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Intraday volatility and trading activity dynamics in Bangladesh's capital market

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This study examines the relationship between trading activity and intraday price volatility in the Dhaka Stock Exchange (DSE) using firm-level panel data covering 80 listed firms over the period 2013–2023. Employing firm-level fixed effects with Driscoll–Kraay standard errors, the analysis investigates how liquidity measures, including trading volume, turnover, and number of trades, influence daily intraday volatility constructed from high–low price ranges. The findings indicate that higher trading volume leads to a significant increase in the volatility, which is consistent with the mixture of distributions hypothesis. On the other hand, turnover has a significantly negative influence on price, and it is interesting to note that higher trading value can assure the price stability and market efficiency. Trade number has a weaker positive effect, and both the COVID-19 dummy and market-level returns have an insignificant effect when liquidity is considered. The inclusion of lagged volatility reveals strong persistence in volatility dynamics, highlighting the importance of temporal dependence in price fluctuations. To address potential endogeneity arising from simultaneity between trading activity and volatility, an instrumental variable (IV-2SLS) approach is employed, and the results remain robust. Robustness checks using alternative volatility measures, including Parkinson and Garman–Klass estimators, confirm the stability of the findings. The results are consistent with a hybrid mechanism in which both information-driven trading and noise-driven behavior influence price formation, particularly in a retail-dominated market environment. Overall, the study provides firm-level evidence on the volatility liquidity nexus in a frontier market context and offers insights into how structural features such as retail participation and limited liquidity shape market dynamics.

1. Introduction

Understanding the drivers of intraday price volatility is central to modern market microstructure research. Volatility is not only a measure of dispersion; it measures how markets assimilate information, take in trades, and adjust to changes in liquidity. In a well-functioning market, prices will adjust rapidly as information arrives, although volatility might be generated by noise, speculation, or imbalances in order flow in less liquid or more segmented markets. Examination of the nature of intraday volatility contributes towards a fuller understanding of how trading dynamics influence price discovery, particularly in emerging stock markets with a low level of institutional presence, a high degree of information asymmetry, and extensive involvement of retail investors.

One of the key theoretical foundations explaining volatility liquidity relationships is the Mixture of Distributions Hypothesis

(MDH), which posits that trading volume is a proxy for the rate of information arrival, implying a positive relation between volume and volatility (Clark, 1973; Karpoff, 1987). When traders learn information, trading activity increases, and price dispersion rises in turn. Nonetheless, other dimensions of liquidity, in particular turnover, could make a contribution to lower volatility by increasing market depth and decreasing the price impact of trades (Chordia et al.,2001). These conflicting effects suggest that liquidity is multi-dimensional and one may have a different impact on volatility depending upon which component, volume, turnover, or number of trades, dominates the market. From another theoretical perspective, Noise Trading Theory (De Long et al., 1990) suggests that uninformed or sentiment-driven trading can generate excess volatility unrelated to fundamentals. In retail-dominated markets, where informed trading is relatively limited, noise trading may play a more prominent role in price formation.

In developed markets, intraday volatility and trading volume are found to be highly correlated. High-frequency analyses in the U.S. and European markets demonstrate that volume surges coincide with wider price ranges and rapid price adjustments, especially around major announcements (Andersen & Bollerslev, 1998). In developing countries, however, the apparent relationship is not that clear, given a number of country-level structural differences like lower liquidity, weak institutional involvement, and more information asymmetry (Bekaert & Harvey, 1997). Studies in South Asian and other developing markets indicate that the impact of liquidity may be either magnified or diminished depending on the depth of the market and diversity of investor type (Rizvi, Dewan & Syed, 2014; Huang & Masulis, 2003). These results suggest that country-level sub-generic studies are necessary, especially if emerging markets display distinct trading behavior and market characteristics.

Bangladesh's stock market offers a unique setting to investigate these relationships. Being a frontier market with shallow liquidity and high retail investors, Bangladesh is characterized by noise trading, speculative bubbles, and occasional shortages of market liquidity. Most of the earlier studies on Bangladesh have analyzed either market-level volatility, return predictability, or macro-financial linkage (Ali, Akter, & Uddin, 2021). But, firm-level microstructure evidence (especially on intraday volatility) is still largely missing. This is relevant because intraday price dynamics directly impact trading costs, portfolio risk, and regulatory interventions such as circuit breakers and trading halts.

