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Empirical Significance of Movements in Stock Trading Platforms in NSE Market Structure

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Structured Abstract

Purpose

The study aims to evaluate if movements in a specific platform can be considered a proxy for information flow to ascertain signals useful for trading decisions.

Design/methodology/approach

Correlation analysis is conducted to understand the relationship between trade movements in different platforms, followed by the OLS model to evaluate the impact of trade movements on return and variance. The impact of platform-wise trade movement on the conditional volatility is tested with a modified GARCH model. The coefficients of the models are observed to identify the impact of trade movements in the specific platform on return and volatility.

Findings

The study identifies linearity in trade movements across the trading platform. Significant relationships with index, return, and volatility are identified for specific platforms compared to other platforms. Volatility persistence is identified due to trade movement in a certain platform when it is introduced as an explanatory variable in the modified GARCH model.

Research limitations

The current study is restricted to NSE, India. The study can be extended to stock markets that allow different platforms for trading. Also, the high-frequency/intra-day data can be studied for further evidence that can be useful for ascertaining signals for real-time trading.

Practical Implications

Real-time traders can draw insights by observing the platform-wise trading movements, which exhibit significance as a proxy for information flow to improve trading decisions.

Social Implications

The study observes the platform-wise trade movement and its relationship with market dynamics providing a surveillance model that observes the market eco-system to surmount the brunt of technology.

Originality and value

This study is unique as it encounters two interesting features of the new age market – (i) trading platforms, with technology advantage as constructed by exchanges, and (ii) trade movements - that are seldom pursued together to bring insights.

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Abstract

Information is the game-changer in the stock market environment. The distinction in terms of access to trade information (colocation, high frequency, direct market access, and smart order routing trades), machine interfered decisions making (Algorithmic-trades), and conventional trades (non-algorithmic trades) with or without mobile/internet connectivity defines market microstructure in a new perspective. The study evaluates movements along with price and volatility to understand the significance of trading movements in each platform. The study provides evidence that non-algorithmic trades are independent of market return and volatility while colocation trades are asymmetric. The GARCH framework identifies that colocation, internet, and algorithmic platforms explain volatility persistence for the study period. The study concludes that the trade movement of a specific platform acts as a proxy for information flow to identify signals for trade decisions by the traders of other platforms.

Keywords: Volume of Trade, Returns, Volatility, Trading Platforms, Conditional Volatility, GARCH

JEL code: G1, G12

1. Introduction

The trade movements are a reflection of information events Karpoff (1987). The sequential information arrival hypothesis (SIAH) states that the information is sequentially dissimilated to the investors and reflected in phases reaching equilibrium in price. The Mixture Distribution Hypothesis (MDH) states that information arrival is a mixing variable to explain the volume and price movement. When information is the key, technology has a huge role in such information dissimilation and assimilation. The impact of trading technology is evident and often not measured. There are several commonly used trading platforms across the different countries, out of which Non-Algorithmic, Mobile, Internet, Colocation, Algorithmic, Direct Market Access, and Smart Order Routing are common in exchanges. Respective exchange defines the platform's feature, framework, and operation scope. The current study refers to National Stock Exchange (NSE) website to identify the differences between platforms.

For instance, the colocation platform has the advantage of technology in terms of low latency. In contrast, the algorithmic trading platform has the advantage of decision-making without human emotions, and the traditional traders have the advantage of receiving the intermediary's assistance. Thus, the platforms such as direct market access, smart order routing, internet, and mobile platform are distinct based on speed or technology as discussed by the respective exchange for executing the trade decisions. Understanding each platform's intensity, impact, and significance on the stock market economy provides a new perspective to elaborate on the market microstructure. The motivation and usefulness of assessing the significance of trading platforms are identified based on gaps identified in the literature and certain impactful instances reported in India, an emerging market. To quote a few:

1. The colocation scam and its immeasurable impact, as reported by the exchange
2. Technical glitches while trading
3. Covid-induced technology dependence draws greater attention to evaluating platform-wise movement

With this background, the referred traditional market tales suggest that the trade volume positively relates to the return and fluctuations. There is substantial evidence and record across the markets for the same, but little evidence to find if this folklore is good in a technically evolved market environment. Based on the literature, the study identifies the link between trade movements and the advancement in information flow as a research gap and addresses the following objectives – (a) To assess if the increased trade movements in one platform also show a similar increase in all the other platforms.

(b) To evaluate the significance of trade movement of a specific platform on return and variance.

(c) To measure if the volume movement in any platform supports assessing conditional volatility.

By evaluating the set objective, the study adds evidence to the literature that trading volume from a specific platform can be identified as a proxy for information flow by other platforms.

2. Literature Review

The first part discusses the functional studies in constructing the methodology for evaluating the volume-return relationship. The second part presents the literature useful for interpreting the volume–volatility link and related models. The study refers to research related to specific platforms to understand the feature of the respective platform.

(a) Karpoff's (1986, 1987) study presents an asymmetric relationship between volume and change in price. For the first part of the study, the study refers to SIAH formulated by Copeland (1976), which states that the information arrives in the market in sequential and random order. Based on this, the study assumes that the platform-wise traders possess the same set of information, followed by a demand curve shift in each platform till all the traders receive the information. When traders receive the information at the final stage, it leads to an inset of equilibrium in respective platforms. Though other phenomena can be recognized, the study makes assumptions to comprehend the operational efficiency and significance of respective platforms. Following this, methods adopted by researchers are seeking to understand the implication derived from trade movements. The evidence from the study conducted by Chen et al. (2001), Mahanjan & Singh (2008), and Gupta et al. (2018) tests the causal relationship between return and volume, providing evidence from nine national markets that volume and return are caused by each other. Moslehpour et al. (2022) consider the GARCH model to assess the risk spillover caused during the pandemic in two different markets. Gupta et al. (2019) evaluate volatility in the crude oil market as an impact of news announcements. The current study also takes motivation from the alternative perspectives of Liu et al. (2021), which considers the frequency at which volume data is available and its information content to forecast returns using the GARCH-MIDAS model. The study refers to the GJR-GARCH framework of the study conducted by Kao et al. (2020) that presents the existence of threshold effects between return, volume, and volatility.

In line with this literature, the study evaluates if platform-wise trade movements have any role in forecasting by evaluating the relationship between volume movement and change in price. Therefore, to evaluate such a relationship, the framed OLS allows two coefficients, out of which one coefficient measures the change in price and volume, ignoring the direction, while the other coefficient allows asymmetry. The study repeats the same with squared returns allowing an additional description of raw volatility. Also, we refer to the methodology adopted by Lamoureux & Lastrapes (1990) for the second part of the study. The study evaluates the relationship between volume and unconditional volatility by modifying the GARCH model as Brailsford (1996) researched. Henry & McKenzie (2006) studied the impact of short sales in detail by expanding the then-existing 90s literature, which primarily focuses on volume as a whole, providing a new perspective.

