tbody>
</table>

| $\rho_{1,2}$ | 0.6866 | 199.9503 | $\rho_{1,3}$ | 0.6423 | 117.8522 | $\rho_{2,3}$ | 0.7481 | 182.5395 |
| $R_{2,2}^{\Delta}$ | 0.002 | $R_{2,2}^{\Delta}$ | 0.002 | $R_{2,3}^{\Delta}$ | 0.005 | $R_{2,3}^{\Delta}$ | 0.008 |

| $LB_{2,2}^{\Delta} (2)$ | 78.244 | $LB_{2,2}^{\Delta} (2)$ | 312.03 | $LB_{2,2}^{\Delta} (2)$ | 52.524 |
| $AC_{2,2}^{\Delta} (2)$ | 0.028 | $AC_{2,2}^{\Delta} (2)$ | 0.047 | $AC_{2,2}^{\Delta} (2)$ | 0.011 |
| $LB_{2,3}^{\Delta} (2)$ | 64.954 | $LB_{2,3}^{\Delta} (2)$ | 15.346 | $LB_{2,3}^{\Delta} (2)$ | 8.9202 |
| $AC_{2,3}^{\Delta} (2)$ | 0.009 | $AC_{2,3}^{\Delta} (2)$ | 0.012 | $AC_{2,3}^{\Delta} (2)$ | 0.007 |
Intraday trading volume and international spillover effects

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Abstract

The objective of this paper is to explore whether lagged trading activity in one market contributes to the return and volatility process in other market using 5 minute concurrent data from the German and the U.K equity markets. Our results lend support to our initial premise that if international investors have access to the same information set (as held by domestic traders), then by observing foreign trading activity, market makers adjust prices to reflect their expectation of the security value conditional on all available information including prior trades. Our findings clearly indicate that intraday trading volume contains predictive power for cross border return and volatility processes. Moreover, these volume effects are found to be asymmetric in the sense that impact of positive volume changes is larger on foreign stock market volatility than the impact of negative changes.

Key words: Intraday; Trading volume; conditional mean; volatility spillovers; Flexible Fourier Form; EGARCH; Asymmetry

JEL classifications: G14, G15

The author would like to thank Johan Knif, Kenneth Högholm, and the discussant and other participants at the 2008 INFINITI conference in Trinity College Dublin, Ireland for useful suggestions and comments. I am also grateful to Olsen & Associates for providing the stock market data. Any remaining errors are the responsibility of the author.
1 Introduction

Global pricing of securities and surge in world capital flow have led to increased financial markets integration in recent years. The explanation of such phenomenon may lie in a common pricing factor. Furthermore, since due to technological advancements, traders may have instant access to the similar information set, it is not surprising to notice strikingly high (contemporaneous) correlations among markets with overlapping trading hours [Harju and Hussain (2006)]. However, such explanations do not fully account for lagged information spillover findings that have been reported in many studies using high frequency intraday data [Jeong (1999), Harju and Hussain (2006)]. This gap motivates us to seek an alternative way to test the hypothesis of intraday spillover effects resulting from foreign market’s trading behavior.

This line of research is motivated by recent empirical evidence suggesting that volume has predictive content for future price changes. As argued by Blume, Easley and O’ Hara (1994), volume may be predictive of short-run movements in stock prices. This is consistent with microstructure effects arising from the adjustment of prices to public and private information. This paper extends this view to an international setting by examining whether cross-border spillovers are sensitive to interaction with trading volume.

Researchers have long established an empirical relationship between trading volume and stock return volatility. The premise underlying theoretical and empirical models is that price movements are caused by the arrival of new information and by the process that incorporates new information into market prices. Some of the news is public (e.g. unemployment statistics, earnings announcements), but most of the news is private (including interpretations of the public information) and this latter type of event motivates trade in response to the arrival of new information.

The literature exploring the dynamic relationship between trading volume and volatility can be divided into two main categories. First thread of literature focuses on the causal relationship between the price volatility and trading volume in the same market [for example, Chen, Firth and Rui (2001)]. While, the second strand
encompasses the information linkages literature focusing on the spillovers between small and large stocks and across international financial markets. However, the papers studying the dynamic interaction between volume and volatility across international equity markets have generally concentrated on the sequentially traded markets using intradaily data [for example, Gagnon and Karolyi (2003), Lee and Rui (2002)].

This paper fills the gap by examining interaction of intraday trading volume and dynamic return and volatility spillovers in an international setting. The main objective of this paper is to explore whether lagged trading activity in one market contributes to the return and volatility process in another market using 5 minute concurrent data from German and the U.K equity markets. The use of trading volume enables us to measure information transmission mechanism across two stock markets.

There are two possible explanations for lagged intraday spillovers findings. First, due to market imperfections, one of these markets may reflect information faster. Therefore, any spillovers in that period can be attributed to the gradual dissemination of foreign information (mainly arising from foreign price changes). Second, since the information about the foreign market movements (trading behavior) becomes available to domestic investors after the trade, it may take time for the market to resolve heterogeneous interpretation of foreign information. As a result, spillovers effects from foreign market to the local market will be observed.

Among previous research, Ito and Lin (1993) have examined interaction among returns, volatility and trading volume between the U.S. and Japanese stock markets by using intradaily data. They found support for the contemporaneous correlations across two markets, but not for the lagged volume and volatility spillover across these markets. These findings can be viewed in line with mixture of distributions hypothesis which assumes that the rate of information flow is a driving force for both volatility and volume (simultaneously). Fleming et al. (1999) examine the volatility dynamics of intraday yield changes in the U.S. Treasury Market. They find no support for the volume effect on the volatility of other trading centers, demonstrating that while volume may have heat wave effects on volatility, it does not have meteor
shower effects. They conjecture that overseas trading may be comprised of a disproportionate share of speculative trading so that overseas trading more closely measures the heterogeneity in traders' beliefs.

Gagnon and Karolyi (2003), using intraday prices for the S&P 500 and Nikkei Stock Average and aggregate trading volume for the New York and Tokyo Stock Exchanges, offer some evidence that the return spillovers are sensitive to interactions with trading volume in both markets. These cross-market effects with volume are revealed in both close-to-open and open-to-close returns and often exhibit non-linearities which are not predicted by theory. Kim (2005) analyzes the US and four advanced Asia–Pacific stock markets of Australia, Japan, Hong Kong and Singapore. His findings suggest that the lagged volume spillovers from the US on the conditional volatilities of the other markets are generally significant and positive. Lee and Rui (2002) report that the US trading volume contains an extensive predictive power for the UK and Japanese markets returns, volatility and volume. Their results emphasize the importance of the information contained in the US volume for international financial markets.

This paper differs from the earlier papers in at least two ways. First, unlike standard spillover literature, this paper examines the effect of foreign trading volume on domestic market's return and volatility in an intraday setting.1

The usage of high frequency transaction data on two major European stock markets enables us to disentangle the two possible channels of information transmission across markets, namely return volatility and trading volume. Second, this paper encompasses the theoretical market microstructure literature in which traders and market makers learn from watching market data, and it is this learning process that leads to price adjustments.

1 Since we examine the effect of XDAX30 volume on return and volatility process in FT100, German and the UK stocks markets should be considered as foreign and domestics markets respectively in our study hereafter.
The main findings of our study are as follows. First, we clearly show that intraday trading volume contains predictive power for cross border return and volatility processes. Second, these volume effects are found to be asymmetric in the sense that impact of positive volume changes is larger on foreign stock market volatility than the impact of negative changes. Overall, we conclude that past periods’ foreign trading volume can be viewed as an important determinant of financial market variables.

The remainder of this paper proceeds as follows. Section 2 firstly describes the data used in this study and presents some statistics of stock returns, and then exhibits intraday behavior of trading volume. Section 3 discusses the methodology for the estimation of mean and volatility models considered in this paper. Empirical findings for each model are reported in section 4. Section 5 contains summary of the paper and concluding remarks.

2 Data

Intraday data for prices were obtained for two major European stock indices, XDAX 30 of Germany and FTSE 100 of UK. In addition, transaction data with respective time and date for each stock of XDAX 30 were also acquired. We use regularly spaced 5 minute interval data for the period May 1, 2004 through September 30, 2005. Thus each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET.

After filtering the data for outliers and other anomalies, the continuously compounded returns are calculated as \( R_{i,t} = 100 \times \log \left( \frac{P_{i,t}}{P_{i,t-1}} \right) \), where \( P_{i,t} \) represents the price level in market \( i \) at time \( t \).
Summary statistics for intraday 5-minute returns are presented in Table 1. The average return of both markets is almost zero. The slightly positive first order return autocorrelation, $\rho(1)$ for FT100 may be attributed to stale prices. While XDAX30 displayed small negative return autocorrelation signaling market microstructure effects. The first order autocorrelation coefficient of squared returns is an indication of volatility clustering typically found in financial markets.

The intraday volatility patterns for both markets are depicted in Appendix A. The systematic pattern in average volatility across the trading day can clearly be noticed. These seasonal patterns in the volatility of financial markets have important implications for modeling the volatility of high frequency returns. These patterns are so distinctive that there is a strong need for taking them into account before attempting to model the dynamics of intraday volatility. Following Andersen and Bollerslev (1997, 1998), the returns were filtered from intraday seasonalities using Flexible Fourier Form (FFF) transformation. Intraday averages of squared filtered returns are also shown in Appendix A. Our results confirm that FFF is a successful technique in removing the seasonal pattern in intraday volatility.