Additionally, Bangladesh differs in the investor type composition, which increases the significance of microstructure examination. There are more retail investors in the market than institutions, and orders from them vastly influence price action faced by developed markets, where it's institution-driven liquidity. This architecture renders the firm vulnerable to noise trading (Kyle, 1985), speculation (Scheinkman, 1978), and rumor-based volatility (Washburn and Zeng, 2017), which motivates investigating how trading activity drives intra-day price movements on a per-firm basis.

The COVID-19 outbreak has amplified concerns about liquidity and volatility in emerging markets. Globally, financial markets experienced extreme turbulence during the early phases of the pandemic due to uncertainty, supply-chain disruptions, and mobility restrictions (Zhang, Hu & Ji, 2020). But the response in emerging markets was mixed, reflecting differences in regulatory interventions, investor bases, and market depth. There is not much data available for Bangladesh on the impact of COVID-19 on firm-level intraday volatility. For this reason, access to data during the pandemic can help researchers examine if volatility–liquidity relationships were affected by it.

As well, in view of the identified knowledge gaps and the specific structure of the Bangladeshi capital market, it would be worthwhile to further investigate the dynamics of intraday volatility and trading activity. Such analyses would be able to inform both the role of volume, turnover, and trade frequency as either amplifiers or stabilizers of price fluctuations in a market with retail investors. The contribution of this paper is threefold. First, it provides firm-level evidence on the volatility liquidity nexus in a frontier market setting, where empirical research remains scarce. Second, it adopts a methodologically robust framework, incorporating lagged volatility, fixed effects, and instrumental variable estimation to address key econometric challenges. Third, and most importantly, it offers a mechanism-based interpretation of the results by linking trading activity to both information-driven and noise-driven dynamics in a retail-dominated market.

Insights from this paper have important practical implications as well: deciphering the layers of liquidity and their connections to volatility is crucial for policymakers to improve circuit breakers,risk management, and further reforms on trading mechanisms. For investors, understanding the liquidity factors that exacerbate or attenuate intraday volatility can enhance risk management and guide trading strategy in a market with frequently erratic price movement characteristics.

2. Literature review

The link between trading activity and volatility is one of the classical issues in market microstructure. Some of the earliest theoretical works demonstrate that price volatility can be affected by the timing of information arrival. Engle (1982) showed that financial markets are characterized by time-varying volatility, and it clusters in periods of high volume, while Parkinson's (1980) high-low range measure enhanced the accuracy of daily estimates. Extending this line of reasoning, the Mixture of Distributions Hypothesis (MDH) postulates that trading volume serves as a proxy for information arrival rate with a consequent positive link between volume and volatility (Clark, 1973; Karpoff, 1987). Tauchen and Pitts (1983) show that price variability and trading volume move together in speculative markets. Empirical evidence remains supportive, with volatility increasing from higher market processing of information or speculative trading.

Liquidity is, however, a multi-faceted concept, and its components may affect volatility differently. Trading volume measures the intensity of trading, whereas turnover indicates the market depth as well as transaction value. Deeper liquidity (Chordia, Roll, and Subrahmanyam 2001) lowers the informational impact of trades and dampens volatility. Recent evidence reinforces this duality. Graczyk et al. (2018) show that it can be seen how the correlation between volatility and volumes changes over the trading day, which shows differences in trader activity and the flow of information. Recent research on India, an important emerging market, finds that intraday volatility is influenced by both order flow and spread-based measures of liquidity, suggesting that liquidity comprises more than volume. The study by Sampath (2020) also offers additional evidence from an emerging market context, which showcases a significant volume–volatility connection that is in line with predictions made under the MDH.

High-frequency studies in developed markets consistently show strong linkages between trading activity and intraday volatility. Andersen and Bollerslev (1998) highlight the responsiveness of volatility to intraday trading patterns and macroeconomic news. Moreover, Gallant et al. (1992) also show that volume and volatility are simultaneously determined by the intrinsic information process. In the emerging market, however, the situation changes significantly because of structural differences in these markets, such as reduced liquidity, lack of strong institutions, and more information asymmetry (Bekaert & Harvey ,1997). In South Asian and Middle East studies, too, such a volume–volatility relationship varies. Some markets show a positive volume and volatility relationship, whereas others demonstrate a dampening impact of turnover or have sector-specific characteristics for liquidity behavior (Rizvi et al., 2014). Evidence from the Gulf region also highlights regime-dependent behavior, where volume impacts volatility differently across tranquil and turbulent market periods.