In contrast to using volume as a proxy, interesting literature from China, Shen et al. (2018) provide evidence to show the impact of information flow using search engine results as proxies to understand the volatility in returns. Tajmazinani et al. (2022) provide evidence that a combination of technical and news sentiment is a proxy for information flow and developing trading strategies. The study refers to the mentioned literature to estimate the importance of tools assessing the flow of information. The study also refers to the research work such as Lakonishok & Maberly (1990) on institutional and individual investors concerning the weekend effect, Mahajan & Singh (2009), Zhang et al. (2014), Balcilar et al. (2017) on bitcoin return and volatility prediction based on volume, Koubaa & Slim (2019) on volume threshold, which provides valuable insights on how to progress with the study. Based on the reaction to information, Ilomäki & Laurila (2018) classify traders as informed and uninformed traders to measure the effect of noise trading using the movement. The study uses the literature mentioned above to assess the movement-based impact on market dynamics.

(b) The second part of the study refers to MDH as modified by Andersen (1996) and developed by Clark (1973) to outperform the prior study in terms of adding informational asymmetries and liquidity requirement as two variables that motivate the trading when information arrives. Epps and Epps (1976) also studied MDH to combine and link changes in price, volume, and the rate at which the information flows. Lamoureux and Lastrapes (1990), based on MDH (1976), evaluate the presence of autoregressive conditional heteroskedasticity effects. Related papers such as Sharma et al. (1996), Brailsford (1996), Omran & McKenzie (2000), Belhaj & Abaoub (2015), Kapusuzoglu & Ceylan (2018), Bouras et al. (2019), Liu et al., (2021) provides good evidence of the same. Some study, such as Fleming et al. (2006), present evidence that volume does not include the ARCH effect and states that improved GARCH models with volume data are prone to bias caused by the correlation between explanatory variable and regression error term. This study serves as a piece of evidence that there is a relationship between nonpersistent volatility and volume. Sampath & Garg (2019) document the strong positive relationship between trade movement and returns volatility in the Indian exchange. Jain & Biswal (2022) study the volatility as an effect of the foreign institutional investors (FII) using the EGARCH model and states that FII purchases and sales impact the increase and decrease of the volatility respectively. Studies such as Lakshmi (2012) and Chandra (2012) present volume and symmetric volatility evidence. When a group of investors participates in the market, the volume generated by the foreign institution stabilizes the Chinese market and contributes to market efficiency Schuppli & Bohl (2010). Ferreira et al. (2017) present evidence of domestic investors' consistency in trading volume as they have information asymmetry. These studies draw insights into the market and the class of investors based on volume, information flow, return, and volatility. Graczyk & Queiros (2018) present intraday evidence of volatility and volume correlation and highlights the relevance of SIAH and MDH. Kumar (2019) studies return volatility and trade movements, the relationship's direction, and concludes with a negative contemporaneous relationship between volume and volatility and linear and non-linear Granger causality. Kudryavtsev (2020) states that the tendency of price reversals after substantial price moves does not change even when event-specific trade volume and other market dynamics are accounted for when exploring the correlation between significant price movement and return. The study also refers to Li & Wu (2006), Naufa et al. (2019), and Kim et al. (2019), which evaluates based on the google search volume-volatility relationship, another study by Lang et al. (2021), volume – volatility prediction in the context of the search engine, Chundakkadan & Nedumparambil (2021) to assess the impact of volume and volatility. Srilakshminarayana (2021) discusses the tail behavior of the Nifty 50 implying the usefulness of studying the index behavior in decision making, and the current study considers two stock indices to understand the effect of trade movement in a specific platform.

Other studies, such as Smirlock and Starks (1985, 1988), provide evidence that the relationship between volume and price is asymmetric, and the later study presents a strong positive lagged relationship between both variables. Results on evaluating the predicting ability of trading volume and momentum presented by Lee & Swamminathan (2000) and supporting evidence presented by Bekaert and Wu (2000), which adds to the speed of information transmission in markets, support the current study in the construction of the framework. Also, to understand the existing literature that establishes platform-wise features, few studies concerning algorithmic trading conducted by Hendershott & Riordon (2009) and Frino et al. (2017) consider volume movement. The former study states that algorithm-initiated trades are negatively related to the trade movement and volatility in the first fifteen minutes of commencement of a trading session. The later study concentrates on the algorithmic trading volume generated pre- and post-earning announcements where the volume shows a lead-lag relationship. In the post-earning announcement period, there is a reverse in the relationship. Brogaard et al. (2015) studied the market movement and liquidity induced due to colocation trades. The referred literature discusses only the traits of trade movement in a specific platform but does not comparatively present their effects. The study includes trading movement as a time-varying component referring to Yuan (2019), which provides evidence that including such a component delivers better accuracy than constant coefficient models.

Based on the literature discussed above, the study assumes that the volume and price react to the information available during the day. The intraday movements are nothing but the sum of daily return and volume of trading. The study assumes that the information dissemination rate across different trading platforms infuses variation across the day with a difference in magnitude of change in price and volume caused by a particular platform. The joint distribution will follow the bivariate normal form; two independent variables are normally distributed as in the Central limit theorem. The volume of trading in each platform and daily returns drawn from the arrival rate of information and reaction to it differs. The turnover or volume in the different platforms presents a mixture of distribution evidence.

The test of unconditional distribution of returns will get rejected in normality. In that case, the study expects a conditional distribution. The study tests the relationship and impact caused by a change in price and information flow. Platform-wise volume is used as a proxy and mixing variable to provide an indirect test for the link between change in price and information flow. If there is a serial correlation in information arrival, then the information process will lead to the momentum in squared daily returns. It is viable in the context of ARCH models, as stated in Lamoureux and Lastrapes (1990) and Brailsford (1996). Platform-wise trade movement is added as an exogenous variable to the conditional variance to remove the significance of the coefficient estimates in the GARCH (1,1) model. The study suggests that the volume is a good alternative when there is a reduction in volatility persistence. Volume generated is not viewed collectively as the paper aims to apprehend each platform's significance. However, it also avoids the multicollinearity aspect. If the movement of variables in each platform is correlated, it might weaken the statistical power of the linear model. Therefore, the study does not consider the trading volume collectively. Thus, the paper stands unique in terms of considering each platform movement individually, and such an aspect provides a comparative case to interpret the results.

3. Data and Methodology

The study sets the hypothesis to evaluate the short-term influence of trading volume on different platforms for a period not exceeding one year. The study presents the results conducted with the prior pandemic data, i.e., between 1-4-2018 to 31-3-2019 totaling 247 trading days. The study period chosen enables the analysis to provide an unbiased inference by aligning to the scope of the paper without the influence of pandemic period fluctuations. The data includes total purchase and sale transactions executed and the turnover value of the trades in a particular platform instead of considering volume as a whole as evaluated by the study conducted by Brailsford (1996). The historical data is accessed manually through the official NSE records website, which is available to the public. Firstly, the trade movement of the equity segment data is subdivided in terms of Non-Algorithmic (NAL), Mobile (MOB), Internet (IBT), Colocation (COL), Algorithmic (NAL), Direct Market Access (DMA), and Smart Order Routing (SOR). The study employs a sample of 1729 data points spread across seven trading platforms for analysis.

