“Does colocation improve price volatility? Evidence from the Indian stock market”

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DOES COLOCATION IMPROVE PRICE VOLATILITY? EVIDENCE FROM THE INDIAN STOCK MARKET

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Abstract

This paper examines the impact of colocation (permitting traders to place their servers in close proximity to exchange servers) on the price volatility at India's fastest exchange, which operates at 6 microseconds. The study employs the event study method to examine the relationship between colocation and price volatility. The study analyzed daily trading data from the Bombay Stock Exchange (BSE) Sensex-30 index from January 1, 2000 to December 31, 2023. The findings of the study suggest a remarkable level of stability at BSE following the implementation of colocation in November 2010. Furthermore, there is substantial evidence of improved price volatility following the reduction in latency at BSE. The colocation has positively supported high-frequency trading, leading to improved price volatility in the Indian securities market. The study conducted additional analyses to assess its robustness and found qualitatively similar results. The study has implications for regulatory bodies, retail investors, market participants, and other interested stakeholders, providing valuable insights into the efficiency of colocation implementation at BSE.

Keywords price volatility, algorithmic trading, high frequency trading, colocation, latency, market efficiency, Bombay Stock Exchange

JEL Classification G14, G10, G12, G15

INTRODUCTION

Financial market innovations and enhancements in market quality have been largely driven by technological breakthroughs (Nejad, 2022; Kirste et al., 2024). Financial markets have changed significantly since computer technology automated trading. Computer algorithms are being utilized to facilitate trade decisions and automate financial markets (Chaboud et al., 2014; Hernes et al., 2024). Investor competition has shifted from trading floors to server rooms, where computers prevail (Gao et al., 2022). How fast and well these computer algorithms perform today determines traders' competitive edge (Hernes et al., 2024). Innovations like algorithmic trading (AT), high-frequency trading (HFT), and colocation services (COLO) have had a profound effect on investors and marketplaces. These advancements have brought about significant changes in both the technological and economic aspects of trading (Zhang & Riordan, 2011). Automated trading refers to the utilization of computer algorithms to make trading decisions, execute orders, and manage them post-placement (Hendershott et al., 2011)[1]. HFT, in contrast, employs advanced and intricate strategies that leverage the rapid connectivity and computational power of com-

1 As per SEBI, "any order that is generated using automated execution logic shall be known as algorithm trading".

puters (Bershova & Rakhlin, 2013)[2]. In accordance with a circular issued by the Bombay Stock Exchange (SEBI) on December 1, 2016 (SEBI, 2016), the colocation facility enables trading members and data vendors to position their trading or data-vending systems in close proximity to the exchanges' premises. Trading based on algorithms is a subset of a much larger, more general trend of technological innovation in the capital markets. AT is just one example of this trend. In fact, computer-operated trading based on algorithms and automation has improved efficiency by lowering costs, reducing human error and volatility, and increasing liquidity (as per the panel discussion in a seminar by the Department of Economic Affairs and the National Institute of Financial Management (NIFM, 2018). The push towards "faster, cheaper, and better" is inevitable as it is profitable, and the financial business is no stranger to such pressures (Kirilenko & Lo et al., 2013). It is evident from the growth exhibited by algorithm-based trading. For instance, over eight years, between 2010 and 2018, the share of AT in Indian cash and derivatives markets increased from an average of 9.26 percent to 49.8 percent. (Sharma, 2018). AT accounts for more than 40% of all orders placed on both the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE) (Bhagat, 2018).

A colocation facility is another important technological innovation in the financial market. Frino et al. (2014) define colocation as a facility offered by an exchange, in which it rents a trading business space next to the exchange's trading facility. This accelerates the dissemination of time-sensitive information, as traders' high-speed servers are situated in proximity to the exchange infrastructure. The BSE introduced a colocation facility on November 15, 2010, which brings path-breaking opportunities for investors and starts the race to secure space to host their servers on the BSE premises. Within a year, by October 13, 2015 (Rukhaiyar, 2023), with a median response time of 6 microseconds, BSE emerged as India's fastest exchange. BSE is renowned for its exceptional speed, boasting a remarkable 6 microsecond execution time, making it the fastest exchange globally. The exchange has established a State-of-the-Art Data Center to manage colocation facilities. The response time for an order has a round-trip delay of approximately 16 microseconds, including 10 microseconds of colocation network latency (BSE Limited).