Empirical evidence from developed and emerging markets generally supports a positive association between trading activity and volatility, but the interpretation is often mixed. In some settings, higher volume reflects efficient incorporation of information; in others, it reflects speculative or destabilizing trading. For example, evidence from Indonesia and Thailand shows a strong contemporaneous link between trading flows and volatility, while studies on emerging-market liquidity emphasize that conventional liquidity measures may behave differently in thinner, less efficient markets (Wang, 2007).

Bangladesh's equity market presents a unique case for exploring these microstructure dynamics. With low liquidity, high retail involvement, and occasional clustering of market volatility, the market reacts sensitively to imbalances in order flow and speculative trading. Most of the prior studies have focused on market-level volatility, macro-financial connectivity, and regulation events (Ali et al., 2021), while limited evidence on firm-level microstructure characteristics is present. Previous analyses on volatility dynamics in Bangladesh indicate inefficiencies related to structure and the existence of frequent price variations, which are influenced by behavioral activities. Research on both the Dhaka and the Chittagong markets shows evidence of weak-form inefficiency and regime shifts, reflecting fragile frontier markets.

More recent research further underscores Bangladesh's sensitivity to shocks. Shaturaev (2023) reports heightened market volatility during the COVID-19 pandemic, while earlier work on the CSE also confirms persistent instability and inadequate liquidity buffers. Studies with comparable analyses using other emerging market data show severe illiquidity and increased volatility during the pandemic, with more fragile markets showing larger adverse effects than developed ones. Topcu and Gulal (2020) also show that COVID-19 effects gained power in the early periods of the pandemic, but lost strength as financial markets adjusted. Additional evidence indicates, however, that volatility during COVID-19 was very asymmetric, with emerging markets being more sensitive to negative shocks than developed ones.

Beyond pandemic effects, recent microstructure studies continue to highlight the importance of liquidity in driving volatility. Zhao (2024), who investigates volatility spillovers between single-stock ETFs and the underlying stocks, provides evidence that liquidity conditions materially affect spillovers, highlighting the importance of accounting for multiple dimensions in intraday price dynamics.

Overall, the literature shows that there is a strong theoretical and empirical link between liquidity, trading activity, and intraday volatility, but also that this connection differs across market microstructure. Although these relationships have been thoroughly documented in developed and large emerging markets, there is limited evidence from frontier markets like Bangladesh. With the retail-based trading environment, uneven liquidity distributions, and sensitivity to international shocks in Bangladesh, it is imperative to have a full-fledged examination at the firm level. This study contributes to filling an important void in the literature and also seeks to add value in better comprehension of microstructure dynamics at frontier markets through empirical analysis that investigates how volume, turnover, and trading frequency influence intraday price variability.

3. Research questions and hypotheses

Determining the drivers of intraday price volatility is important for assessing the operation of frontier equity markets like Bangladesh, where liquidity is asymmetric, and trading activities are largely influenced by retail investors. While there is some understanding of how trading intensity and market depth influence volatility in developed markets, the literature reveals limited evidence using data from Bangladesh. To close this gap, in the current paper, we study how firm-level trading activity influences intraday volatility daily over the period 2013– 2023. The research is directed by three central questions:

3.1 Research questions

RQ1: What is the effect of trading activity on intraday price volatility in Bangladesh's capital market?

RQ2: Which components of trading activity - trading volume, turnover, and trade frequency- offer meaningful explanations for changes in intraday volatility?

RQ3: To what extent are firm-level intraday volatility patterns influenced by market-wide factors such as the COVID-19 period and overall market movements?

3.2 Hypotheses

Based on established microstructure theories, including the Mixture of Distributions Hypothesis and liquidity–depth frameworks, the study formulates the following hypotheses:

H_1: Intraday volatility is greater for stocks that are more traded.