As presented in table 4, there is a high correlation between the trade movements on the platform, causing multicollinearity, which weakens the statistical power of the regression equation. Therefore, the data is individually evaluated, enabling the analysis to align with the aim and scope. The variables are individually assessed and inferred to present comparative results. The other data set used in the study is the Nifty 50 and Nifty 500 return series for the period mentioned. Nifty500 reports a total value of 96.5%, and Nifty50 observes 53.4% of the total traded value for the six months ending March 2019 (Source: NSE website). Table 1 presents the summary statistics of the Nifty 50 and Nifty 500 series as percentage continuously compounded daily returns for the study period. Table 2 shows the descriptive statistics of volume of trading (Table 2(a)) and Value of trading (Table 2(b)) for each platform, respectively. The summary statistics show that the NAL traders execute more trades on average, followed by COL trades in both measures.

Table 1 Summary Statistics of Continuously Compounded Return of Nifty 50 and Nifty 500

	Nifty 50	**Nifty500**
Mean	0.000524	0.000277
Median	0.000628	0.001
Maximum	-0.022974	-0.0263
Std Dev	0.007834	0.008059
Sum	0.129519	0.0684
Sum Sq. Dev	0.015097	0.0159977

Source: Author's Calculation based on NSE Data

Table 2 Summary Statistics – (a) Volume and (b)Value of Trading in Equity Segment

TABLE 2(a)	***AL_ VOLUME***	***NAL_ VOLUME***	***DMA_ VOLUME***	***COLO_ VOLUME***	***IBT_ VOLUME***	***MOB _VOLUME***	***SOR_ VOLUME***
Mean	2489058.698	2857548.976	161450.1976	2774507.75	2093228.335	942117.7298	186596.5766
Std Err	41467.44424	22229.72231	4651.265059	39886.52183	16161.92659	10741.78281	5321.970626
Median	2385640.5	2879276	149792.5	2667718	2079305.5	944222.5	174507
Std Dev	653029.9649	350074.017	73248.1954	628133.5739	254518.2745	169161.7648	83810.47723
Range	4784585	3434266	438206	5411986	2660507	1389936	636050
Min	32764	775004	1	322852	535410	255372	1259
Max	4817349	4209270	438207	5734838	3195917	1645308	637309
Sum	617286557	708672146	40039649	688077922	519120627	233645197	46275951

TABLE 2(b)	***AL_ VALUE***	***NAL_ VALUE***	***DMA_ VALUE***	***COLO_ VALUE***	***IBT_ VALUE***	***MOB_ VALUE***	***SOR_ VALUE***
Mean	104592773361	183239882912	6549701026	180750607013	103897055179	54904269151	7138671336
Std Err	2633544387	1929466478	226679800	2790259092	824939418	661051567	163178070
Median	92848334113	184575097430	5851166233	172519779286	103491016470	55590933809	6694886301
Std Dev	41473098487	30385268488	3569757061	43941044120	12991158949	10410250483	2569730821
Range	430194268781	284598412580	33699552281	428534615102	134986503763	76353203355	19328695923
Min	987816179	34084204135	574	17147687299	17300401504	9690554963	18535183
Max	431182084960	318682616715	33699552854	445682302401	152286905267	86043758318	19347231105
Sum	25939007793572	45443490962291	1624325854478	44826150539185	25766469684505	13616258749552	1770390491277

Source: Author's Calculation based on NSE Data

The study attempts to address the following questions, considering these facets and the theory discussed in the literature review section -

(a) Do all the platforms represent the same trading direction on any given day?

(b) Does the trade movement in each platform cause a significant impact on return and return volatility individually?

(c) Does the platform-wise trade have any explanatory power of current conditional volatility and can be regarded as a proxy for information flow individually to ascertain trading signals by other platform traders?

The research questions are addressed with the support of literature by confirming the viability of using volume as a proxy variable for information flow. Further, as quoted in the review section, the study refers to literature that discusses the direction of the price and volume movement to be in the same direction to predict the asymmetric relationship between the platform-wise volume and price. Following the literature, which states that the return follows a normal distribution, the link between a price change and information is tested for the respective platforms. The study tests the following hypothesis to attain the research objective question –

H1: There is linearity in trade movements across the trading platforms.

H2: Upward index movement is related to higher trading volume in a specific trading platform than downward movement.

H3: The non-normal distribution of return is due to the information arrival (i.e., volume in the respective trading platform).

The differences in the trade direction in the trade platforms are assessed to justify the hypothesis. The relationship between the trade movements in the different venues is then evaluated using the correlation technique, which helps to establish the differences. Based on the established differences in platform-wise trade movements, the study proceeds with the OLS method's help to identify if the upward index movement is related to higher trading volume than downward movement.

The coefficients of the return-based model and its significance are useful to compare the importance of the volume of trading on one platform over the other. The squared return model measures the impact of trade movement on volatility. Finally, a modified GARCH model is used to observe volatility persistence after introducing trade movement in the variance equation. Such a modified model helps to identify the non-normal distribution of return in the respective platform due to the information arrival.

First, the volume movement in each segment is assessed to evaluate the uniformity of increase or decrease in the volume of trading. If the Volume (V) at a Time (t) is greater than the volume of trade at t-1, it is considered an increase in trading volume. If the volume of t is less than t-1, then the movement decreases the trading volume. The increase or decrease in trading volume is assessed in respective trading platforms across the study period. After determining the daily data direction of volume movement in the individual platform, it is compared with the direction of movement with every other platform for t, t+1, t+2, and so on for the whole study period. The instance of difference in direction is counted to calculate the total percentage of different directions, i.e., increase or decrease in trading volume in each platform. When the trading volume is evaluated on a tick-by-tick basis, the difference in the trade movement as a market reaction may be assessed in greater detail. Table 3 presents the number of times there is a difference in trading movement direction as a percentage for the study period. The ratio of differences in movement in the paired platform is calculated as follows –

$$\% \text{ Difference in the Direction of Volume of Trading} = \frac{\text{Instances of Difference in Volume of Trading}}{\text{Total Trading Days}}$$

Table 3 Summary of Differences in Volume Movement Across Different Platforms of Trading

	AL	NAL	DMA	COLO	IBT	MOB	SOR
AL	-	31.17%	42.11%	29.55%	33.20%	34.41%	36.44%
NAL	31.17%	-	40.89%	24.29%	23.89%	29.15%	38.46%
DMA	42.11%	40.89%	-	40.89%	44.53%	43.32%	47.77%
COLO	29.55%	24.29%	44.53%	-	25.51%	16.60%	41.70%
IBT	33.20%	23.89%	44.53%	25.51%	-	16.60%	35.63%
MOB	34.41%	29.15%	43.32%	43.32%	16.60%	-	41.70%
SOR	36.44%	38.46%	47.77%	41.70%	35.63%	35.63%	-

Source: Author's Calculation based on NSE Data

As mentioned, the entire trading day for the study period is 247 days, out of which the volume of trade executed in Algorithmic platform and non-algorithmic platform differs in direction at 77 instances, i.e., 31.17% of the time when the trading volume in algorithmic trade increases, the trades in non-algorithmic mode decreases or vice-versa. From table 3, it can be noted that the trade volume executed through mobile and internet-based trading moves closely, i.e., there is only 16.60% instances where volume reaction differs between mobile and internet trading platform, whereas the volume of trade executed through Direct Market Access differs in direction with all other platforms at a minimum rate of 40.89%. From the data, it is evident that volume moves in a different direction on different platforms. The direction of trade movement ratio can be considered a proxy for understanding the difference in the assimilation of information on various platforms. However, the study limits the scope of assessing the trade movements' strengths or weaknesses, which will also offer useful insight.