<table>
<thead>
<tr>
<th></th>
<th>FT100</th>
<th>XDAX30</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0000</td>
<td>0.0001</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.3292</td>
<td>-0.2756</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.1685</td>
<td>0.4166</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.0124</td>
<td>0.0200</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.7002</td>
<td>0.0104</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>32.3727</td>
<td>19.9164</td>
</tr>
<tr>
<td>AC return (1)</td>
<td>0.0050</td>
<td>-0.007</td>
</tr>
<tr>
<td>AC squared return (1)</td>
<td>0.1960</td>
<td>0.129</td>
</tr>
<tr>
<td>Observations</td>
<td>35598</td>
<td>35598</td>
</tr>
<tr>
<td>Percentage of zero returns</td>
<td>2.5300</td>
<td>0.241</td>
</tr>
</tbody>
</table>

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---

2 These effects disappear when we leave out the first 10 minute observations.

3 Please see Appendix B for details on Flexible Fourier Form transformation.
2.1 XDAX30 Volume

The XDAX30 index reflects the largest and most actively traded German companies that are listed at the Frankfurt Stock Exchange. The volume series is generated by aggregating the volume across all XDAX30 stocks. A few missing observations were interpolated to obtain a continuous series. Figure 1 displays average intraday volume (average number of shares traded for each 5 minute interval) for the XDAX30 index.

The first two 5-minute opening observations were excluded from Figure 1 due to the scaling problem caused by overnight trading halt. As can be seen, volume is highest during the morning hours of the trading day, and above its daily average until 11:55, before falling rapidly and then rising again after 13:30. After 14:35, volume starts to increase and depicts a stable pattern until end of the trading day. This volume pattern is similar to that of the intraday volatility shown in Appendix A, which displays a rise at 14:35 and a level shift after 15:35. Harju and Hussain (2006) associate this volatility pattern to the scheduled U.S. macroeconomic news announcements and the opening of the New York stock exchange at 14:30 and 15:30 respectively.

![Figure 1. Average intraday volume (number of shares traded) for XDAX30](image)

4 Total number of interpolated observations was 74.
2.2 Cross market correlations

Table 2 provides a matrix of contemporaneous correlations between 5-minute filtered returns, squared filtered returns and XDAX30 trading volume. The cross correlation coefficients of 0.58 and 0.46 for returns and their squares respectively indicate strong co movement at intraday levels. However, as can be noticed, the coefficients measuring correlation between trading volume and returns are numerically small and negligible for both simple and squared returns in both markets.

Table 2

<table>
<thead>
<tr>
<th></th>
<th>FT100 Return</th>
<th>XDAX30 Return</th>
<th>XDAX30 Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>FT100 Return</td>
<td>1.00</td>
<td>0.58</td>
<td>-0.02</td>
</tr>
<tr>
<td>XDAX30 Return</td>
<td>1.00</td>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>XDAX Volume</td>
<td></td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

Cross correlations of 5-minute squared filtered returns and trading volume

<table>
<thead>
<tr>
<th></th>
<th>FT100 Squared Return</th>
<th>XDAX Squared Return</th>
<th>XDAX30 Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>FT100 Squared Return</td>
<td>1.00</td>
<td>0.46</td>
<td>0.06</td>
</tr>
<tr>
<td>XDAX30 Squared Return</td>
<td>1.00</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>xdax30 Volume</td>
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<td>1.00</td>
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</table>

3 Research Methodology

The main objective of this paper is to investigate whether intraday return and volatility transmissions can be explained by foreign trading mechanism. We assert that traders extract the information content by observing foreign trading activity and price the securities based on that information. If this proposition holds, we will find a
significant relationship between domestic return/ volatility and lagged foreign trading volume.\textsuperscript{5}

We set out by combining continuous filtered returns from both countries and XDAX30 volume to obtain contemporaneous 5-minute time series. We use log volumes in order to avoid any problem arising from non-stationarity of the series. Many studies have shown that the trading volume and volatilities are higher at the open. Thus, we leave the first ten minute observations out to avoid over-night returns and higher volume observed after the trading halt. We also check the hypothesis of whether the time series of stock returns and trading volume can be assumed to be stationary by using the augmented Dickey-Fuller (ADF) test. Our results (Appendix C) show that all three time series can be considered stationary.

Our empirical analysis consists of two parts. The first part concentrates on the relationship between FTSE100 returns and XDAX30 trading volume. While the second part deals with estimating the effect of lagged trading volume in Germany on the return volatility in the UK market, which is the one of the central hypothesis of our study.

3.1 Return spillover and trading volume


\textsuperscript{5} Unfortunately the intraday data on the UK aggregate trading volume was not available for this study. However, it is important to note that if the domestic volume has an impact on the return/ volatility, the unavailability of data on the UK trading volume may lead to an omitted variable bias in the estimation.

\textsuperscript{6} See also [Suominen (2001)], he develops an equilibrium model in which traders estimate the availability of private information using past periods' trading volume and use this information to adjust their strategies.
this view to an international setting by allowing trading volume to play the role of a signal filter for changing cross market correlations over time. However, they argue that liquidity based price movements, which are typically associated with higher trading volume will not only be more likely to be reversed in the next trading period in the same market but will also be less likely to spill over to the other market, because it does not necessarily reflect a fundamental revaluation of the market. Similarly, information based price movements in one market, which are typically associated with normal volume, are more likely to be positively correlated with the price change in the other market.

We test this hypothesis with intraday 5 minute return data for German and the UK stock markets and XDAX30 trading volume. The return model employed in this paper can be written as:

\[ R_{t,UK} = w + \beta_0 R_{t-1,UK} + \beta_1 R_{t-1,GER} + \beta_2 \log(volume)_{t-1,GER} \]  

(1)

Where \( R_{t,UK} \) is 5-minute return vector for FTSE100, while \( R_{t-1,GER} \) and \( \log(volume)_{t-1,GER} \) represent lagged return and log volume series for XDAX30 index respectively. If \( \beta_1 \) and \( \beta_2 \) are significantly different from zero, they will show the effect of German market return and trading volume on UK market’s subsequent return respectively.

### 3.2 Volatility spillover and trading volume

Following Nelson (1991), we use exponential GARCH (EGARCH) to measure the effect of trading volume on return volatility. The EGARCH model offers greater flexibility over other GARCH type models. First, it imposes no positivity constraints on estimated parameters and explicitly accounts for asymmetry in asset return volatility. We allow the lagged volume and squared returns from XDAX30 to enter the volatility equation for FTSE returns. The model can be written as:

\[ logh_{t,UK} = \gamma_0 + \gamma_1 logh_{t-1,UK} + \delta g_{UK}(Z)_{t-1,UK} + \theta_1 \log R^2_{t-1,GER} + \theta_2 \log(volume)_{t-1,GER} \]  

(2)

Where
\[ g_{UK}(Z)_{t-1, UK} = \phi_1((Z)_{t-1, UK}) + \phi_2\left(\left|Z_{t-1, UK}\right| - E\left(\left|Z_{t-1, UK}\right|\right)\right) \]

And

\[ z_t = \frac{\mu_t}{\sqrt{\gamma_t}}, \]

where \( \gamma_1 \) is the volatility persistence parameter of the London stock market. The parameters \( \theta_1 \) and \( \theta_2 \) measure the impact of the squared German market returns (as a proxy of German stock market volatility) and volume on the volatility of the UK, respectively.

The function \( g(\cdot) \) contains two parameters which define the `size effect' and the `sign effect' of the shocks on volatility. The first is a typical ARCH effect while the second is an asymmetrical effect, for example, the leverage effect. The term \( \phi_2\left(\left|Z_{t-1, UK}\right| - E\left(\left|Z_{t-1, UK}\right|\right)\right) \) determines the size effect and the term \( \phi_1((Z)_{t-1, UK}) \) determines the sign effect. The parameter \( \phi_2 \) is thus typically positive and \( \phi_1 \) is negative. If \( \phi_1 = 0 \), large innovations increase the conditional variance if \( \left|Z_{t-1, UK}\right| - E\left(\left|Z_{t-1, UK}\right|\right) > 0 \) and decrease the conditional variance if \( \left|Z_{t-1, UK}\right| - E\left(\left|Z_{t-1, UK}\right|\right) < 0 \).

If the parameters \( \theta_1 \) and \( \theta_2 \) are significantly non-zero, it shows that the exogenous effects of German return volatility and trading activity are transmitted to UK market volatility. These tests are for the null hypotheses of zero coefficients.

### 3.3 Asymmetric volume effect

An asymmetric volume effect on domestic stock returns and volatility is well documented [see for example, Ying (1966), Karpoff (1987)]. The common finding is that the mean returns and their volatilities are higher following an increase in trading volume. In addition to investigate an asymmetric volume effects in five different equity markets, Gerlach et al. (2006) examine whether return spillover effects also display such asymmetries. Their findings show that return spillovers generally exhibited asymmetries with respect to the U.S trading volume.
We also test asymmetric reactions of volatility in response to changes in volume by including a dummy variable in Equation (2) that equals one for a positive change and zero for a negative change in volume. The following equation formally tests whether UK volatility reacts to changes in German trading volume in an asymmetric fashion.

\[
\log h_{t,UK} = \\
\gamma_0 + \gamma_1 \log h_{t-1,UK} + \delta g_{UK}(Z)_{t-1,UK} + \theta_1 \log R^2_{t-1,GER} + \theta_2 \log (volume)_{t-1,GER} + \\
\theta_3 dummy\, vol_{t-1,GER}
\] (3)

Again, if the parameter \( \theta_3 \) is significantly non-zero, it shows that German trading volume has an asymmetric effect on the UK return volatility.