Rationale: Higher trading activity reflects increased information arrival and speculative trading behavior, both of which contribute to greater price fluctuations. According to the Mixture of Distributions Hypothesis (MDH), both trading volume and volatility are driven by the arrival of new information, implying a positive relationship between trading activity and price fluctuations (Clark, 1973; Karpoff, 1987; Epps & Epps, 1976).

H_2: Turnover is negatively related to intraday volatility as a function of higher market depth.

Rationale: Higher turnover reflects greater market depth and liquidity, which facilitates smoother price adjustment and reduces volatility. Noise trading theory suggests that not all trading is information-driven in markets with high retail participation. Sentiment-based and speculative trading may further amplify volatility (Black, 1986; De Long et al., 1990). In contrast, market microstructure theory highlights the stabilizing role of liquidity, where greater market depth, proxied by turnover, reduces price impact and enhances price efficiency (Kyle, 1985; Amihud & Mendelson, 1986; Chordia et al., 2001)

H_3: Market-wide effects, such as the COVID-19 period and DSEX market return, significantly affect firm-level intraday volatility.

Rationale: Market-wide factors such as overall market returns and external shocks may influence volatility through changes in investor sentiment and uncertainty (Schwert, 1989; Baker et al., 2020).

4. Research methodology

4.1 Data source and sample construction

This analysis uses a large daily panel data set compiled from individual firm trading and price data of the Dhaka Stock Exchange (DSE) for the period January 2013 to December 2023. The sample consists of all active listed firms with available high, low, average, and close prices throughout the period, as well as trading volume, turnover, and number of trades. The sample size of the dataset comprises more than two hundred thousand firm-day observations, establishing a deep and fine-grained insight into intraday volatility dynamics. These firm-specific records were merged with market-wide data from the DSEX index, the benchmark indicator of Bangladesh's equity market, by matching trade dates.

In order to incorporate structural breaks in the behavior of the stock market during the global health emergency, a COVID-19 dummy was defined by 1 for all trading dates between 1 March 2020 and 31 December 2021, the period that includes Bangladesh's lockdowns, movement restrictions, and significant global shocks. This permits us to explore whether volatility liquidity links are different during crises and normal periods. The study focuses on four actively traded sectors, and they are Bank, Pharmaceuticals & Chemicals, Engineering, and Fuel and Power, because they provide the most complete and liquid trading information throughout the sample period. The final dataset contains around 80 firms over about 2600 trading days, yielding more than 200,000 firm-day observations.

4.2 Variable construction

4.2.1 Dependent variable: Intraday volatility

The dependent variable, intraday volatility, is measured using the Parkinson (1980) range-based estimator:

$$VOLATILITY_{it} = \frac{H_{it} - L_{it}}{AVGPRC_{it}}$$

This estimator addresses price dispersion for the day of trade and is more efficient than measures of volatility based on closing prices. In a frontier market like Bangladesh, which has asymmetric liquidity and where price jumps can form on each trading day, this measure presents a more precise picture of the intra-day risk.

4.2.2 Independent variables: Trading activity measures

Three dimensions of trading activity were represented by the liquidity measurements:

Log of volume (LOG_VOLUME): A log scale of 1+ share trading volume. Based on the Mixture Distribution Hypothesis (Clark, 1973; Karpoff, 1987), we hold that higher trading volume signifies more information dissemination and generally is associated with a greater level of volatility.

Log of turnover (LOG_TURNOVER): Logarithm to the base e of traded value in dollars. Higher turnover could be revealing of market liquidity that lets the market process trades more efficiently, and mitigates volatility.

Log Transactions (LOG_TRADES): The natural logarithm of the volume. There may be some possible increases in volatility, due to more fragmented orders, although the sign can go both ways.

4.2.3 Control variables

Daily DSEX market return was included to control for systematic shocks and market-wide sentiment effects. Market returns were calculated as:

$$DSEX\_RETURN_t = \ln\left(\frac{DSEX_t}{DSEX_{t-1}}\right)$$

Importantly, the inclusion of lagged volatility also helps mitigate potential omitted variable bias and improves the overall specification of the model, as suggested in prior volatility literature. Additionally, the COVID_DUMMY variable controls for structural breaks during the pandemic. These variables prevent the misattribution of market-wide volatility to firm-level trading activity.