Based on the figures quoted in table 3, the study further evaluates the relationship between the volume of trading on different platforms and its effects on index movements. The study is structured to present the results in 5 sections. The first section discusses the empirical relationship between the number of shares traded on different platforms and the relationship between the turnover or the value of the trades. The second section discusses the relationship between platform-wise movement and the indices. Presenting the impact of volume on volatility is the aim of the third part of the study, while the fourth section discusses the cross-correlation between different trading platforms. The fifth section discusses the limitations and findings and presents the future scope of research, followed by a conclusion. Every section discusses the method and results individually.

4. Relationship Between Trade movement in Different Platforms

The daily trading volume and the value of the same at a given time t were standardized by subtracting the mean (μ) and dividing by the standard deviation (σ) of the respective trading volume measure as mentioned in equation 1, Brailsford (1996). The standardizing is done to compare the scores accurately. The same standardized data used in this section has been used in the regression analysis in the later sections. This step ensures that the volume as a variable used for the study contributes to the scale.

$$V_t = \frac{V_t - \mu}{\sigma} \quad \text{-----------------------------} \ (1)$$

Table 4 presents the empirical relationship between the volume of trading on different trading platforms. This table describes the size and direction of the relationship between the volume and the value of trades executed on different platforms. The table value does not mean any change in trading volume in one platform is a cause of change in the volume in other trading platforms.

It can be noted that only mobile trading (MOB) and smart order routing (SOR) platforms have a negative relationship (-0.0412), implying that when there is a decrease in volume in MOB, there is an increase in SOR or vice-versa, which is statistically insignificant. However, when the value of shares, i.e., turnover generated in the segment, is considered for evaluating the relationship between MOB and SOR, it exhibits a positive relationship producing an upward slope on the scatterplot. A greater absolute value of the relationship can be observed between the turnover generated by COL-AL (0.7136) and AL-DMA (0.8968). A strong positive correlation is observed between the number of shares traded and the turnover generated in COL-IBT (0.8342) and COL-MOB (0.9189). The same kind of relationship can be identified in the turnover generation of COL-IBT (0.8655) and COL-MOB (0.9219). The relationship between non-algorithmic trading (NAL) is asses to present only a weak positive relationship in terms of volume and turnover. NAL-DMA (0.0197) and NAL-MOB (0.0143) record a statistically insignificant relationship.

Table 4 - Relationship Between Volume & Value of Trading in Different Platforms of Trading

r		NAL		COL		AL		DMA		IBT		MOB		SOR	
		Vol	**Val**	**Vol**	**Val**	**Vol**	**Val**	**Vol**	**Val**	**Vol**	**Val**	**Vol**	**Val**	**Vol**	**Val**
NAL	r	1.0000	1.0000												
	P	----	----												
COL	r	0.1140	0.4970	1.0000	1.0000										
	P	0.0001	0.0000	----	----										
AL	r	0.1904	0.5001	0.5891	0.7136	1.0000	1.0000								
	P	0.0000	0.0000	0.0000	0.0000	----	----								
DMA	r	0.0197*	0.4064	0.5664	0.6553	0.4117	0.8968	1.0000	1.0000						
	P	0.4893	0.0000	0.0000	0.0000	0.0000	0.0000	----	----						
IBT	r	0.2421	0.5376	0.8342	0.8655	0.5357	0.5163	0.3824	0.4440	1.0000	1.0000				
	P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	----	----				
MOB	r	0.0143*	0.3597	0.9189	0.9219	0.3519	0.5173	0.5501	0.5131	0.7627	0.8520	1.0000	1.0000		
	P	0.6161	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	----	----		
SOR	r	0.2060	0.4133	0.1281	0.4623	0.4401	0.5248	0.1504	0.4378	0.1497	0.3356	-0.0412*	0.3066	1.0000	1.0000
	P	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1473	0.0000	----	----

Source: Author's Calculation * p value insignificant at 0.05 level

NAL – Non-Algorithmic Trading; COL – Colocation Trading; AL-Algorithmic Trading; DMA-Direct Market Access; IBT-Internet Based Trading; MOB – Mobile Trading; SOR-Smart Order Routing. * Represents statistical insignificance

Vol – No of Shares traded; Val – The turnover value of the shares traded excluding other costs.

5. Platform-wise Volume and Price Movements

The literature supports the number of shares traded and the gross turnover generated, i.e., the value of shares employed as proxies. Several inconsistencies are reported by Brailsford (1996). Therefore, the current study considers both measures. Indices are considered proxies for price movement in the market, states Osamwonyi & Evbayiro-Osagie (2012), so the study employs indices to understand the effect of variables. Based on the literature, the following two ways are employed to measure the market movement in seven different modes of trading along with indices:

- Daily quantity of trade moves in platforms
- Value, i.e., turnover generated in each platform daily (excludes other costs)

The methodology for this section accommodates the aim of evaluating the relationship between two different market indices, namely Nifty 50 and Nifty 500, and platform-wise trading volume. The evaluation is undertaken by the ordinary least square method of regression which tests the equations from (2) to (8). The stationarity of the data is checked before proceeding with the model. Table 5 presents the results of the ADF test conducted to check the stationarity. This test was conducted on time series data of the trade movements in the individual platform and index returns. All the data are stationary at the level. Therefore, no measure was taken to bring the data to a stationary format.

$$NALV_t = \alpha_1 + \beta_1 |rt| + \beta_2 D_t |rt| + E_t \quad \text{------------------} (2),$$

$$COLV_t = \alpha_2 + \gamma_1 |rt| + \gamma_2 D_t |rt| + E_t \quad \text{------------------} (3),$$

$$ALV_t = \alpha_3 + \delta_1 |rt| + \delta_2 D_t |rt| + E_t \quad \text{------------------} (4),$$

$$DMAV_t = \alpha_4 + \zeta_1 |rt| + \zeta_2 D_t |rt| + E_t \quad \text{------------------} (5),$$

$$IBTV_t = \alpha_5 + \iota_1 |rt| + \iota_2 D_t |rt| + E_t \quad \text{------------------} (6),$$

$$MOBV_t = \alpha_6 + \tau_1 |rt| + \tau_2 D_t |rt| + E_t \quad \text{------------------} (7),$$

$$SORV_t = \alpha_7 + \omega_1 |rt| + \omega_2 D_t |rt| + E_t \quad \text{------------------} (8),$$

where NALVt, COLVt, ALVt, DMAVt, IBTVt, MOBVt, and SORVt are trade movements in their respective platform at time t. The |rt| represents the return of the Nifty 50 and Nifty 500 series of indices. The estimate of |rt| does not allow any asymmetry in the relationship.