4 Empirical Findings

The idea that measure of liquidity such as trading volume can influence asset returns and their volatilities is by now widely accepted. The hypothesis to be tested in our paper is whether intraday trading volume represents a signal of the informativeness for stock returns and volatilities in an international setting as it does in the domestic setting.

The maximum likelihood estimates of equation (1) are reported in the upper panel of Table 3. The findings reveal significant return spillover from German to the UK equity market.

This finding is in line with previous research that has documented similar results at intraday level [see for example Harju and Hussain (2006)]. It is interesting to note that the magnitude of the return spillover is about the same as impact from its own lagged term. However, the main feature of these results is a statistically significant, though small negative effect of the lagged German volume parameter on the UK returns. This finding is in accordance with Gagnon and Karolyi (2003), who also report generally negative relations between stock returns and trading volume in an international setting. Their results showed that return and volatility spillovers between Japan and the U.S are sensitive to trading volume interactions.
If trading volume proxies the heterogeneity in the set of investors holding the stock, then according to Merton (1987), an increase in such heterogeneity would lower the required rate of return on the stocks, which is consistent with our results. These results indicate that high frequency transaction data yields important information to be priced across markets. Moreover, these results are robust to different time periods during our whole sample period.

The lower panel of Table 3 reports estimates from equation (2). Significant volatility transmission ($\theta_1$ of 0.0885 with z-statistic of 76.95) is observed from German to the UK equity market. Many earlier studies have reported similar volatility spillovers using high frequency intraday data [Engle and Susmel (1994), Jeong (1999) and Harju and Hussain (2006)]. However, as stated earlier, the central hypothesis of this

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>$z$-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w$</td>
<td>0.0016</td>
<td>2.73</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>-0.1139</td>
<td>-18.88</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.1146</td>
<td>31.60</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>-0.0002</td>
<td>-2.70</td>
</tr>
</tbody>
</table>

Panel A: Maximum Likelihood estimates of Return Equation

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>$z$-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0$</td>
<td>-1.3068</td>
<td>-30.95</td>
</tr>
<tr>
<td>$\gamma_1$</td>
<td>0.7978</td>
<td>218.83</td>
</tr>
<tr>
<td>$\delta$</td>
<td>-0.0244</td>
<td>-7.56</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>0.0885</td>
<td>76.95</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>0.0224</td>
<td>9.49</td>
</tr>
</tbody>
</table>

Panel B: Maximum Likelihood estimates of Variance Equation

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>$z$-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>34899</td>
<td>R-Squared</td>
</tr>
</tbody>
</table>
paper is to investigate the effect of lagged trading activity in one market on the volatility process of another market.

The lagged XDAX30 trading volume coefficient ($\theta_2$ of 0.0224 with z-statistic of 9.489) shows a statistically significant interaction with UK volatility term. This finding confirms the role of trading volume as a proxy for the information flow in international financial markets. These results lend support to our initial premise that if international investors have access to the same information set (as held by domestic traders), then by observing trading activity, market makers adjust prices to reflect their expectation of the security value conditional on all available information including prior trades.

Furthermore, the $\gamma_4$ coefficient indicates lower persistence (0.798) compared to what has been reported in some earlier studies using intraday data [for example, Jeong (1999) and Harju and Hussain (2006)]. This finding has been discussed widely in financial literature using high-frequency returns that points to a slow hyperbolic rate of decay in the autocorrelation structure of the volatility process [Andersen and Bollerslev (1997)]. Another typical finding, the leverage effect, or asymmetric impact of past innovations on current volatility is significant, lending support to the notion that the volatility process may also be asymmetric.

Table 5 (Appendix D) reports the estimation results of Equation 3, which allows us to measure an asymmetric effect of German trading volume on UK return volatility. The estimation is conducted for volatility equation only, because the effects of German volume on UK returns are not significant.

Asymmetric parameter value ($\theta_3$ of 0.077 with z-statistic of 2.0360) for a dummy variable (dummyvol) is positive and statistically significant. These results suggest a very clear and significant asymmetric reaction for UK volatility to changes in German trading volume.
5 Conclusion

This paper investigated whether lagged trading activity in one market contributes to the return and volatility process in another market using 5 minute concurrent data from German and the U.K equity markets.

The use of trading volume facilitates us to measure information transmission mechanism across two stock markets. This setting allows us to combine the two possible channels of information transmission across markets, with volatility and trading volume providing measures of the significance of the information reflected in other market.

Moreover, this paper also sheds light on market microstructure issues in which traders and market makers learn from watching market data, and it is this learning process that leads to price adjustments.

Overall, we conclude that lagged trading volume plays an important role in explaining international return and volatility transmissions. The examination concerning asymmetries revealed that the impact of positive volume changes is larger on foreign stock market volatility than the impact of negative changes.

These findings shed new light on the application of trading volume in the market integration literature. The availability of trading volume data on smaller intervals has enabled us to measure information transmission mechanism across stock markets. However, it would be worth mentioning in the end that there are certain limitations to our study. The access of high frequency transaction data for other markets such as UK and the U.S would have made it possible to examine the role of trading volume in multi market framework. Another interesting possibility is to test causality in trading volume between FT100 and XDAX30. We look forward to explore these avenues in our future research.
References:


Kim, S-J. (2005), Information leadership in the advanced Asia-Pacific stock markets: Return, volatility and volume information spillovers from the US and


APPENDIX A

a. Average intraday volatility in XDAX30 index

![Graph showing intraday volatility pattern for XDAX30 index]

a. The dashed line depicts intraday volatility pattern for raw 5-minute squared returns versus solid line that represents volatility pattern for filtered returns using Flexible Fourier form transformation.

b. Average Intraday Volatility in FT100 index

![Graph showing intraday volatility pattern for FT100 index]

b. The dashed line depicts intraday volatility pattern for raw 5-minute squared returns versus solid line that represents volatility pattern for filtered returns using Flexible Fourier form transformation.
Appendix B

Following Andersen and Bollerslev (1997, 1998), the following decomposition of the intraday returns was considered⁷:

\[ R_{t,n} = E(R_{t,n}) + \frac{\sigma_t S_{t,n} Z_{t,n}}{N} \]  

(1)

Where \( E(R_{t,n}) \) is the expected 5-minute return, \( N \) refers to the number of return intervals per day and \( Z_{t,n} \) being iid. with zero mean and unit variance. By squaring and taking logs of both sides in equation (1), \( X_{t,n} \) is then defined as:

\[ X_{t,n} = 2 \ln \left| R_{t,n} - E(R_{t,n}) \right| - \ln \left( \sigma_t^2 \right) + \ln \left( N^2 \right) = \ln \left( S_{t,n}^2 \right) + \ln \left( \sigma_t^2 \right) \]  

(2)

Replacing \( E(R_{t,n}) \) by the average of all intraday returns, and \( \sigma_t \) by an estimate from a daily-realized volatility, \( \hat{X}_{t,n} \) was obtained. The seasonal pattern was estimated by using ordinary least square estimation (OLS).

\[ \hat{X}_{t,n} = f(\theta; t, n) + \left( \mu_{t,n} \right) \]  

(3)

\[ f(\theta; t, n) = \sum_{j=0}^{2} \left( \mu_{0,j} \right) + \mu_{1,j} \left( \frac{n}{N_1} \right) + \mu_{2,j} \left( \frac{n^2}{N_2} \right) + \sum_{i=1}^{5} \lambda_{i,j} \sum_{j=1}^{5} \gamma_{i,j} \cos\left( 2\pi \frac{i}{N} \right) + \delta_{i,j} \sin\left( 2\pi \frac{i}{N} \right) \]  

(4)

Where \( N_1 = (N+1)/2 \), and \( N_2 = (N+1)(N+2)/6 \) are normalizing constants. The model for equity market returns sets \( j = 1 \), and \( p = 2 \) based on the Schwartz criterion. This

---

⁷ Detailed discussion on Flexible Fourier Form (FFF) can be found in Andersen and Bollerslev (1997, 1998).
specification allows the shape of the periodic pattern in the market to also depend on the overall level of the volatility. Also the combination of trigonometric functions and polynomial terms are likely to result in better approximation properties when estimating regularly recurring cycles. For the information variables $I_{t,n}$, major US macroeconomic news announcements were used that reflect higher volatility in European equity markets. Furthermore, three time specific dummy variables were generally included to minimize the distortion that may otherwise arise from the distinct volatility periods shown in Appendix A. The intraday seasonal volatility pattern was then determined by using

$$S_{t,n} = \exp\left( \hat{f}_{t,n} / 2 \right)$$

(5)

The deseasonalized intraday returns were then obtained simply by $\tilde{R}_{t,n} = R_{t,n} / \hat{S}_{t,n}$. 
Appendix C

Unit root tests

Time series modeling assumes that the variables we are employing are stationary. We check the hypothesis of whether the time series of stock returns and trading volume can be assumed to be stationary by using the augmented Dickey-Fuller (ADF) test. This test is based on the regression:

\[ y_t = \mu + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \]

Where \( y \) is the variable being tested for unit roots (stock return or trading volume), \( \mu \), \( \gamma \) and \( \delta \) are model parameters and \( \varepsilon_t \) is an i.i.d Gaussian \((0, \sigma^2)\) white noise error term. The unit root test is carried out by testing the null hypothesis \( \gamma = 0 \) against the one sided alternative \( < 0 \). Unfortunately the \( \varepsilon \)-Student-statistic of the estimated parameter \( \gamma \) does not have a conventional t-distribution under the null hypothesis of a unit root. Instead, we use the critical values recommended by MacKinnon (1991). If the ADF \( \varepsilon \)-statistic for \( \gamma \) lies to the left of these values, the null hypothesis can be rejected. The results of the unit root tests for the time series of stock returns and trading volume are shown in Table 4.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistics</th>
<th>Critical Value (1%)*</th>
</tr>
</thead>
<tbody>
<tr>
<td>FT100 Return</td>
<td>-73.18493</td>
<td>-3.430364</td>
</tr>
<tr>
<td>XDAX30 Return</td>
<td>-190.09</td>
<td>-3.430364</td>
</tr>
<tr>
<td>XDAX30 Volume</td>
<td>-27.95816</td>
<td>-3.430364</td>
</tr>
</tbody>
</table>

*MacKinnon critical values for rejection of hypothesis of a unit root.

