The Intraday Behaviour of Bid-Ask Spreads, Trading Volume and Return Volatility: Evidence from DAX30

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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.

Keywords: Intraday, Conditional volatility, Trading volume, Bid-ask spread, Asymmetry

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. (Note 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 DAX30 constituents. .

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 DAX30 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 (DAX30), 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 DAX30 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 DAX30 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 DAX30 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. (Note 2) Thus each trading day is divided into 102 successive 5-minute intervals.

After filtering the data for outliers and other anomalies, the continuously compounded returns are calculated as $r_{i,t} = 100 \times [\log(P_t) - \log(P_{t-1})]$, where $P_{i,t}$ represents the price level in market i at time t.

The 5-minute proportional bid-ask spreads were calculated as BAS=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 DAX30 stocks. A few missing observations were interpolated to obtain a continuous series. (Note 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. (Note 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. (2003), 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 DAX30 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. (Note 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.

2.1 Cross Correlations

Table 2 presents the correlation matrix of return volatility, trading volume and Bid-ask spreads for the whole sample. (Note 6) 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.

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 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. We take a fresh empirical look at the intraday patterns in return volatility, trading volume and bid-ask spread using the aggregate data on DAX30 constituents.

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 DAX30 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 DAX30 index. This finding is in line with Harju and Hussain (2010), who report similar pattern for four major European stock market indices, FTSE100, DAX30, 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 (2010) 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 (2010) 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.

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).

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 numbers 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. (Note 7) We further examine this by looking at the intraday volume patterns for individual stocks. (Note 8) 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 DAX30 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 DAX30 stocks. (Note 9)

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 follows closely that of reported by Theissen and Freihube (2001) (Note 10), 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 volume. (Note 11) 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 Appendix A1 (Appendix A). 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 seasonalities using Flexible Fourier Form (FFF) transformation. (Note 12) Intraday averages of absolute filtered returns are also shown in Appendix A2 (Appendix A). 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 DAX30 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. 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 (not shown here) reveal 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:

$$r_t = a_0 + e_t \, , \tag{1}$$

where

$$e_t \sim N(0, h_t). \tag{2}$$

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 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 DAX30 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). (Note 13) The model can be written as:

$$logh_t = \gamma_0 + \gamma_1 logh_{t-1} + \delta g(Z)_{t-1} + \theta_1 ExpVol_t + \theta_2 UnexpVol_t + \theta_3\, logSBAS_t \tag{3}$$

Where

$$g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)] \tag{4}$$

and

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

where $\gamma_1$is the volatility persistence parameter of the filtered returns. The parameters θ_1 and θ_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 θ_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 θ_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 θ_3 is expected to be positive. In summary, an information arrival would be expected to induce an increase in volatility.

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 $\emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$determines the size effect and the term $\emptyset_1[(Z)]_{t-1}$ determines the sign effect. The parameter $\emptyset_2$ is typically positive and $\emptyset_1$ is negative. If $\emptyset_1 = 0$, 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 θ_1, θ_2 and $\theta_3$are significantly non-zero, the results will indicate 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.

$$logh_t = \gamma_0 + \gamma_1 logh_{t-1} + \delta g(Z)_{t-1} + \theta_1 ExpVol_t + \theta_2 UnexpVol_t + \theta_3\, logSBAS_t + \theta_4 dumUnexpVol_t \quad (5)$$

The parameter θ_4 measures the asymmetric effect of trading volume on return volatility. The estimated coefficient for θ_4 is expected to be positive to prove the positive asymmetric effect.

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. (Note 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:

$$\mathrm{logh_t} = \gamma_0 + \gamma_1 \mathrm{logh_{t-1}} + \delta \mathrm{g(Z)_{t-1}} + \theta_1 \mathrm{log(ExpVol)_{t-1}} + \theta_2\, \mathrm{log(SBAS)_{t-1}} \quad (6)$$

The parameters θ_1 and θ_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 DAX30 filtered returns, it is mean reverting, indicating an eventual return to a normal level.

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.

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.

The estimated coefficient θ_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. (Note 15) 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. (Note 16)

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 DAX30 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 DAX30 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.

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Notes

Note 1: Many market microstructure papers regard the bid-ask spread as a proxy for information asymmetry, such as Lee, Mucklow and Ready (1993).

Note 2: For DAX30, 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).