Advancements in technology have restructured the way securities are traded through computer-based systems. Subsequently, technology has also played a vital role in the further development of the securities market by introducing stock market innovations such as AT, HFT, and COLO. Overall, the financial markets have grown dramatically over the last two decades (Zhou et al., 2019). In India, SEBI has issued several circulars (dated March 30, 2012; May 21, 2013; May 13, 2015; and December 1, 2016) to provide guidelines on AT and HFT (SEBI, 2018a) and explain the objectives of introducing these innovations. Additionally, these circulars express SEBI's major concern about maintaining the quality and fairness of the Indian securities market in the presence of AT, HFT, and COLO. Hence, we are motivated to empirically examine the impact of technological innovations such as AT, HFT, and COLO on market quality. It has been three decades since the introduction of AT and HFT in developed markets (SEBI, 2018b). AT and HFT in developed markets like the US and the UK account for a large share of total trading volume (Petukhina et al., 2021). Similarly, there is a likelihood that AT and HFT impact market quality and fairness in developing markets (Virgilio, 2019). It is well established in the existing literature on developed markets that market innovations (AT and HFT) affect market quality, either positively or negatively. Now, it is imperative to study the impact of AT, HFT, and colocation in a developing market like India. This motivates us to examine the impact of colocation on price volatility, thereby adding value to the existing literature.

2 There is a slight difference between AT and HFT in terms of the duration of execution of trades, the use of sophisticated strategies, and participants who are using these strategies. Mean reversion, trend-following, and arbitrage are among the strategies utilised by AT firms. On the other hand, HFT firms employ the following essential strategies: market-making, liquidity provision, arbitrage, and generating rapid price movements.

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1. LITERATURE REVIEW

The growing adoption of AT has attracted considerable scholarly attention due to its implications for market quality. A substantial body of literature suggests that AT enhances market quality by improving key dimensions, including price discovery, liquidity, and volatility management. Empirical evidence provided by Dubey et al. (2022), Frino et al. (2020), Conrad et al. (2015), Chaboud et al. (2014), and Seo and Chai (2013) demonstrates that the increasing use of AT contributes to more efficient markets through enhanced liquidity and more effective price discovery mechanisms. These studies argue that the speed, precision, and automation associated with algorithmic trading facilitate the rapid incorporation of information into asset prices, thereby improving overall market efficiency. However, the existing literature presents mixed evidence regarding the effects of AT on market quality across different market environments. One stream of research, primarily focusing on developed financial markets, reports that AT significantly improves market liquidity by reducing transaction costs and narrowing bid–ask spreads (Mestel et al., 2018). Another strand of literature documents adverse effects, suggesting that AT may deteriorate certain aspects of market quality, particularly during periods of market stress or heightened uncertainty (Brogaard et al., 2017; Bershova & Rakhlin, 2013; Arumugam et al., 2023). For example, Hendershott et al. (2011) examined the influence of AT on multiple liquidity measures and found that algorithmic trading enhances market liquidity while simultaneously improving the informativeness of quoted prices. Similar evidence is reported by Mestel et al. (2018) for the Austrian Stock Exchange, where the adoption of algorithmic trading was associated with improved liquidity conditions. Further, Jarnecic and Snape (2014) study order-submission tactics and liquidity provision between high- and non-high-frequency traders in the London stock market limit order book. Their study suggests HFT increases market liquidity. In contrast, Brogaard et al. (2017) examine the impact of HFTs on liquidity, focusing on the September 2008 short-sale ban. Their findings indicate that HFT activities negatively affect liquidity during the highly volatile period of the short-sale ban. Similarly, Friederich and Payne (2015) investigate the effect of the Italian Stock Exchange's implementation of a penalty for high order-to-trade ratios (to discourage high-frequency quote submission) on market liquidity. Results indicate that HFT has decreased liquidity. Thus, previous literature suggests contradictory findings across studies, showing either positive or negative associations between AT and HFT and market quality measures. Similarly, there is a lack of consensus about the influence of AT on market quality and efficiency. Consequently, it is essential to investigate further to furnish data about the influence of current financial market developments, such as HFT and colocation, on market quality with respect to price volatility.