The estimate of the parameter \( \gamma \) is negative and statistically significant at all traditional significance levels. Thus, our results show that all three time series can be considered stationary.
Appendix D

Table 5. The maximum likelihood estimates of the Return and Variance equations.

The maximum likelihood estimates were obtained using regularly spaced 5 minute interval data for the period May 1, 2004 to September 30, 2005. Each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET. The estimation was done assuming normal distribution for the following return and variance equations respectively:

\[ R_{t,UK} = w + \beta_0 R_{t-1,UK} + \beta_1 R_{t-1,GER} + \beta_2 \log(\text{volume})_{t-1,GER} \]

\[ \log h_{t,UK} = \\
\gamma_0 + \gamma_1 \log h_{t-1,UK} + \delta g_{UK}(Z)_{t-1,UK} + \theta_1 \log R_{t-1,GER}^2 + \theta_2 \log(\text{volume})_{t-1,GER} + \theta_3 \text{dummy} \text{vol}_{t-1,GER} \]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Maximum Likelihood estimates of Return Equation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w )</td>
<td>0.0014</td>
<td>2.48</td>
</tr>
<tr>
<td>( \beta_0 )</td>
<td>-0.1147</td>
<td>-18.86</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.1134</td>
<td>31.21</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.0002</td>
<td>-2.45</td>
</tr>
<tr>
<td>Panel B: Maximum Likelihood estimates of Variance Equation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \gamma_0 )</td>
<td>-1.4333</td>
<td>-33.28</td>
</tr>
<tr>
<td>( \gamma_1 )</td>
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<tr>
<td>( \delta )</td>
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<td>( \theta_1 )</td>
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<td>( \theta_2 )</td>
<td>0.0263</td>
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<tr>
<td>( \theta_3 )</td>
<td>0.1534</td>
<td>15.73</td>
</tr>
</tbody>
</table>

Observations 34899 R-Squared 0.019
The Intraday Behaviour of Bid-Ask Spreads, Trading Volume and Return Volatility: Evidence from XDAX30

SYED MUJAHID HUSSAIN
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Abstract
This paper undertakes a fresh empirical investigation of key financial market variables and the theories that link them. We employ high frequency 5-minute data that include transaction price, trading volume, and the close bid and ask quote for the period May 5, 2004 through September 29, 2005. We document a number of regularities in the pattern of intraday return volatility, trading volume and bid-ask spreads. We are able to confirm the reverse J-shaped pattern of intraday bid-ask spreads with the exception of a major bump following the intraday auction at 13:05 CET. The aggregate trading volume exhibits L-shaped pattern for the German blue chip index, while German index volatility displays a somewhat reverse J-shaped pattern with two major bumps at 14:30 and 15:30 CET. Our empirical findings show that contemporaneous and lagged trading volume and bid-ask spreads have numerically small but statistically significant effect on return volatility. Our results also indicate asymmetry in the effects of volume on conditional volatility. However, inclusion of both measures as proxy for informal arrival in the conditional volatility equation does not explain the well known volatility persistence in intraday stock returns.

Key words: Intraday; conditional volatility; trading volume; bid-ask spread; asymmetry; Flexible Fourier Form; EGARCH

JEL classifications: G14, G15

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1 Introduction

Many studies have supported the conjecture that price volatility and trading volume are jointly determined. Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983) argue that volume and volatility are jointly endogenous variables that covary in response to external order or information shocks. The mixture of distribution hypothesis (MDH) developed by Clark (1973) implies that the volume-volatility relation is dependent upon the rate of information flow into the market. The theory assumes that all traders simultaneously receive the new price signals and immediately shift to a new equilibrium. Thus, both volatility and volume change contemporaneously in response to the arrival of new information.

Other researchers relate the observed relationship of volume and volatility to private information. Copeland (1976) and Jennings, Starks and Fellingham (1981) develop models based on the sequential information arrival hypothesis (SIAH). In these models, an individual trader receives a signal ahead of the market and trades on it, thereby creating volume and price volatility. As a result, volatility and volume move in the same direction.

Many recent papers have examined the empirical relationship between price volatility and trading volume. Using intraday data for 30 stocks in the Dow Jones Industrial Average (DJIA), Darrat et al. (2003) report that high trading volume causes high return volatility in accordance with SIAH hypothesis. Darrat et al. (2007) test for intraday lead-lag relationship between trading volume and volatility of large and small NYSE stocks in two cases: with and without identifiable public news. Their results generally support SIAH which assumes that the information comes in sequence and thus traders react to this new information sequentially, suggesting that in the presence of public information, volume and volatility may Granger-cause each other. Floros and Vougas (2007) examine the relationship between daily trading volume and return volatility in the Greek stock index futures market. They find evidence of contemporaneous and lagged effect of trading volume on absolute returns for the Greek blue chip index (FTSE/ASE20). However their analysis does not reveal any significant relationship between trading volume and absolute returns for the mid-cap index (FTSE/ASE40).
In line with the microstructure theory, some researchers have also examined the role of bid-ask spread on price change volatility.¹

Rahman et al. (2002) estimate GARCH model for a sample of 30 NASDAQ stocks using intraday 5-minute returns. After including contemporaneous and lagged volume and bid-ask spreads, proxied for the rate of information flow as exogenous variables, they find positive and statistically significant but numerically very small effect of both variables on conditional volatility. Furthermore, their results suggest that none of the exogenous variables significantly reduce volatility persistence effects for their sample returns. Worthington and Higgs (2003) measure the role of information arrival proxied by contemporaneous and lagged bid-ask spread and volume on intraday return volatility for individual stocks in the Australian stock market. They conclude that the influence of bid ask on volatility is relatively larger, while the effect of volume is more general but relatively small. Wang and Yau (2000) using data on future markets show that trading volume, bid-ask spread and price volatility are jointly determined. With regard to volatility estimation, their results indicate a positive relationship with bid-ask spread and a negative relationship with lagged trading volume.

The objective of this paper is twofold. Firstly, it explores intraday regularities in key financial markets’ variables of stock return variability, trading activity, and liquidity measure. The proportional bid-ask spreads (PABS) are used to proxy the market liquidity, while the trading volume is used as a measure of trading activity. Secondly, this study examines the intraday relationship between stock market volatility, trading activity and liquidity using aggregate data on XDAX30 constituents.

¹ Many market microstructure papers regard the bid-ask spread as a proxy for information asymmetry, such as Lee, Mucklow and Ready (1993).
Numerous empirical models have been proposed to test the relationship between return volatility and information arrival. Many papers have examined the dynamic volume-volatility relation based on the mixture of distribution hypothesis, which assumes a joint dependence of volatility and volume on the underlying information flow. However, the models based on MDH have some limitations. For example, They do not allow for serial dependence in return volatility conditional on the underlying information flow [(Rahman et al. (2002)]. Accordingly, in this paper, we examine the role of trading volume and bid-ask spreads (as proxies for information flow) on return volatility in a GARCH type setting. It is important to note that we treat both trading volume and bid-ask spreads as mixing variable in return volatility equation as we study the relationship between return volatility and information arrival in one direction.

This paper presents a number of improvements over earlier studies of the same kind. First, it takes into account the strong intraday seasonal pattern in return variability before attempting to model the conditional volatility. Second, we split the volume into expected and unexpected components. The unexpected volume is believed to capture deviations in the relative participation rate of informed traders. Furthermore, we also examine whether the price volatility responds asymmetrically to volume shocks depending on whether the volume is above or below its expected level. Third, our model allows for serial dependence in return volatility conditional on the underlying information flow. Finally, this study provides additional intraday evidence on the relationship between return volatility, trading activity and market liquidity variables at the aggregate level for XDAX30 constituents.

The main findings of this paper are as follows: We are able to confirm the reverse J-shaped pattern of intraday bid-ask spreads with the exception of a major bump following the intraday auction at 13:00 CET. The aggregate trading volume exhibits L-shaped pattern for the German blue chip index (XDAX30), while German index volatility displays a somewhat reverse J-shaped pattern with two major humps at 14:30 and 15:30 CET. These findings are contrary to the U-shaped pattern found in previous studies [e.g., (Wood, McInish, and Ord (1985), McInish and Wood (1990a) and Harris (1986)]. Furthermore, our empirical findings suggest that the intraday return volatility is inversely related with contemporaneous and lagged expected...
trading volume, and positively related with unexpected volume. While we find a significant and positive relationship between the return volatility and both, the contemporaneous and lagged bid-ask spreads. Our results also indicate asymmetry in the effects of volume on conditional volatility. However, our findings demonstrate that the introduction of contemporaneous or the lagged trading volume and bid-ask spreads do not significantly remove GARCH effects in intraday return volatility.