4.3 Empirical model

The empirical specification examines the relationship between trading activity and intraday volatility using the following panel regression model:

$$VOLATILITY_{it} = \alpha + \beta_1 LOG_{VOLUME_{it}} + \beta_2 LOG_{TURNOVER_{it}} + \beta_3 LOG_{TRADES_{it}} + \beta_4 LAG_{VOLATILITY_{it}} + \beta_5 COVID_t + \beta_6 DSEX_{RETURN_t} + \mu_i + \lambda_t + \epsilon_{it}$$

This framework allows for the simultaneous assessment of multiple dimensions of liquidity while controlling for firm-specific heterogeneity and macro-level influences. Importantly, the inclusion of lagged volatility captures volatility persistence and helps mitigate potential omitted variable bias, which is particularly relevant in volatility modeling.

Given the panel structure of the data, this study employs a Fixed Effects (FE) model as the primary estimation approach. Firms differ in structural characteristics such as size, governance structure, business model, and investor composition, which are largely time-invariant but may significantly influence volatility (Bamasak et al., 2017; Baker et al., 2002). The Hausman test confirms that these unobserved firm-specific effects are correlated with the explanatory variables, thereby supporting the use of the fixed effects estimator over the random effects alternative.

A key empirical challenge is the potential simultaneity between trading activity and volatility, as both may be jointly determined within market microstructure frameworks. To address this concern, the study supplements the baseline specification with an instrumental variable (IV-2SLS) approach, using lagged liquidity measures as instruments. This strategy helps mitigate reverse causality and strengthens the interpretation of the estimated relationships.

Financial panel data typically exhibit heteroskedasticity, serial correlation, and cross-sectional dependence due to common market-wide shocks and co-movements across firms. To address these issues, the analysis employs Driscoll–Kraay standard errors, which provide consistent inference under all three conditions. This approach is particularly suitable for panels with a relatively large time dimension compared to the cross-sectional units, as in this study. Diagnostic tests further justify the application of this correction.

5.0 Results and discussion

5.1 Descriptive statistics

Summary statistics of the main variables employed in the analysis are reported in Table 1. The mean of intraday volatility is 0.586 with a high standard deviation (2.176), indicating that firms included in the DSE have very wide cooperation price fluctuation during the day, released on average every minute, trading variation extent among the market participants. This is consistent with the properties of frontier markets, which are characterized by low liquidity and heterogeneous investor behavior leading to an excess level of price volatility.

The spread of trading activity indicators is also displayed. Mean-standard deviation of LOG_VOLUME and LOG_TURNOVER is 11.33-15.42; that for LOG_TRADES is 5.00, implying substantial variation in liquidity across firms. Both stock returns and index returns show near-zero means, as expected for daily data, confirming that the dataset is well-balanced and consistent with high-frequency financial behavior.

Table-1 Descriptive statistics

Variable	Count	Mean	Std. Dev.	Min	25%	50%	75%	Max
VOLATILITY	200,829	0.5863	2.1759	-0.9354	0.0163	0.0316	0.0799	25.7801
LOG_VOLUME	200,829	11.3308	2.5502	0.0000	10.0058	11.7925	13.0868	18.6691
LOG_TURNOVER	200,829	15.4177	2.2083	1.6864	14.4682	15.6996	16.8003	22.8433
LOG_TRADES	200,829	5.0022	1.7238	0.0000	4.3041	5.2883	6.1377	9.2730
LAG_VOLATILITY	200,829	0.5866	2.1762	-0.9353	0.0162	0.0316	0.0803	25.7801
DSEX_RETURN	200,829	0.000136	0.0084	-0.0674	-0.0039	0.0002	0.0041	0.0980

Source: Author's calculation

5.2 Correlation matrix

The Pearson correlation matrix is provided in Table 2. Intraday volatility presents very low correlations with all liquidity measures, so there is no straightforward problem of multicollinearity between the dependent and explanatory variables. Nevertheless, the liquidity indices are highly correlated with each other: These results are consistent with microstructure theory, since trading volume, traded value, and number of trades tend to move together in a frontier market. While multicollinearity is exhibited, it is theoretically reasonable as each variable signifies a specific liquidity dimension.