The dummy variable Dt = 1; if the return is less than zero and when the index returns are greater than or equal to 0, Dt = 0.

Table 5 Augmented Dickey-Fuller test for Stationarity

	At level with trend and Intercept		
	t statistics	**P value**	**Inference**
ALGO	(-4.143897)	0.0062	Stationary
COLO	(-4.921762)	0.0004	Stationary
DMA	(-4.485026)	0.0019	Stationary
IBT	(-5.769334)	0.0000	Stationary
MOB	(-3.468648)	0.0451	Stationary
NAL	(-8.899671)	0.0000	Stationary
SOR	(-6.665078)	0.0000	Stationary

Nifty 50	(-15.13778)	0.0000	Stationary
Nifty 500	(-15.09257)	0.0000	Stationary

Source: Author's Calculation based on NSE Data

All the results reported in Table 6 are significant at a 0.05 level using a two-tailed test indicating strong support for the model. Irrespective of the direction of price change, the estimates β1, γ1, δ1, ζ1, ι1, τ1, and ω1, which measures the relationship between change in index and volume, are significantly positive across all the trading platform in the employed two measures of trading movement. The β2, γ2, δ2, ζ2, ι2, τ2, and ω2 are included to provide an allowance for evaluating asymmetry in the relationship. The statistically significant negative value of β2, γ2, δ2, ζ2, ι2, τ2, and ω2 indicates the slope for the negative returns. It also implies that if the returns are negative, they will be lesser than the slope of the positive returns. In other words, the response slope for negative returns is smaller than the response slope for non-negative returns.

Let us consider the instance of the non-algorithmic trading volume. The slope coefficient of the relationship for negative returns in the non-algorithmic trading (NAL) platform in terms of the number of shares traded is 1.51 & -1.99, and the value of shares traded is -1.78 & 2.57, two measures employed to understand the price change reflected in the Nifty 50 index. In the case of the Nifty 500 index, the same two measures report a slope coefficient of 2.25 and -3.18 (volume of shares traded) and -1.39 and 1.24 (value of shares traded). An interesting insight that can be noted from the presented result is that certain measures report a negative slope coefficient. The results signal that for every negative movement in the index, the standardized level of trading volume declines with the absolute magnitude of change in the index across the platforms.

Table 6 Relationship between Standardized Trading Volume/ Value in different Platforms and Continuously Compounded Returns of Nifty 50 and Nifty 500

PLATFORM	Nifty 50		Nifty 500	
	Volume	Value	Volume	Value
NALV				
$\alpha 1$	0.60014	0.53129	0.59311	0.527304
(t-statistic)	(57.54794)	(48.97677)	(57.13992)	(50.68809)
β_3	1.513067*	-1.783459*	2.256047*	-1.390251
(t-statistic)	(0.95230)	(-1.07909)	(1.44206)	(-0.882261)*
β_4	-1.98986	2.57306*	-3.179394*	1.235748
(t-statistic)	(-0.74881)	(0.91068)	(-1.22646)	(0.478215)
F-Test	0.460448*	0.582343*	1.039907*	0.514133
(Prob. Value)	0.63155	0.55936	0.35505	0.598665
COLV				
α_2	0.40542	0.34932	0.40305	0.350222
(t-statistic)	(36.52070)	(34.62136)	(36.42601)	(36.30342)
γ_3	6.29802	4.26216	6.38274	4.132154
(t-statistic)	(3.72371)	(2.77264)	(3.84763)	(2.827743)
γ_4	-15.93975	-10.63446	-16.11407	-10.27075
(t-statistic)	(-5.63492)	(-4.13632)	(-5.86281)	(-4.286024)
F-Test	17.97661	9.57653	19.76512	10.28737
(Prob. Value)	0.00000	0.00010	0.00000	0.000051
ALV				

α_3	0.46811	0.230294	0.46601	0.22793
(t-statistic)	(34.70812)	(23.93919)	(34.55131)	(24.78915)
δ_3	8.11770	0.904876*	8.153172	1.220111
(t-statistic)	(2.05483)	(0.617379)	(4.032421)	(0.876028)
δ_4	-14.66219	-3.149344	-14.98856	-3.882199
(t-statistic)	(3.43670)	(0.200100)	(-4.473762)	(-1.699752)**
F-Test	9.28436	1.238492*	10.08333	1.993483*
(Prob. Value)	0.00013	0.291636	0.000062	0.138433
DMAV				
α_4	0.34359	0.185265	0.337486	0.177651
(t-statistic)	(20.26726)	(17.24705)	(19.94374)	(17.38049)
$\zeta 3$	3.108452**	0.78488	3.725748	1.824023
(t-statistic)	(1.20348)	(0.432903)	(1.468705)*	(1.178106)*
ζ_4	-8.49550	-2.834663	-10.12408	-5.291391
(t-statistic)	(-1.96662)	(-1.035603)	(-2.40852)	(-2.084073)
F-Test	2.337561**	0.902847	3.561461	2.765918**
(Prob. Value)	0.09472	0.046764	0.029883	0.064892
IBTV				
α_5	0.55896	0.626756	0.557274	0.628759
(t-statistic)	(60.27524)	(64.35594)	(60.29877)	(67.3217)
$\iota 3$	2.24852	1.577043*	2.219894	1.129993
(t-statistic)	(1.59144	(1.062847)	(1.602291)*	(0.798742)*
ι_4	-9.28546	-5.085863	-9.379372	-4.370403
(t-statistic)	(-3.92944	(-2.049397)	(-4.085608)	(-1.883827)**
F-Test	13.32000	2.946733	15.08775	2.874301
(Prob. Value)	0.00000	0.054383	0.000001	0.053369
MOBV				
α_6	0.46238	0.574356	0.466212	0.583302
(t-statistic)	(38.91756)	(41.52668)	(38.9169)	(43.79903)
$\tau 3$	2.868421	2.36004	1.992164	0.917902*
(t-statistic)	(1.58464)	(1.137027)	(1.109302)	(0.455016)
$\tau 4$	-11.10308	-6.175702**	-9.360206	-3.198334*
(t-statistic)	(-3.02747)	(-1.752281)	(-3.145457)	(-0.966814)
F-Test	11.02941	1.764601	9.652188	0.696445*
(Prob. Value)	0.00003	0.073433**	0.000092	0.499341
SORV				
α_7	0.25965	0.330334	0.254554	0.338132
(t-statistic)	(19.95644)	(25.04296)	(19.65573)	(26.61851)
ω_3	-2.609955*	4.899472	3.18634**	3.159331**
(t-statistic)	(1.13166)	(2.437913)	(1.641239)	(1.641919)
ω_4	-10.92002	-12.69285	-12.00612	-10.08648
(t-statistic)	(-3.29374)	(-3.776262)	(-3.732122)	(-3.196575)
F-Test	9.45223	8.230188	11.49566	7.070867
(Prob. Value)	0.00011	0.000348	0.000017	0.001035