The rest of the paper proceeds as follows: Section two describes the data used in this study. Section three explores intraday patterns in return volatility, trading volume and bid-ask spreads. The empirical methodology is presented in section four. Section five reports the major findings of this study and the paper is summarized in Section six.

2 Data

This paper employs an aggregate data on XDAX30 constituents, which enables us to undertake a fresh empirical investigation of key financial market variables and the theories that link them. We obtain time stamped intraday transaction data including the bid and ask quotes at the time of the trade for each of the XDAX30 constituents. The data contains transaction price, trading volume, and the close bid and ask quote for each 5-minute period. The analysis covers the period from May 5, 2004 to September 29, 2005.

The XDAX30 index measures the performance of 30 largest German companies in terms of order book volume and market capitalization. The index is based on prices generated in the electronic trading system Xetra and its calculation starts at 09:00 and ends at 17:30 CET. Thus each trading day is divided into 102 successive 5-minute intervals.

2 For XDAX30, the continuous trading ends at 17:30 CET. However, the post trading continues until 20:30 CET for individual stocks. Please also note that hereafter, all the times are shown in central European times (CET).
After filtering the data for outliers and other anomalies, the continuously compounded returns are calculated as $r_{it} = 100 \times [\log(P_t) - \log(P_{t-1})]$, where $P_{it}$ represents the price level in market $i$ at time $t$.

The 5-minute proportional bid-ask spreads were calculated as $BAS = \frac{ASK - BID}{(ASK + BID)/2}$. These 5-minute proportional spreads were then averaged across all the stocks in the sample. Next, the trading volume represents the total number of shares traded for each stock in each 5-minute interval. The aggregate volume series (Vol) was then generated by combining the volume across all XDAX30 stocks. A few missing observations were interpolated to obtain a continuous series.³

The intraday transaction data files contained raw data. We use a number of filters to clean the data to ensure the accuracy of the calculated variables.⁴ The intraday prices, trading volume and bid-ask spreads were then matched for each time interval, and for each day in order to obtain a contemporaneous and continuous time series data. Graphical results are reported using the carefully calculated variables as mentioned above.

Following Andersen et al. (2002), intraday return volatility is calculated as absolute measure of returns. Summary statistics for intraday 5-minute returns and their absolute measure are presented in Table 1. The average return for XDAX30 is almost zero. The return series exhibits deviation from normality as the excess kurtosis and skewness are clearly significant. Furthermore, returns displayed small negative but statistically significant (at 5% level) return autocorrelation signaling market microstructure effects.⁵ Whereas, absolute returns display a positive and statistically significant serial correlation at all reasonable levels, which can be viewed as an indication of volatility clustering typically found in financial markets, where large changes tend to be followed by large changes of either sign.

³ Total number of interpolated observations was 74.
⁴ For example, we deleted all the bid-ask quotes where bid price was greater than the ask price.
⁵ These effects disappear when we leave out the first 10-minute observations.
Notes: AC(1) and AC(2) are first and second order autocorrelation coefficients respectively.

2.1 Cross Correlations

Table 2 presents the correlation matrix of return volatility, trading volume and Bid-ask spreads for the whole sample. The three variables are positively correlated. The correlation coefficient between trading volume and return volatility is 0.43, indicating contemporaneous relation among variables. While the correlation coefficient (0.29) between return volatility and bid-ask spread also indicates a positive but relatively small contemporaneous relationship. However, the association between trading activity and liquidity measures is 0.19, which do not represent any potential problem arising from multicollinearity in econometric modeling.

6 We also check the contemporaneous correlation among these three variables for the first 10 minute period. The correlation coefficients are higher for the first 10 minute period of the trading day. For example, the correlation coefficients amount to 0.59 and 0.38 between return volatility and trading volume, and return volatility and bid-ask spreads respectively.
Voluminous research has documented the existence of intraday periodicities in returns, return volatility, bid-ask spreads and trading volume, in both equity and foreign exchange markets. Among the earlier studies, intraday U-shaped pattern in return variance were demonstrated by Wood, McInish, and Ord (1985), McInish and Wood (1990a) and Harris (1986). Jain and Joh (1988), McInish and Wood (1990b) reported intraday U-shaped patterns in trading volume. Brock and Kleidon (1992) report that bid-ask spreads tend to be higher at the beginning and the end of the trading day, thus follow a U-shaped pattern during the day.

There are different explanations for intraday regularities observed in key financial markets’ variables. Admati and Pfleiderer (1988) relate the U-shaped (also sometimes referred as reverse J shaped) pattern in volume and volatility with the private information. They argue that high volume in a particular time segment reveals the presence of asymmetric information as noise traders camouflage the activities of the informed traders, and this gives rise to the volatility. Therefore, volume and volatility move in the same direction. In contrast, Brock and Kleiden (1992) argue that trading halts and different trading strategies at the open and close of the markets form these volume patterns. Since, in their model, high volume is associated with the high liquidity demand at the open and close of the trading day, spreads will also follow a U-shaped pattern during the day. We take a fresh empirical look at the intraday patterns in return volatility, trading volume and bid-ask spread using the aggregate data on XDAX30 constituents.

<table>
<thead>
<tr>
<th>r</th>
<th>Vol</th>
<th>BAS</th>
</tr>
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<tbody>
<tr>
<td>r</td>
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<td></td>
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<tr>
<td>Vol</td>
<td>0.43</td>
<td>1</td>
</tr>
<tr>
<td>BAS</td>
<td>0.29</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Table 2
Cross correlations of 5-minute absolute returns, trading volume and Bid-Ask spreads

3 Intraday Patterns

Voluminous research has documented the existence of intraday periodicities in returns, return volatility, bid-ask spreads and trading volume, in both equity and foreign exchange markets. Among the earlier studies, intraday U-shaped pattern in return variance were demonstrated by Wood, McInish, and Ord (1985), McInish and Wood (1990a) and Harris (1986). Jain and Joh (1988), McInish and Wood (1990b) reported intraday U-shaped patterns in trading volume. Brock and Kleidon (1992) report that bid-ask spreads tend to be higher at the beginning and the end of the trading day, thus follow a U-shaped pattern during the day.

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3.1 Intraday return volatility

Researchers have found compelling evidence that intraday return volatility exhibits U-shaped pattern. This pronounced U-shaped pattern in equity markets has been reported by, among others, McInish and Wood (1990), Werner and Kleiden (1996) and Abhyankar et al. (1997). Figure 1 displays the average intraday absolute returns for the XDAX30 index. Contrary to earlier evidence of distinct U-shaped pattern in the intraday volatility of price changes, we find a pattern close to reverse J-shape for the XDAX30 index. This finding is in line with Harju and Hussain (2006), who report similar pattern for four major European stock market indices, FTSE100, XDAX30, SMI and CAC40. The intraday return volatility is highest at the beginning of the trading day, before falling rapidly until 14:30 CET. After 14:30, the intraday volatility demonstrates a clear level shift and three major jumps at 14.35, 15.35, and 16.05. Harju and Hussain (2006) convincingly related this level shift and rise in volatility to the U.S. scheduled macro news announcements at 14:30 and 16.00, and the opening of NYSE at 15:30. However, it is interesting to note that volatility is highest for the first ten minutes of morning trading. When we leave out the first two observations, the distinct early volatility spike disappears. Harju and Hussain (2006) empirically show that following 09:15, the intraday volatility pattern would resemble U-shape after controlling for the NYSE opening and major scheduled U.S announcements.

![Figure 1. Average intraday volatility for the XDAX 30 index](image-url)
3.2 Intraday Volume

The aggregate trading volume for each 5-minute period averaged across all the trading days is shown in Figure 2. We find a L-shaped pattern in intraday volume which is in contrast to earlier findings, such as Chan, Christie and Schultz (1995) and Abhyankar et al. (1997) who report U-shaped and M-shaped pattern for NASDAQ and the UK stocks, respectively.

In line with earlier studies, volume is found to be highest during the first ten minute period of the trading day. However, it is interesting to note that it does not increase towards the end of business hours. When we drop the first two observations, volume does not exhibit any systematic pattern during the day. Though trading activity increases moderately after 13:30 and remains quite stable for the rest of the day, it does not rise near the end of trading day as have been reported in earlier studies. This contrasts with the U-shaped pattern for NYSE stocks reported by Brock and Kleidon (1992) and McInish and Wood (1990).

![Figure 2. Average intraday volume for the XDAX 30 index](image)

We conjecture that some measurement errors may have caused this unusual pattern in aggregate intraday trading volume. We investigate this by examining the number of stocks traded for each time interval. Our investigation reveals that the highest
number of stocks were traded during the first five minute period. After departing from the morning peak, trading activity for individual stocks remains stable until 12:00 before declining sharply until 13:30. Though the numbers of stocks traded picked up again after 13:30, the trading activity was recorded for fewer stocks after 16:00. In accord with our intuition, the aggregate intraday volume pattern coincided with the number of stock traded per time interval. We infer that the infrequent trading for individual securities significantly affected the intraday pattern in volume aggregated across all the trading days in our sample. We further examine this by looking at the intraday volume patterns for individual stocks. The intraday patterns for selected stocks in XDAX30 are displayed in appendix A. Most of the individual stocks generally exhibit typical U-shaped or inverted J-shaped pattern, thus confirming the earlier results for equity markets.