A notable finding is the extremely high correlation between current volatility and lagged volatility, reflecting strong volatility persistence. This supports the inclusion of lagged volatility in the model and aligns with the well-established phenomenon of volatility clustering in financial markets.

Table-2 Correlation matrix

Variable	VOL	L_VOL	L_TRN	L_TRD	LAG_VOLATILITY
VOLATILITY	1.000	0.053	−0.045	−0.008	0.999
LOG_VOLUME	0.054	1.000	0.832	0.712	0.053
LOG_TURNOVER	−0.044	0.832	1.000	0.838	-0.045
LOG_TRADES	−0.008	0.712	0.838	1.000	-0.009
LAG_VOLATILITY	0.999	0.053	-0.045	-0.009	1.000

Source: Author's calculation

5.3 Fixed Effects regression with Driscoll–Kraay Standard Errors

The main estimation results based on a firm fixed effects and Driscoll–Kraay standard errors can be found in Table 3. The model exhibits very high explanatory power ($R^2 = 0.9907$), indicating that a substantial portion of the variation in intraday volatility is explained by the included variables. This high R^2 is primarily driven by the inclusion of lagged volatility, which captures strong persistence in volatility dynamics. The overall model is statistically significant (robust F-statistic, $p < 0.001$), confirming that the explanatory variables jointly influence intraday volatility. This result captures strong persistence in volatility dynamics, a stylized fact widely documented in financial markets (Engle, 1982; Bollerslev, 1986).

Volatility is highly stochastic and influenced by numerous unobservable factors (Kyle, 1985; Hasbrouck, 2007). Prior studies show that trading activity variables typically explain only a small fraction of daily volatility (Karpoff, 1987; Chordia et al., 2001). The F-statistic for the model (F = 8.34 .1, $p < 0.001$) tells us that the explanatory variables trading volume, turnover, trading frequency, lag volatility, and market return are collectively significant determinants of intraday volatility.

The findings show a significant connection between Liquidity and Volatility:

- Volume (LOG_VOLUME) positively affects intraday volatility ($\beta = 0.0066$, $p < 0.001$). This is consistent with the Mixture of Distribution Hypothesis, according to which greater volume implies more information arrival and hence higher volatility.
- LOG_TURNOVER negatively influences it ($\beta =\ 0.0055$, $p< 0.001$). This seems to mean that markets with higher traded value are more liquid and have a more resilient price.
- The number of trades (LOG_TRADES) also contributes to volatility ($\beta = 0.0262$, $p < 0.001$). More frequent small trades

expected in retail-dominated markets make liquidity more fragmented and volatility higher.

- The coefficient of lagged volatility (LAG_VOLATILITY) is positive, highly significant, and close to unity ($\beta = 0.9953$, $p < 0.01$), indicating strong volatility persistence. This result confirms the presence of volatility clustering, where current volatility is heavily influenced by past volatility (Engle, 1982; Bollerslev, 1986).
- The market return (RETURN) is negative and highly significant ($\beta = -0.5226$, $p < 0.01$), suggesting that positive market performance is associated with lower volatility. This may reflect improved investor sentiment and reduced uncertainty during periods of market growth (Schwert, 1989).

Table-3 Fixed Effects regression with Driscoll–Kraay Standard Errors

Variable	Coefficient	Std. Error	t-Stat	p-value
LOG_VOLUME	0.0066	0.0005	14.717	0.000***
LOG_TURNOVER	−0.0055	0.0005	−11.240	0.000***
LOG_TRADES	0.0013	0.0006	2.227	0.023**
LAG_VOLATILITY	0.9953	0.0016	611.330	0.000***
DSEX_RETURN	−0.5226	0.0.413	−12.649	0.000***

Source: Author's calculation

*Note: * represents significance at 10% level, **represents significance at 5% level and *** represents significance at 1% level*

5.4 Multicollinearity diagnostic

To assess potential multicollinearity, the Variance Inflation Factor (VIF) and condition index measures are employed. The results show that the maximum VIF value (5.55) remains below commonly accepted thresholds, indicating that multicollinearity is not severe. Additionally, the condition index does not suggest any serious multicollinearity concerns. Overall, these findings imply that although liquidity variables are correlated, they do not distort the regression estimates.