Note 3: Total number of interpolated observations was 74.

Note 4: For example, we deleted the bid-ask quotes where bid price was greater than the ask price.

Note 5: These effects disappear when we leave out the first 10-minute observations.

Note 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.

Note 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.

Note 8: We pick 6 stocks from DAX30 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. The intraday patterns for selected stocks in DAX30 are not shown here to save the space. However, the figures are available upon request from the author.

Note 9: The intraday call auction begins at 13:00 for DAX30 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 equal means was rejected. Consequently it seemed that the intraday call auction significantly induces higher bid-ask spread for the subsequent period.

Note 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.

Note 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)].

Note 12: See Andersen and Bollerslev (1997, 1998) for practical details on FFF.

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

$$logh_t = \gamma_0 + \delta g(Z)_{t-1} + \gamma_1 logh_{t-1}, \text{ Where } g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$$

Note 14: The first order serial correlation of trading volume and bid-ask spreads is 0.313 and 0.221 respectively.

Note 15: 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.

Note 16: 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.

Table1. Summary statistics for intraday 5-minute raw returns and absolute returns

	r	|r|
Mean	0.0006	0.0487
Minimum	-2.2865	0.0000
Maximum	1.8499	2.2865
Standard Deviation	0.0849	0.0695
Skewness	-0.9391	8.5289
Kurtosis	78.0200	146.3980
AC (1)	-0.0100	0.1510
AC (2)	-0.0010	0.1320
Observations	36720	36720

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

Table2. Cross correlations of 5-minute absolute returns, trading volume and Bid-Ask spreads

	|r|	Vol	BAS
|r|	1		
Vol	0.43	1	
	(90.27)		
BAS	0.29	0.19	1
	(58.11)	(37.83)	

Table3. 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.

Table4. Cross correlations of 5-minute absolute filtered returns, trading volume and Bid-Ask spread

	|r|	Vol	BAS
|r|	1		
Vol	0.12	1	
	(23.66)		
BAS	0.20	0.19	1
	(38.94)	(37.83)	

Table 5. The maximum likelihood estimates of benchmark EGARCH model

	Coefficient	Std. Error	z-Statistic	Prob.
γ_0	-0.4596	0.0075	-61.2078	0.0000
γ_1	0.9590	0.0008	1148.1210	0.0000
$\emptyset_2$	-0.0153	0.0013	-11.7416	0.0000

Notes: The maximum likelihood estimates were obtained using regularly spaced 5 minute filtered returns 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: $logh_t = \gamma_0 + \delta g(Z)_{t-1} + \gamma_1 h_{t-1}$

Where $g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$

Table 6. The maximum likelihood estimates of conditional volatility equation

	Coefficient	Std. Error	z-Statistic	Prob.
γ_0	0.094011	0.027846	3.376057	0.0007
γ_1	0.918714	0.001509	608.6259	0.0000
θ_1	-3.48E-06	1.23E-07	-28.42173	0.0000
θ_2	7.96E-06	1.48E-07	53.93891	0.0000
θ_3	0.138753	0.005162	26.87766	0.0000
$\emptyset_2$	-0.001847	0.00194	-0.952046	0.3411

Notes: The maximum likelihood estimates were obtained using regularly spaced 5 minute filtered returns 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: $\mathrm{logh_t} = \gamma_0 + \gamma_1 \mathrm{h_{t-1}} + \delta \mathrm{g(Z)_{t-1}} + \theta_1 \mathrm{ExpVol} + \theta_2 \mathrm{UnexpVol} + \theta_3 \,\mathrm{logSBAS}$,where $g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$

Table 7. The maximum likelihood estimates of conditional volatility equation

	Coefficient	Std. Error	z-Statistic	Prob.
γ_0	0.138794	0.030252	4.587869	0.0000
γ_1	0.903727	0.001816	497.6414	0.0000
θ_1	-3.98E-06	1.26E-07	-31.5619	0.0000
θ_2	6.02E-06	1.47E-07	40.86946	0.0000
θ_3	0.171317	0.005621	30.47732	0.0000
θ_4	0.096708	0.004675	20.68476	0.0000
$\emptyset_2$	0.002191	0.002101	1.042782	0.2970

Notes: The maximum likelihood estimates were obtained using regularly spaced 5 minute filtered returns 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:

$logh_t = \gamma_0 + \gamma_1 h_{t-1} + \delta g(Z)_{t-1} + \theta_1 ExpVol + \theta_2 UnexpVol + \theta_3\, logSBAS + \theta_4 dumUnexpVol$, *where* $g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$

Table 8. The maximum likelihood estimates of conditional volatility equation

	Coefficient	z-Statistic	Prob.
γ_0	-0.2848	-14.44	0.00
γ_1	0.9568	1066.82	0.00
θ_1	-0.0096	-9.67	-0.01
θ_2	0.017	4.62	0.02
$\emptyset_2$	-0.014	-10.05	0.00

Notes: The maximum likelihood estimates were obtained using regularly spaced 5-minute filtered returns 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: $\mathrm{logh_t} = \gamma_0 + \gamma_1 \mathrm{logh_{t-1}} + \delta \mathrm{g(Z)_{t-1}} + \theta_1 \mathrm{log(ExpVol)_{t-1}} + \theta_2 \,\mathrm{log(SBAS)_{t-1}}$,where $g(Z)_{t-1} = \emptyset_1[(Z)]_{t-1} + \emptyset_2[(|Z_{t-1}|) - E(|Z_{t-1}|)]$.

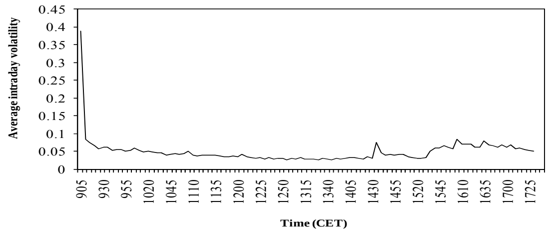

Figure 1. Average intraday volatility for the DAX 30 index

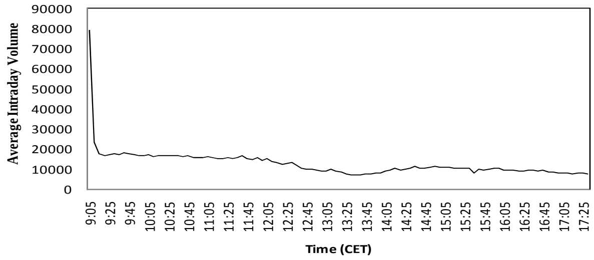

Figure 2. Average intraday volume for the DAX 30 index

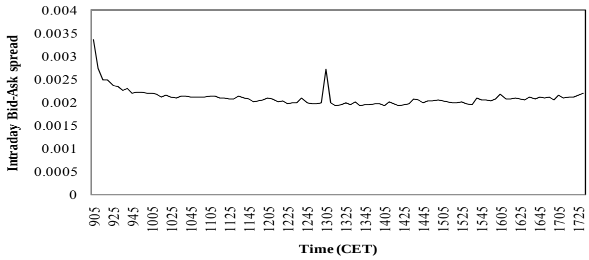

Figure 3. Average intraday spread for the DAX 30 index

Appendix A

The Figure A1 and A2 represent autocorrelation pattern of raw and filtered absolute returns and average intraday volatility pattern for each 5-minute interval respectively.

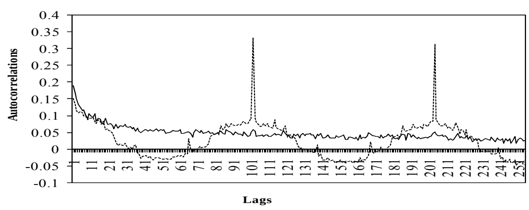

Figure A1. Autocorrelation pattern of 5-minute raw and filtered absolute return. The dashed and the solid line depict the autocorrelation coefficients for raw and filtered absolute returns for the DAX30 index respectively.

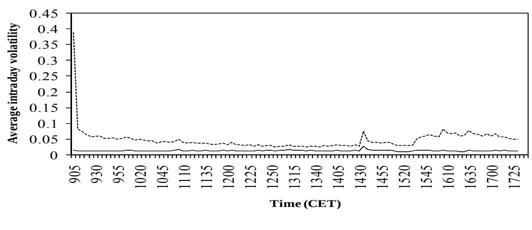

Figure A2. Average intraday volatility pattern for each 5-minute interval. The dashed and the solid line show the average raw and filtered absolute returns for the DAX30 index respectively.