3.3 Intraday bid-ask spread

Figure 3 shows the intraday pattern of the proportional bid-ask spreads for the XDAX30 index, measured at each five minute interval across all 360 trading days in our sample.

The average spread declines sharply in the first ten minutes of the trading day and then remains constant with the exception of 13:00 CET when it sharply rises for a five minute period following the call auction for the XDAX30 stocks.

---

7 We also check this by calculating the correlation coefficient between the number of stocks traded and intraday average trading volume for each time interval. The estimated correlation coefficient is 0.91, which clearly indicates the intraday averages of aggregate volume are significantly affected by the number of stocks traded per time period.

8 We pick 6 stocks from XDAX30 constituents based on market capitalization. The first three stocks are selected from the companies with higher market capitalization, while the last three are picked from the low turnover companies.

9 The intraday call auction begins at 13:00 for XDAX30 stocks. The intraday call auction is usually conducted between 13:00 and 13:02. However, on Eurex settlement days, the call phase of the intraday auction lasts 5 minutes for DAX stocks. We verify that temporary halt in trading activity during the intraday auction at 13:00 have significant impact on average bid-ask spreads. An independent sample T-test was conducted for equality of means for spreads recorded at 13:00 and 13:05. Using a one percent significance level, the null hypothesis of
Figure 3. Average intraday spread for the XDAX 30 index

Although the average spreads tend to slightly increase near the end of the trading day, we do not find evidence supporting typical U-shaped pattern for intraday spreads reported in e.g., Brock and Kleidon (1992), Ahn et al. (1999) and Ahn et al. (2002). However, our finding of a rather reverse J-shaped pattern in intraday spreads follow closely that of reported by Theissen and Freihube (2001), Abhyankar et al. (1997) and McInish and Wood (1992).

4 Methodology

We develop a set of empirically testable hypotheses to explore the impact of trading volume and bid-ask spreads on the conditional volatility of intraday returns. We divide trading volume into two components; expected and unexpected trading
equal means was rejected. Consequently it seemed that the intraday call auction significantly induces higher bid-ask spread for the subsequent period.

10 Theissen and Freihube (2001) show almost a similar pattern for DAX stocks. However, they delete the interval in which the intraday call auction is conducted beginning at 13:00 for DAX stocks.
Unexpected trading volume is closely related with informed trading [Easley and O’Hara (1992)]. Because investors are sensitive to unexpected information, they will adjust their position to respond to any new information, making the impact of unexpected trading volume different than that from expected volume. Accordingly, this paper empirically examines whether surprises in trading volume convey more information and, thus measures the precise effect of surprise in trading activity. We hypothesize that price change volatility is positively related to unexpected volume and negatively related to expected volume. In addition, we examine the impact of introducing the bid-ask spread in conditional variance equation. We conjecture that the bid-ask spread is another measure of information flow into the market. We hypothesize that an information arrival would be expected to induce an increase in volatility.

Before attempting to model return volatility, we examine the pronounced pattern typically found in intraday return variability measures. The correlogram of absolute returns is depicted in Figure B1 (Appendix B). As can be clearly noticed, high autocorrelations were clustered around the opening and closing of each trading day. The source for this characteristic is the intraday seasonal volatility pattern depicted in Figure 1, i.e., high volatilities at the opening and closing of the trading day caused the autocorrelation pattern to behave in a cyclical fashion. These patterns are so distinctive that there is a strong need for taking them into account before attempting to model the dynamics of intraday return volatility. Andersen and Bollerslev (1997) note that standard ARCH models imply a geometric decay in the return autocorrelation structure and simply cannot accommodate strong regular cyclical patterns. Following Andersen and Bollerslev (1997, 1998), the returns were filtered from intraday seasonalties using Flexible Fourier Form (FFF) transformation. Intraday averages of absolute filtered returns are also shown in Figure B2 (Appendix

---

11 Two different methods of decomposing trading volume are discussed in Danielsson and Payne (2001). We use ARMA model to generate expected volume and use the residual as unexpected volume. The use of expected volume in return volatility equation also reduces the well known simultaneity bias [Board et al. (2001)].

12 See Andersen and Bollerslev (1997, 1998) for practical details on FFF.
B). The results confirm that FFF is a successful technique in removing the seasonal pattern in intraday volatility.

Table 3 presents summary statistics for 5-minute filtered and absolute filtered returns. The average return for XDAX30 remains to be almost zero with a small negative, though statistically insignificant return autocorrelation. The filtered return series exhibit significant skewness and excess kurtosis, again violating the normality condition. The first and second order autocorrelation coefficients of absolute returns are significant and even more pronounced when compared to raw returns. These significant serial correlations in absolute returns again point to volatility persistence typically observed in stock returns.

Table 3
Summary statistics for intraday 5-minute filtered returns and absolute filtered returns

|                      | r       | |r|    |
|----------------------|---------|---------------------|
| Mean                 | 0.0001  | 0.0133              |
| Minimum              | -0.2649 | 0.0000              |
| Maximum              | 0.3915  | 0.3915              |
| Standard Deviation   | 0.0195  | 0.0142              |
| Skewness             | -0.0417 | 4.0470              |
| Kurtosis             | 19.0620 | 46.3350             |
| AC (1)               | -0.0070 | 0.1900              |
| AC (2)               | -0.0080 | 0.1670              |
| Observations         | 36719   | 36719               |

Notes: AC(1) and AC(2) are first and second order autocorrelation coefficients respectively.

The correlation matrix for the filtered volatility measure, trading activity and liquidity is shown in Table 4. It is important to notice that the contemporaneous correlations are considerably smaller compared to those calculated with raw absolute returns.
Furthermore, before employing the variables in econometric modeling, we check the stationarity condition for the time series of stock returns, trading volume and bid-ask spreads using the augmented Dickey-Fuller (ADF) test. Our results in Table 5 (Appendix C) show that all three time series can be considered stationary.

As shown in Table 3, the serial correlation does not indicate any predictable component of filtered returns. Hence, we define the returns as a mean model:

$$r_t = a_0 + e_t,$$  \hspace{1cm} (1)

where

$$e_t \sim N(0, h_t).$$  \hspace{1cm} (2)

The residual series $e_t$ is expected to be uncorrelated since no autocorrelation is observed in 5-minute filtered return series. Now we move on to modeling return volatility in the next sub section.

### 4.1 Conditional Volatility Model

We use contemporaneous trading volume and bid-ask spread as explanatory variables in the variance equation. The volume-volatility relation is a well documented empirical fact found for most types of financial contracts, including stocks, Treasury bills, currencies and various futures contracts [Girard and Biswal (2007)]. The main theoretical explanation for the relation is that the arrival of new information makes prices adjust to new equilibria over time. Since trading volume is the reflection of the process through which information is incorporated into stock prices, one way of proxying the arrival of this trade information is to introduce the

\begin{table}
\centering
\caption{Cross correlations of 5-minute absolute filtered returns, trading volume and Bid-Ask spread}
\begin{tabular}{|c|c|c|}
\hline
 & $|r|$ & Vol & BAS \\
\hline
$|r|$ & 1 & & \\
Vol & 0.12 & 1 & \\
BAS & 0.20 & 0.19 & 1 \\
\hline
\end{tabular}
\end{table}
volume of trade into the conditional volatility equation. Lamoureux and Lastrapes (1990), for example showed that the introduction of the contemporaneous and lagged volume reduces the GRACH effect in the U.S stock return data. However Chen, Firth, and Rui (2001) report that the persistence in volatility is not eliminated when lagged or contemporaneous trading volume level is incorporated into the GARCH model, a result contradicting the findings of Lamoureux and Lastrapes (1990). Arago and Nieto (2005) argue that it is more appropriate to split trading volume into two components: the expected volume and the other, termed unexpected volume motivated by the unpredictable flow of information to the market. They find that although the effects of the unexpected volume on volatility are much greater than those of total volume, inclusion of unexpected volume in the variance equation does not reduce the persistence of volatility or GARCH effects. Bessembinder and Seguin (1993) also investigate whether the effect of volume on volatility is homogeneous by separating volume into expected and unexpected components. They find that unexpected positive volume shocks produce larger effects on price volatility than negative shocks, pointing to the asymmetric effects of trading volume. Moreover, Rahman et al. (2002), beside trading volume, introduce a bid-ask spread as a measure of information that flows into the market with the argument that bid-ask spread narrows when information flow increases and widens when information flow decreases. Their results show a positive and statistically significant but numerically small effect of both variables on conditional volatility. However, none of the exogenous variables significantly reduce volatility persistence effects for their sample returns. Overall, there exists a rather inconclusive evidence in previous literature with respect to the volatility persistence parameter when mixing variables are included in volatility equation. This motivates us to model the volatility dynamics in the presence of information arrival proxies using aggregate data on XDAX30 constituents.