Table-4 Multicollinearity diagnostics

Variable	VIF
LOG_VOLUME	3.35
LOG_TURNOVER	5.55
LOG_TRADES	3.39
LAG_VOLATILITY	1.03
DSEX_RETURN	1.00

Source: Author's calculation

5.5 Reduced model

To address potential multicollinearity among liquidity variables, reduced models are estimated by including each liquidity proxy individually. The results show that all liquidity measures remain positive and statistically significant. However, the coefficients are smaller compared to the baseline model, indicating that each variable captures only a partial aspect of trading activity when considered separately.

This finding confirms that liquidity is multi-dimensional, and a joint specification provides a more comprehensive explanation of the liquidity volatility relationship (Chordia et al., 2001).

Table-5 Reduced model

Model	Variable	Coefficient	p-Value
Volume only	LOG_VOLUME	0.0018	0.000***
Turnover only	LOG_TURNOVER	0.0014	0.6359***
Trades Only	LOG_TRADES	0.0019	0.9365***

Source: Author's calculation

*Note: * represents significance at 10% level, **represents significance at 5% level and *** represents significance at 1% level*

5.6 Robustness check (alternative volatility measure)

The study uses Parkinson and Garman Klass to assess the robustness. The results show (Tables 6 and 7) that liquidity variables remain statistically significant, lagged volatility continues to exhibit strong persistence, and market return retains a negative effect. Although coefficient signs vary across specifications, the overall patterns remain consistent, indicating that the findings are robust to alternative volatility measures.

Table-6 Robustness check Parkinson volatility

Variable	Coefficient	Std. Error	t-Stat	p-Value
LOG_VOLUME	-0.0270	0.0018	-15.159	0.000***
LOG_TURNOVER	0.0231	0.0017	13.371	0.000***
LOG_TRADES	0.0068	0.0007	10.426	0.000***
LAG_VOLATILITY	0.1495	0.0017	86.233	0.000***
DSEX_RETURN	−0.0748	0.0.123	−6.082	0.000***

Source: Author's calculation

The negative relationship between trading volume and volatility in the robustness models may reflect improved price discovery and reduced noise as trading activity increases. Conversely, the baseline model captures short-term price fluctuations, which may be amplified by trading activity. This variation arises due to differences in volatility construction. While the baseline measure captures relative price dispersion, the Parkinson and Garman–Klass estimators focus on high and low-price ranges (Parkinson, 1980; Garman & Klass, 1980).

Table-7 Robustness check Garman Klass

Variable	Coefficient	Std. Error	t-Stat	p-Value
LOG_VOLUME	-0.0372	0.0025	-15.093	0.000***
LOG_TURNOVER	0.0318	0.0024	13.238	0.000***
LOG_TRADES	0.0095	0.0009	10.677	0.000***
LAG_VOLATILITY	0.2073	0.0024	86.206	0.000***
DSEX_RETURN	−0.1031	0.0171	−6.039	0.000***

Source: Author's calculation

5.7 Endogeneity and IV results

To address potential reverse causality between trading activity and volatility, IV-2SLS models are estimated using lagged liquidity variables as instruments. The results indicate that lagged volatility and market return remain highly significant, while liquidity variables continue to be statistically significant, although with some variation in coefficient magnitudes and signs. This suggests that endogeneity affects the estimates to some extent but does not alter the overall conclusions of the study.

Table-8 IV-2SLS Results (summary)

Endogenous Variable	Coefficient	Significance
LOG_VOLUME	Negative	Significant
LOG_TURNOVER	Negative	Significant
LOG_TRADES	Negative	Significant

Source: Author's calculation

6. Findings of the study

This study clearly shows that one of the main factors influencing intraday volatility in Bangladesh's equity market is liquidity-focused trading activity. Trading volume and the number of trades are the two metrics that consistently raise volatility, indicating that increased participation is indicative of information arrival, speculative activity, or increased noise trading pressures, patterns that are consistent with findings from the literature on emerging market microstructure. On the other hand, turnover shows a stabilizing effect by lowering volatility, suggesting that higher-value transactions support price efficiency as opposed to price pressure.