Source: Author’s Calculation * Insignificant ** Significant at 0.10 level; All the other values are significant @ 0.05 level

4.1 The coefficient that Measures Price Change and Volume

The evaluation reports that irrespective of the direction of the index, the trading movement aspect reports a positive coefficient. There is an exception in the case of SOR in the Nifty 50. Furthermore, NAL reports a negative coefficient in both indices.

4.2 The coefficient that allows the asymmetry

Considering the number of traded shares to measure trade movement, the study identifies that the coefficients are negative in both indices. However, for the value of the trading measure, the NAL platform reports a positive coefficient. The positive coefficient signals that the slope of the negative return is comparatively smaller across the platforms than the positive return except for NAL. The difference in slope coefficient of platform-wise trading volume and index movement between negative and non-negative returns is also measured. For instance, the slope coefficient of NAL platform is -0.47679 (volume), 0.78960 (value) for Nifty 40 and 0.92335 (volume), -0.15450 (value). The study notes that the Nifty50 traded value measure for NAL represents a decrease in the value of trades with the absolute price change. A similar pattern is identified in the value measure of the MOB platform with a coefficient of 0.91790.

Interestingly, all the other platforms have a negative slope. The observations imply that when the indices move downwards, i.e., in case of negative price movement, the NAL, and MOB platform traders' trade value declines with the price change. The results are strong significance for COL trades and weak for NAL, whereby other platforms show variation in significant coefficient.

5. Relationship between Volume in Different Platforms and Volatility

The second set of equations ranging from (8) to (15) uses squared returns instead of absolute returns as a measure of change in the index value. The difference between equations (2) to (8) and equations (8) to (15) measures the change in the index (squared return), which is a representation of price change variables, a crude measure of volatility. This set of equations is formulated to test the relationship between the platform-wise trading volume and an alternative specification of raw volatility. Results of the ordinary least squares are reported in table 7.

$$NALV_t = \alpha_8 + \beta_3 r_t^2 + \beta_4 D_t r_t^2 + E_t \quad \text{------} (9),$$

$$COLV_t = \alpha_9 + \gamma_3 r_t^2 + \gamma_4 D_t r_t^2 + E_t \quad \text{------} (10),$$

$$ALV_t = \alpha_{10} + \delta_3 r_t^2 + \delta_4 D_t r_t^2 + E_t \quad \text{------} (11),$$

$$DMAV_t = \alpha_{11} + \zeta_3 r_t^2 + \zeta_4 D_t r_t^2 + E_t \quad \text{------} (12),$$

$$IBTV_t = \alpha_{12} + \iota_3 r_t^2 + \iota_4 D_t r_t^2 + E_t \quad \text{------} (13),$$

$$MOBV_t = \alpha_{13} + \tau_3 r_t^2 + \tau_4 D_t r_t^2 + E_t \quad \text{------} (14),$$

$$SORV_t = \alpha_{14} + \omega_3 r_t^2 + \omega_4 D_t r_t^2 + E_t \quad \text{------} (15).$$

Table 7 Relationship between Standardized Trading Volume / Value in different Platforms and Squared Returns of Nifty 50 and Nifty 500

PLATFORM	Nifty 50		Nifty 500	
	Volume	Value	Volume	Value
α8	0.601077	0.524662	0.599347	0.523107

(t-statistic)	78.444290	65.622120	77.984680	65.167200
β_3	110.5150*	-61.93782*	137.7285*	-62.99518*
(t-statistic)	1.190906	-0.639400	1.588369	-0.695363
β_4	-46.25166*	83.078840	-54.35093*	132.0497*
(t-statistic)	-0.412611	0.710302	-0.504812	1.174272
F-Test	0.905967*	0.269982*	1.570075*	0.6999505*
(Prob. Value)	0.405506	0.763621	0.210124	0.497825
COLV				
$\alpha 9$	0.428721	0.364468	0.425921	0.361413
(t-statistic)	52.641960	49.275900	52.717000	48.192280
γ_3	328.010300	227.026500	310.438800	241.778500
(t-statistic)	3.324227	2.533359	3.405608	2.915934
γ_5	148.05870*	96.13108*	221.799100	128.851600
(t-statistic)	1.242721	0.375200	1.959625	1.251919
F-Test	18.918480	10.660240	22.821300	14.008890
(Prob. Value)	0.000000	0.000036	0.000000	0.000002
ALV				
$\alpha 10$	0.489141	0.235051	0.487293	0.233366
(t-statistic)	49.535960	33.212700	49.264900	32.898140
δ_3	452.777100	27.09729*	421.684800	35.23749*
(t-statistic)	3.784566	0.316062	3.773964	0.660200
δ_4	-122.0048*	96.1651*	-57.512610	120.5269*
(t-statistic)	-0.844588	0.928968	-0.414541	0.226400
F-Test	10.702380	1.413850*	11.436210	2.227628**
(Prob. Value)	0.000035	0.245190	0.000018	0.100971
DMAV				
$\alpha 11$	0.355314	0.189427	0.352524	0.185238
(t-statistic)	28.525500	23.929620	28.266200	23.430870
$\zeta 3$	156.7472*	48.52954*	152.1288*	84.66277*
(t-statistic)	1.038642	0.505994	0.280700	0.948893
ζ_4	135.2501*	38.74330*	201.7418	87.20413*
(t-statistic)	0.742232	0.334559	1.154707	0.787388
F-Test	2.793504**	0.623749*	3.910440	2.363587**
(Prob. Value)	0.063165	0.536788	0.021300	0.092633
IBTV				
$\alpha 12$	0.571812	0.633037	0.569519	0.632319
(t-statistic)	83.835040	0.007137	83.981330	88.296720
$\iota 3$	107.3647*	81.80156*	102.484700	65.51195*
(t-statistic)	1.299210	86.468750	0.181700	0.810579
ι_4	258.892200	125.8302*	304.590700	16.8229*
(t-statistic)	0.010000	104.405300	0.001500	1.603057
F-Test	13.538160**	4.067325	16.677610	4.653387
(Prob. Value)	0.099885	0.018297	0.000000	0.010391
MOBV				
$\alpha 13$	0.478107	0.582278	0.477360	0.583268
(t-statistic)	54.621050	0.000000	54.363890	57.012780