Following Nelson (1991), we use an exponential GARCH model (EGARCH) to estimate the conditional volatility equation for filtered returns. The EGARCH model offers greater flexibility over other GARCH type models. As, it imposes no positivity constraints on estimated parameters and explicitly accounts for asymmetry in asset return volatility. Furthermore, we introduce contemporaneous trading volume and
bid-ask spreads as mixing variable for information arrival in volatility equation. In addition to looking at the contemporaneous effects, we also examine if mixing variable have any significant effect on the volatility persistence parameter as reported by Lamoureux and Lastrapes (1990). The model can be written as:

$$log h_t = \gamma_0 + \gamma_1 log h_{t-1} + \delta g(Z)_{t-1} + \theta_1 ExpVol_t + \theta_2 UnexpVol_t + \theta_3 logSBAS_t$$

(3)

Where

$$g(Z)_{t-1} = \phi_1[(Z)]_{t-1} + \phi_2[|Z_{t-1}|] - E(|Z_{t-1}|)$$

(4)

And

$$z_t = \frac{\mu_t}{\sqrt{h_t}}$$

Where $\gamma_1$ is the volatility persistence parameter of the filtered returns. The parameters $\theta_1$ and $\theta_2$ measure the impact of the expected and unexpected volume on the volatility of equity returns. While $\theta_3$ measures the impact of bid-ask spread on conditional volatility.

We expect $\theta_1$ to be negative as expected volume is unlikely to be private information driven and thus should lead to decreased return volatility. In other words, the increased liquidity trading is associated with lower volatility. However, the coefficient $\theta_2$ is expected to be positive if unexpected volumes are largely asymmetric information driven. Similarly, the return volatility will rise in response to an increase in bid-ask spreads, thus parameter $\theta_3$ is expected to be positive. In summary, an information arrival would be expected to induce an increase in volatility.

---

13 In order to facilitate the comparison of volatility persistence parameters, we first estimate the standard EGARCH model of the following form:

$$log h_t = \gamma_0 + \delta g(Z)_{t-1} + \gamma_1 log h_{t-1}$$

Where $g(Z)_{t-1} = \phi_1[(Z)]_{t-1} + \phi_2[|Z_{t-1}|] - E(|Z_{t-1}|)$
The function $g(.)$ contains two parameters which define the `size effect' and the `sign effect' of the shocks on volatility. The first is a typical ARCH effect while the second is an asymmetric effect, usually described as the leverage effect. The term $\varphi_2([Z_{t-1}] - E([Z_{t-1}])$ determines the size effect and the term $\varphi_1([Z])_{t-1}$ determines the sign effect. The parameter $\varphi_2$ is typically positive and $\varphi_1$ is negative. If $\varphi_1 = 0$, large innovations increase the conditional variance if $([Z_{t-1}] - E([Z_{t-1}]) > 0$ and decrease the conditional variance if $([Z_{t-1}] - E([Z_{t-1}]) < 0$.

If the parameters $\theta_1, \theta_2$ and $\theta_3$ are significantly non-zero, it shows the exogenous effects of trading activity and liquidity on return volatility. These tests are for the null hypotheses of zero coefficients.

4.2 Asymmetric volume effect

An asymmetric volume effect on stock-return volatility is well documented [see for example, Ying (1966), Karpoff (1987)]. The common finding is that the return volatilities are higher following an increase in trading volume.

We also test asymmetric reactions of volatility in response to changes in volume by including a dummy variable in equation (3) that equals one for a positive change and zero for a negative change in unexpected volume. The following equation formally tests whether return volatility reacts to changes in trading volume in an asymmetric fashion.

\[
\log h_t = \gamma_0 + \gamma_1 \log h_{t-1} + \delta g(Z)_{t-1} + \theta_1 \text{ExpVol}_t + \theta_2 \text{UnexpVol}_t + \\
\theta_3 \log \text{SBAS}_t + \theta_4 \text{dummUnexpVol}_t \tag{5}
\]

Again, if the parameter $\theta_4$ is significantly non-zero, it shows that trading volume has an asymmetric effect on return volatility.

4.3 Lagged Effects

Rahman et al. (2002) and Darrat et al. (2003) report that trading volume in stock markets contains relevant information for predicting future volatility. Accordingly, we also check if lagged trading activity and liquidity variables have significant effect
on subsequent return volatility. The trading volume and bid-ask spreads exhibit significant first order serial correlation.\textsuperscript{14} Thus, in order to avoid any potential problem of simultaneity bias, we separately test for the lagged effects of trading volume and bid-ask spread in the following equation:

\[
\log h_t = \gamma_0 + \gamma_1 \log h_{t-1} + \delta g(Z)_{t-1} + \theta_1 \log(\text{ExpVol})_{t-1} + \theta_2 \log(\text{SBAS})_{t-1}
\]

(6)

The parameters $\theta_1$ and $\theta_2$ measure the impact of the lagged expected trading volume and bid-ask spreads on the volatility of equity returns.

5 Empirical Findings

Table 5 reports the coefficient estimates of the benchmark EGARCH model. All the coefficients are highly significant. The parameter measuring the asymmetry is negative and significant, suggesting the presence of a leverage effect. The volatility persistence parameter amounts to 0.96 for intraday XDAX 30 returns. This supports the common finding that high frequency data exhibits long-memory volatility dependencies in intraday equity returns. Nonetheless, though the degree of volatility persistence is high in the XDAX30 filtered returns, it is mean reverting, indicating an eventual return to a normal level.

\textsuperscript{14} The first order serial correlation of trading volume and bid-ask spreads is 0.313 and 0.221 respectively.
The estimated coefficients of intraday volatility equation (3) are presented in Table 6. There is a significant and positive relationship between the return volatility and the contemporaneous bid-ask spreads. This finding is consistent with the results reported in Wang and Yau (2000), who argue that the positive relation between bid-ask spreads and price volatility indicates that an increase in liquidity (narrowing spreads) will reduce price volatility.

**Table 5.** The maximum likelihood estimates of benchmark EGARCH model

The maximum likelihood estimates were obtained using regularly spaced 5-minute interval data for the period May 5, 2004 to September 29, 2005. Each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET. The estimation was done assuming normal distribution for the following equation:

$$\log h_t = \gamma_0 + \delta g(Z)_{t-1} + \gamma_1 \log h_{t-1},$$

where

$$g(Z)_{t-1} = \phi_1[(Z)_{t-1} + \varphi_2[|Z_{t-1}|] - E(|Z_{t-1}|)].$$

<table>
<thead>
<tr>
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<th>Coefficient</th>
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<td>-0.4596</td>
<td>-61.21</td>
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<td>$\phi_1$</td>
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<td>113.00</td>
<td>0.00</td>
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<td>$\varphi_2$</td>
<td>-0.0153</td>
<td>-11.74</td>
<td>0.00</td>
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</table>

The estimated coefficients of intraday volatility equation (3) are presented in Table 6. There is a significant and positive relationship between the return volatility and the contemporaneous bid-ask spreads. This finding is consistent with the results reported in Wang and Yau (2000), who argue that the positive relation between bid-ask spreads and price volatility indicates that an increase in liquidity (narrowing spreads) will reduce price volatility.

**Table 6.** The maximum likelihood estimates of conditional volatility equation (3)

The maximum likelihood estimates were obtained using regularly spaced 5-minute interval data for the period May 5, 2004 to September 29, 2005. Each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET. The estimation was done assuming normal distribution for the following equation:

$$\log h_t = \gamma_0 + \gamma_1 \log h_{t-1} + \delta g(Z)_{t-1} + \theta_1 \text{ExpVol} + \theta_2 \text{UnexpVol} + \theta_3 \log SBAS,$$

where

$$g(Z)_{t-1} = \phi_1[(Z)_{t-1} + \varphi_2[|Z_{t-1}|] - E(|Z_{t-1}|)].$$

<table>
<thead>
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<tr>
<td>$\gamma_0$</td>
<td>0.094011</td>
<td>3.38</td>
<td>0.00</td>
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<tr>
<td>$\gamma_1$</td>
<td>0.918714</td>
<td>608.63</td>
<td>0.00</td>
</tr>
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<td>$\theta_1$</td>
<td>-3.48E-06</td>
<td>-28.42</td>
<td>0.00</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>7.96E-06</td>
<td>53.94</td>
<td>0.00</td>
</tr>
<tr>
<td>$\theta_3$</td>
<td>0.138753</td>
<td>26.88</td>
<td>0.00</td>
</tr>
<tr>
<td>$\varphi_2$</td>
<td>-0.001847</td>
<td>-0.95</td>
<td>0.34</td>
</tr>
</tbody>
</table>
Moreover, as expected, the intraday return volatility is inversely related with expected volume, and positively related with unexpected volume. These findings demonstrate the importance of dividing the total trading volume into informed and liquidity based trading. Our results suggest that return volatility will rise contemporaneously with the increase in informed trading. While, the increase in liquidity trading will decrease the volatility.

Another interesting finding is that the inclusion of contemporaneous trading activity and liquidity measures in the volatility equation has not remarkably reduced the volatility persistence parameter in comparison with the benchmark model. This finding supports the results of Najand and Yung (1991), Foster (1995) and Rahman et al. (2002) and contrary to those of Lamoureux and Lastrapes (1990).

Table 7 reports the estimation results of equation (5) that allows the effects of unexpected changes in volume on conditional volatility to vary with the sign of shock by introducing dummy variable that equals 1 for positive unexpected shock and zero otherwise.