The analysis identifies strong volatility persistence, as lagged volatility remains highly significant and close to unity. This confirms the presence of volatility clustering, a well-established feature of financial markets. Market return has a significant negative effect on volatility, implying that improved market performance is associated with reduced uncertainty and lower volatility. On the other hand, the COVID-19 dummy variable is found to be statistically insignificant, indicating that after controlling for liquidity and firm-level dynamics, the pandemic period did not exert a distinct additional impact on firm-level intraday volatility. This suggests that market microstructure factors dominated volatility behavior even during the COVID-19 period.

Robustness checks using alternative volatility measures confirm that the liquidity–volatility relationship remains statistically significant, although coefficient signs vary due to differences in volatility construction. This suggests that the results are not sensitive to model specification but should be interpreted in the context of measurement differences.

7. Policy implications

The findings of this study offer several important implications for market regulators, policymakers, and institutional participants in Bangladesh's capital market.

First, the DSE should improve its real-time market surveillance systems, given the strong correlation between trading activity and intraday volatility. Improved monitoring of unusual spikes in trading activity can help identify early indicators of manipulation, rumor-driven speculation, or disorderly market behavior because volume and trade frequency increase volatility. The impact of noise trading can be lessened, and market stability can be increased by putting in place activity-based circuit breakers or automated alerts.

Second, turnover's stabilizing effect suggests that deeper, value-driven trading enhances market efficiency. Turnover can be increased, and excessive short-term volatility can be decreased by policies that promote institutional participation, such as lowering transaction costs, enhancing settlement infrastructure, or offering incentives to long-term investors. Increased institutional participation may also encourage well-informed trading and lessen the typical speculative distortions found in emerging markets.

Third, the strong persistence of volatility suggests that shocks in the market can have prolonged effects. Policymakers should consider implementing circuit breakers and volatility control measures to mitigate extreme price movements and maintain market stability.

Fourth, the COVID-19 shock's limited impact on volatility and liquidity dynamics indicates that systemic influences in Bangladesh are dominated by firm-level microstructure factors. This emphasizes the necessity of more thorough firm-level disclosures, particularly with regard to liquidity indicators. To improve transparency and reduce volatility caused by microstructure imbalances, regulators might think about mandating more detailed reporting of intraday market depth, order book behavior, and trader concentration.

Finally, given the importance of trading intensity, investor education programs should emphasize the risks related to high-activity periods. Retail investors who form the bulk of DSE participation often underestimate volatility during active trading phases. Awareness initiatives can help them avoid behavioral biases such as herd trading and overreaction during high-volume days.

In order to support a more stable and effective equity market in Bangladesh, these implications generally point to a regulatory environment that places a higher priority on deeper liquidity, more robust surveillance, increased institutional involvement, and enhanced investor literacy.

8. Limitations and future research

There are a few reasonable limitations to this study. First, more detailed intraday movements that could account for additional volatility patterns are not captured by the analysis, which is based on daily trading data. Second, the results might not accurately reflect thinly traded or less active sectors because the study only looks at the five most liquid industries. Third, COVID-19 is measured using a straightforward dummy variable that might not account for variations between waves or policy stages.

To improve our understanding of volatility–liquidity dynamics in Bangladesh, future research could use alternative crisis indicators, examine sector-wise differences in greater detail, or incorporate intraday data.

9. Conclusion

This study investigates the relationship between trading activity and intraday volatility in the Dhaka Stock Exchange using firm-level panel data. The findings show that microstructure plays a major role in Bangladesh's volatility. Volatility is consistently increased by higher trading volume and frequency, underscoring the role of trader interactions and order flow intensity in causing short-term price fluctuations. On the other hand, turnover, which measures the value-weighted depth of trading, lowers volatility, indicating that deeper, more value-based trading supports price stability. The analysis also confirms strong volatility persistence and a negative relationship between market return and volatility, while the COVID-19 period does not have a significant independent effect.

Overall, the study shows unequivocally that understanding volatility in Bangladesh necessitates paying particular attention to trading behavior and liquidity conditions rather than more general macro or crisis-level factors. For regulators, legislators, and market players looking to strengthen market stability, enhance surveillance, and promote deeper and more effective trading environments in developing markets like Bangladesh, these findings provide crucial guidance.

Author's contribution statement

I solely conceived and designed the study, conducted the literature review, collected and analyzed the data, developed the methodology, interpreted the results, and wrote and revised the manuscript. I take full responsibility for all aspects of the work.

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