τ3	138.1922**	135.6848*	101.9391*	89.23887*
(t-statistic)	1.303058	0.271300	1.028967	0.772903
τ4	280.100900	76.006696*	335.619500	117.4267*
(t-statistic)	2.187415	0.609200	2.728365	0.819340
F-Test	10.796090	2.336076	11.470380	1.984754*
(Prob. Value)	0.000032	0.098866**	0.000017	0.139627
SORV				
a14	0.275797	0.348878	0.272758	0.348545
(t-statistic)	28.701570	0.000000	28.532830	35.803730
ω_3	111.073500	271.059200	100.8676*	194.3142**
(t-statistic)	0.954053	0.022100	0.935220	1.786430
ω_4	300.383800	95.825990	375.424200	222.4843**
(t-statistic)	2.136855	0.500700	2.80.42424	1.631404
F-Test	8.580386	-8.162477	11.450070	9.051537
(Prob. Value)	0.000250	0.000370	0.000018	0.000161

Source: Author's Calculation * Insignificant at 0.05 level, ** Significant at 0.10 level; All the other values are significant @ 0.05 level

The study interprets from table 7 that the estimates of the coefficients which measure the price change and volume show less significance in terms of variance. Out of the two measures, the consistency of significance is observed in volume over value in both indices. It is also noted that the COL, SOR, MOB, and IBT modes show significance while AL, DMA, and NAL provide weaker support than the absolute return model. As the previous section identifies, the NAL platform shows insignificant inference to points measures raw volatility.

Based on the above tables and comparison with other trading modes, COL highly supports an asymmetric trading volume–return relationship followed by IBT. Such asymmetry can be linked with short selling, as per the study of Karpoff (1987). The movement implies that when the market is bullish, the market may experience heavier trading volume contributed by COL followed by MOB, IBT, and AL which is closely connected with the change in index (price) is the same absolute magnitude compared to bear markets.

6. Trading Volume in Different Platforms and Conditional Volatility

The return for the study period is stationary at the level presented in table 5. This section presents the results of examining the effect of platform-wise trading volume on conditional volatility. The impact on conditional volatility is examined through modification of the ARCH model described above $-r_t = \theta_0 + Б_1\ r_{t-1} + Б_1\ E_{t-1} + E_t$,

where $E_t \mid \Omega_{t-1} \sim N\ (0, h_t)$ $h_1t = ¥_1 + ƛ_1\ h^2_{t-1} + Ϭ_1 E^2_{t-1} + \beta_5\ V_t$ ------------------- (16)

Implying E_t such that Ω_{t-1} (information set available at period (t-1) has the same distribution as a standard normal distribution with mean 0 and conditional variance h_t. Below equations are a representation for respective platforms -

$h_1t = ¥_1 + ƛ_1\ h^2_{t-1} + Ϭ_1 E^2_{t-1} + \beta_5\ NALV_t$ --------------------- (17),

$h_2t = ¥_2 + ƛ_2\ h^2_{t-1} + Ϭ_2 E^2_{t-1} + \gamma_5 COLV_t$ --------------------- (18),

$h_3t = ¥_3 + ƛ_3\ h^2_{t-1} + Ϭ_3 E^2_{t-1} + \delta_5\ ALV_t$ --------------------- (19),

$h_4t = ¥_4 + ƛ_4\ h^2_{t-1} + Ϭ_4 E^2_{t-1} + \zeta_5\ DMAV_t$ --------------------- (20),

h_5t = ¥$_5$+ ƛ$_5$ h^2_{t-1} + Ϭ$_5$$E^2_{t-1}$+ ι_5 IBTV$_t$ --------------------- (21),

h_6t = ¥$_6$+ ƛ$_6$ h^2_{t-1} + Ϭ$_6$$E^2_{t-1}$+ τ_5 MOBV$_t$ --------------------- (22),

h_7t = ¥$_7$+ ƛ$_7$ h^2_{t-1} + Ϭ$_7$$E^2_{t-1}$+ ω_5SORVt --------------------- (23).

GARCH (1,1) model is adopted for comparison. This method is followed based on the literature, Lamoureux & Lastrapes (1990), later modified by Brailsford (1996) with volume to study the conditional volatility. The significance of the coefficients of β5, γ5, δ5, ζ5, ι 5, τ 5, and ω 5 indicates the influence of trading volume in NAL, COL, AL, DMA, MOB, and SOR routing platforms, respectively. The conditional variance equation of the GARCH model is modified to individually include volume in the different platforms as an explanatory variable. The GARCH model for the proposed evaluation is presented as equations from (17) to (23), of which equation (16) represents the wholistic conditional mean with conditional variance. Equations (17) to (23) evaluate each platform's conditional variance individually. The modification enables us to understand the platform-wise influence. As mentioned in section 1, the study considers the two standardized trading volume data measures for all the platforms.

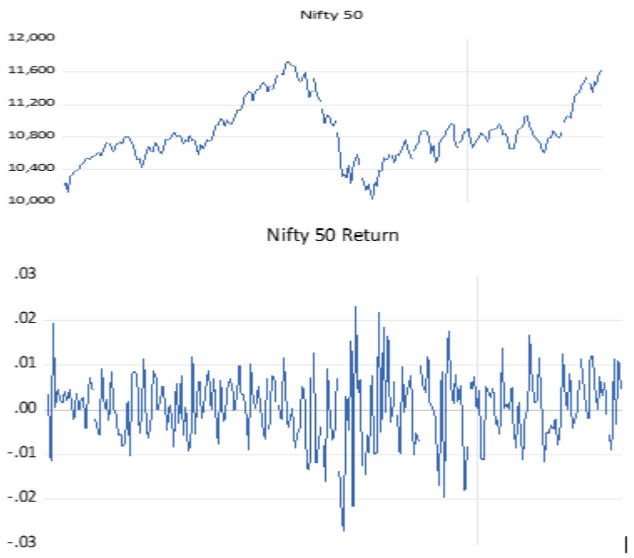

Figure 1. Index and Return

Source: Author's Calculation based on Index Movement

The return for the study period presents high volatility clustering, as presented in figure 1. The ARCH effect is identified in the data. The following is the estimated equation for mean and variance –

r_t = 0.001081-0.700121 r_{t-1} +0.737644 E_{t-1}

(2.37) (-1.87) (2.09)

Where $E_t \mid \Omega_{t-1} \sim N(0, h_t)$

h_t = 0.00000022+ 0.121317 E^2_{t-1} + 0.844078 h^2_{t-1}

(0.96) (2.23) (11.46)