**Table 7. The maximum likelihood estimates of conditional volatility equation (5)**

The maximum likelihood estimates were obtained using regularly spaced 5-minute interval data for the period May 5, 2004 to September 29, 2005. Each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET. The estimation was done assuming normal distribution for the following equation:

\[
logh_t = \gamma_0 + \gamma_1 logh_{t-1} + \delta g(Z)_{t-1} + \theta_1 ExpVol + \theta_2 UnexpVol + \theta_3 logSBAS + \theta_4 dumUnexpVol,
\]

where

\[
g(Z)_{t-1} = \phi_1 [(Z)_{t-1}] + \phi_2 [\phi (|Z_{t-1}|) - E(|Z_{t-1}|)].
\]

<table>
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<th>Symbol</th>
<th>Coefficient</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tr>
<td>(\gamma_0)</td>
<td>0.138794</td>
<td>4.59</td>
<td>0.00</td>
</tr>
<tr>
<td>(\gamma_1)</td>
<td>0.903727</td>
<td>497.64</td>
<td>0.00</td>
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<td>(\theta_1)</td>
<td>-3.98E-06</td>
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<td>(\theta_2)</td>
<td>6.02E-06</td>
<td>40.87</td>
<td>0.00</td>
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<tr>
<td>(\theta_3)</td>
<td>0.171317</td>
<td>30.48</td>
<td>0.00</td>
</tr>
<tr>
<td>(\theta_4)</td>
<td>0.096708</td>
<td>20.68</td>
<td>0.00</td>
</tr>
<tr>
<td>(\phi_2)</td>
<td>0.002191</td>
<td>1.04</td>
<td>0.30</td>
</tr>
</tbody>
</table>
The estimated coefficient $\theta_4$ is positive and statistically significant, which is consistent with the argument that the impact of positive unexpected volume shocks is larger than the impact of negative shocks. This finding is consistent with Bessembinder and Seguin (1993) and Watanabe (2001), who report similar results for futures markets.

The parameters estimating the lagged effects of expected trading activity and bid-ask spreads on conditional volatility (equation 6) are presented in Table 8. The estimates show that the increased liquidity trading will reduce the subsequent volatility, while the higher bid-ask spreads will increase the volatility in next period. These results are intuitive and confirm the earlier results of Rahman et al. (2002) who report positive and significant relationship between the return volatility and lagged bid-ask spread/trading volume for most of the NASDAQ stocks.

Table 8. The maximum likelihood estimates of conditional volatility equation (6)

The maximum likelihood estimates were obtained using regularly spaced 5-minute interval data for the period May 5, 2004 to September 29, 2005. Each trading day is divided into 102 successive 5-minute intervals from 9:00 through 17:30 CET. The estimation was done assuming normal distribution for the following equation:

$$\log h_t = \gamma_0 + \gamma_1 \log h_{t-1} + \delta g(Z)_{t-1} + \theta_1 \log(\text{ExpVol})_{t-1} + \theta_2 \log(\text{SBAS})_{t-1},$$

where

$$g(Z)_{t-1} = \phi_1 [(Z)_{t-1}] + \phi_2 [(|Z_{t-1}|) - E(|Z_{t-1}|)].$$

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_0$</td>
<td>-0.2848</td>
<td>-14.44</td>
<td>0.00</td>
</tr>
<tr>
<td>$\gamma_4$</td>
<td>0.9568</td>
<td>1066.82</td>
<td>0.00</td>
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<tr>
<td>$\theta_1$</td>
<td>-0.0096</td>
<td>-9.67</td>
<td>0.01</td>
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<tr>
<td>$\phi_2$</td>
<td>0.017</td>
<td>4.62</td>
<td>0.02</td>
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<tr>
<td>$\phi_2$</td>
<td>-0.014</td>
<td>-10.05</td>
<td>0.00</td>
</tr>
</tbody>
</table>

In order to check the consistency of our model, we also test the effects of lagged unexpected trading volume on subsequent return volatility. Our estimates yield the significant and negative coefficient, consistent with the results obtained with contemporaneous terms.

Rahman et al. (2002) use total trading volume in their study of NASDAQ stocks. When we use total trading volume in equation 6, the results are similar to those obtained by Rahman et al. (2002). However, it deemed more meaningful to split the trading volume into expected and unexpected component.
Again, confirming the results of Rahman et al. (2002), there is actually no improvement with regard to the GARCH effects after the introduction of lagged trading volume and bid-ask spreads in the volatility equation.

6 Summary and Conclusion

This paper explores the widely observed empirical regularities in intraday return volatility, trading volume and bid-ask spreads using high frequency 5-minute aggregate data on XDAX30 constituents for the period May 5, 2004 through September 29, 2005. Moreover, we also examine the effect of trading activity and liquidity measures as mixing variable on conditional return volatility.

We document a number of regularities in the pattern of intraday return volatility, trading volume and bid-ask spreads. We are able to confirm the reverse J-shaped pattern of intraday bid-ask spreads with the exception of a major bump following the intraday auction at 13:00 CET. We verify that the trading halt during the intraday call auction significantly induces higher bid-ask spread for the subsequent period. The aggregate trading volume exhibits L-shaped pattern for the XDAX30 index, while for individual stocks, we generally find an intraday pattern close to a reverse J shape. The index volatility also displays a somewhat inverted J-shaped pattern with two major humps at 14:30 and the 15:30 CET. These findings are contrary to a U-shaped pattern found in previous studies [e.g., (Wood, McInish, and Ord (1985), McInish and Wood (1990a) and Harris (1986)].

In line with the results of Wang and Yau (2000) and Rahman et al. (2002), our empirical findings suggest a contemporaneous and positive relationship between the intraday return volatility, bid-ask spread and unexpected trading volume. Whereas, the expected trading volume is found to have a negative relationship with conditional return volatility. We also find that higher trading volume and bid-ask spreads increase subsequent volatility.

In general, these results confirm the role of trading volume and bid-ask spreads as proxies for information arrival in producing the intraday return volatility. However, in contrast with Lamoureux and Lastrapes (1990), GARCH effects remain significant even after the inclusion of contemporaneous and lagged trading volume and bid-ask spreads.
spreads in the volatility equation. Our results also indicate asymmetry in the effects of volume on conditional volatility.

Overall, our findings suggest that key financial markets’ variables; return volatility, trading volume and bid-ask spreads exhibit intraday seasonality. We also show that contemporaneous and lagged trading volume and bid-ask spreads have numerically small but statistically significant effect on return volatility. However, inclusion of both measures as proxy for informal arrival in conditional volatility equation does not explain the well known volatility persistence in intraday stock returns. For future research, it would be interesting to incorporate other information variables in the volatility equation to see if they are able to reduce the ARCH effects. Furthermore, the use of contemporaneous variables in the volatility equation could be subject to a specification bias. As pointed out by Fleming et al. (2006), adding volume to the GARCH model implies that volume is treated as exogenous variable, which is contrary to most trading models including MDH. If the volume parameter is endogenous, problems arise in the estimation of the maximum likelihood making it hard to trust the significance of the results. One option for the upcoming research would be to run simultaneous tests including return volatility, trading volume and bid-ask spread.
References


Worthington, A, C. and Higgs (2003), Modelling the intraday return volatility process in the Australian equity market: An examination of the role of information arrival in S&P / ASX 50 stocks, Discussion paper no. 150, School of Economics and Finance, Queensland university of technology, Australia.

Appendix A

The figures shown below display intraday average volume for each 5-minute interval for individual firms in XDAX30. We pick 6 stocks from XDAX30 constituents based on market capitalization. The first three stocks are selected from the companies with higher market capitalization, while the last three are picked from the low turnover companies.
Appendix A (Continued)

Deutsche Börse

Infineon Technologies

Adidas
Appendix B

The Figure B1 and B2 represent autocorrelation pattern of raw and filtered absolute returns and average intraday volatility pattern for each 5-minute interval respectively.

**Figure B1.** Autocorrelation pattern of 5-minute raw and filtered absolute return. The dashed and the solid line depict the autocorrelation coefficients for raw and filtered absolute returns for the XDAX30 index respectively.

**Figure B2.** Average intraday volatility pattern for each 5-minute interval. The dashed and the solid line show the average raw and filtered absolute returns for the XDAX30 index respectively.
Appendix C

Unit root tests

Time series modeling assumes that the variables we are employing are stationary. We check the hypothesis of whether the time series of stock returns, trading volume and bid-ask spreads can be assumed to be stationary by using the augmented Dickey-Fuller (ADF) test. This test is based on the regression:

\[ y_t = \mu + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-1} + \varepsilon_t \]

Where \( y \) is the variable being tested for unit roots (stock return, trading volume or bid-ask spread), \( \mu, \gamma \) and \( \delta_i \) are model parameters and \( \varepsilon_t \) is an i.i.d Gaussian \((0, \sigma^2)\) white noise error term. The unit root test is carried out by testing the null hypothesis \( \gamma = 0 \) against the one sided alternative \( \gamma < 0 \). Unfortunately the \( t \)-Student-statistic of the estimated parameter \( \gamma \) does not have a conventional t-distribution under the null hypothesis of a unit root. Instead, we use the critical values recommended by MacKinnon (1991). If the ADF \( t \)-statistic for \( \gamma \) lies to the left of these values, the null hypothesis can be rejected. The results of the unit root tests for the time series of stock returns, trading volume and bid-ask spreads are shown in Table 5.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Statistics</th>
<th>Critical Value (1%)*</th>
</tr>
</thead>
<tbody>
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<td>Filtered returns</td>
<td>-192.9657</td>
<td>-3.430358</td>
</tr>
<tr>
<td>Volume</td>
<td>-28.02922</td>
<td>-3.430358</td>
</tr>
<tr>
<td>Bid-Ask spread</td>
<td>-21.10545</td>
<td>-3.430358</td>
</tr>
</tbody>
</table>

*MacKinnon critical values for rejection of hypothesis of a unit root.

The estimate for parameter \( \gamma \) is negative and statistically significant at all traditional significance levels. Thus our results show that all three time series can be considered stationary.