The residual diagnostic test confirms a good fit. The persistence of volatility is higher when the coefficient of variance is close to 1. The value is close to 1 (0.96), implying high volatility. The decaying volatility is 0.04, implying that the market will remain volatile irrespective of the positive news. Referring to the ARCH and GARCH coefficients to be less than one and statistically significant, diagnostic tests of standardized residuals using the sign and size bias test, as indicated in the study conducted by Engle & Ng (1993), have been adopted to find only that the model is a good fit. Therefore, the model has no suggestion for an asymmetric GARCH model. The study proceeds with the modified GARCH (1,1) model converging with the aim of the paper, with an altered variance equation as specified in the equation (15) to (22) estimate using the data of trades executed in each platform as an explanatory variable. The results of the standardized value of trading are as obtained below. Additionally, the conditional variance equation of the GARCH (1,1) model again altered with the other measure of trading volume in terms of turnover. The results are quantitatively similar. The results for trade movement as explanatory variables are shown in table 8. The persistence of variance is reduced from 0.96 to 0.89 (COL), 0.90 (AL) and 0.92 (IBT). The estimated model carries the feature of understanding the significance of the coefficients of the platform-wise trading volume. The lagged conditional volatility is considered to identify the insignificance of the coefficients. The results are similar to the literature referred to by Lamoureux and Lastrapes (1990) and Brailsford (1996). It reflects a reduction in the significance and magnitude of the GARCH coefficients. When the actual trading values are compared based on the value of Nifty 50, as presented in table 2, NAL has the highest volume, followed by COL and turnover value, while DMA has the lowest. The results are prima facie evidence that platform-wise trading pattern proxies for the rate of information arrival. It also serves for the existence of the ARCH effect and explains the variance.

7. Implication and Conclusion

Compared with the already existing research of Lamoureux & Lastrapes (1990), Bessembinder et al. (1996), and Shen et al. (2018), which measures information flow and its effect on the price, return, and volatility. Existing studies consider the whole market movement as a proxy, while this novel study identifies the exchange-defined differences in trading platforms, and its technical differences in executing trades can provide additional signals for trade decisions. Therefore, a research gap is addressed to evaluate the relationship between the trade movements to assess if the platform-wise trade movements are useful as a proxy for information flow. As already presented, the study identifies that the trades in all the platforms are significantly correlated. It was also identified that trade movement does not increase or decrease in the same order on all the platforms. Followed by it, the deployed OLS model identifies that except for the NAL platform, all other platforms establish an asymmetric relationship. Trades executed in the NAL platform are independent of the price movement. COL platform is consistent and significant across the measures and indices employed in the study. These two platforms generate high volume but exhibit different movement patterns and features for the respective study period. As the study measures the volume (two scales) in terms of the number of shares traded and the value of shares traded, it identifies inconsistency in the significance of AL, IBT, MOB, DMA, and SOR platforms' relationship with return and volatility. The second part of the study exhibits conditional volatility to be positively related to trading volume in three platforms, namely, COL, AL, and IBT. The study period exhibits that trading volume in a specific platform can account for the extremes of price change. The study also presents evidence that only certain platforms (COL, AL, and IBT) show consistency and significance in acting as proxies for information flow, which are similar to the existing literature. However, the platforms such as NAL, MOB, DMA, and SOR and their trade movements do not show consistent significance and effect on the return, variance, and conditional volatility for the study period. Lakshmi (2022) identifies the tracking difference between the net asset value and the market price of exchange-traded funds.

Table 8 Platforms-wise Trading Volume as Explanatory Variable - Conditional Volatility

TRADING PLATFORM	Mean Equation			Variance Equation			
	Intercept	Coefficient of rt-1	Coefficient of E t-1	Intercept	Coefficient of h2t-1	Coefficient of E2t-1	Volume Coefficient
NAL	0.001081 (-2.33)**	-0.700005 (-1.84)**	0.737549 (-2.09)**	0.000000235 (-0.24)*	0.121728 (-2.15)**	0.843277 (-10.19)**	-0.000000207 (-0.01)*
COL	0.000885 (-2.00)**	-0.708862 (-2.17)**	0.731323 (-2.30)**	-0.00000126 (-2.47)**	0.034869 (-0.74)*	0.826941 (-11.25)**	0.0000407 (-2.42)**
AL	0.001081 (-2.06)**	-0.700623 (-1.99)**	0.729194 (2.16)**	-0.00000888 (-1.81)**	0.073936 (-1.49)**	0.833693 (11.42)**	0.0000265 (2.24)**
DMA	0.001039 (2.29)**	-0.707654 (-1.86)*	0.742171 (2.06)**	-0.00000172 (-0.75)*	0.08049 (1.86)*	0.898224 (-17.07)**	0.00000826 (1.36)*
IBT	0.001083 (2.44)**	-0.73585 (-2.07)**	0.795836 (2.28)**	-0.000016 (-2.19)**	0.071127 (1.29)**	0.857752 (12.00)**	0.0000345 (2.21)**
MOB	0.001166 (2.64)**	-0.680643 (-2.13)**	0.712678 (2.34)**	0.0000124 (-1.26)*	0.139858 (-1.73)**	0.68183 (3.65)*	0.0000463 (1.34)*
SOR	0.000988 (2.27)**	-0.712285 (-1.85)*	0.732502 (1.96)**	-0.00000772 (-2.43)**	0.060597 (1.09)*	0.860215 (11.01)**	0.0000423 (2.76)*

* Insignificant at 0.05 level
** Significant - p value < 0.05

Source: Author’s Calculation

The model proposed in the current study can identify differences in tracking the specific platform trading volume and its relationship with market dynamics. The study concludes with implications for (a) traders and (b) social implications in terms of surveillance and exchange movement tracking -

The trading movement of a platform that exhibits a strong relationship with return and variance also significantly impacts conditional volatility. Platform-wise movement can be considered proxies for information arrival by traders executing trades on other platforms. The current study establishes the significance of the trade movement of platforms with evidence from the NSE market structure. The model is useful to ascertain such evidence, and further research can be conducted on high frequency or intraday level data or stock-wise data incorporating economic effects and anomalies to derive trade signals for decision making. The current study presents evidence for COL trade movements followed by AL and IBT platforms. Based on the data adopted for the study NAL trade platform generates the highest trading volume, and other platforms such as MOB, DMA, and SOR can ascertain volume signals from COL trade movement upon sufficient evidence.

Further, the study was extended to evaluate the effects and influence of trade movement of individual platforms for pandemic and post-pandemic periods, which provides similar results but requires additional model fitting as the data observes regime shift. The study period is limited to pre-pandemic to hold the current study's scope and retain clarity. An extended study with buying and selling classification will be useful to ascertain more appropriate trading signals from the platforms. Countries with different platforms to execute trades that exhibit similar market structures can adopt this model to ascertain the significance of trade movement of a specific platform. The study considers the scam and technical glitches as a side effect of technology. It proposes the current model as a surveillance tool for monitoring the trade movements of the individual platform and their relationship with return and volatility.

Limitations of the Study

The study does not consider the intra-day or tick-by-tick movements of any platform. Considering the stock price and movement in different platforms, the traders can ascertain signals and the study can be extended in this aspect. Extending the study with buy and sell movement in every platform will also provide behavioural insights as the current study has limited scope to study the significance of platform-wise trading movement.

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