Furthermore, several studies have examined the role of HFT and its impact on financial markets (Zhang & Riordan, 2011; Biais & Foucault, 2014; Aït-Sahalia & Brunetti, 2020; Bazzana & Collini, 2020; Yacoubian, 2025). For instance, Boehmer et al. (2021) and Bershova and Rakhlin (2013) show that HFT improves overall market liquidity, whereas a few other studies argue for the negative association between HFT and market liquidity, volatility, and price discovery (Kwan & Philip, 2015; Bershova & Rakhlin, 2013; Kelejian & Mukerji, 2016). However, mixed findings from existing studies have led to ongoing debate over whether HFT is beneficial or harmful to the market (Virgilio, 2019; Chung & Lee, 2016; O'Hara, 2015; Stiglitz, 2014; Vuorenmaa, 2012). Hence, the impact of HFT on market quality, in terms of volatility, needs to be further evaluated in greater detail.

A colocation facility is another important technological innovation in the financial market. Frino et al. (2014) define colocation as a facility offered by an exchange, in which it rents a trading business space next to the exchange's trading facility. The proximity of the dealers' high-speed servers to the exchange infrastructure expedites the flow of time-sensitive information. Thanks to colocation services, latency has been cut in half, from milliseconds to billionths of a second, and speeds have been increased. Budish et al. (2015) argue that traders use cutting-edge technology and place computers near trading venues to reduce order latency and gain an advantage over other traders by receiving information faster. Further, they also argue that in today's "millisecond environment," computer algorithms respond 100 times faster than a human trader can blink. Alternatively, Hasbrouck and Saar (2013) analyze the impact of low-latency trading on market quality under normal conditions, as well as when prices are falling, and when economic uncertainty is high. Their findings indicate that augmenting low-latency activity enhances two major indicators of market quality: liquidity and volatility.

Given the mixed evidence in the literature on the influence of financial market innovations, such as AT, HFT, and COLO, on market quality in many developed countries, this remains an unexplored area in the Indian market. It becomes pertinent to study in the Indian market, given the growth of such trading. To the best of our knowledge, this is the first study to assess the impact of the enhancement in the speed of colocation facility at BSE on market volatility.

Therefore, the purpose of this study is to examine the impact of colocation on price volatility in the Indian stock market, with a specific focus on the BSE. By employing an event study approach, the study aims to assess whether the introduction of colocation and the associated reduction in latency have enhanced market stability and efficiency.

2. DATA AND METHODS

This section provides a comprehensive overview of the data, including an explanation of how the key variables are constructed. The data used in this study contain India's fastest exchange (with a speed of 6 microseconds). We have collected data from January 2000 to December 2023 from various sources, including the ProwessIQ database published by the Center for Monitoring Indian Economy (CMIE), the BSE India website, and the Bloomberg database. The dependent variable for the study is volatility, defined as the level of price fluctuation of index i on day t, measured by daily price movement. We incorporate a widely used price range measure to address market volatility, as discussed in previous studies (Boehmer et al., 2018; Kirilenko et al., 2017; Hasbrouck & Saar, 2013). The measure is described in detail below.

$$PVOL_{i,t} = \frac{High_{i,t} - Low_{i,t}}{(High_{i,t} + Low_{i,t})/2}, \tag{1}$$

where $PVOL_{i,\,t}$ represents index i 's price volatility on day t; $High_{i,\,t}$ and $Low_{i,\,t}$ represents the day's highest and lowest transaction prices. Further, we adopt high- and low-price volatility as proxies for market volatility (Frino et al., 2014). To examine the relationship between colocation and market volatility, we employ two dummy variables, COLO and COLOFAST, as the independent variables of interest. In detail, we examine the data for three periods: pre-colocation (NonCOLO), post-colocation (COLO), and post-colocation with higher latency ($COLO_{FAST}$). Further, the *NonCOLO* period is studied in two parts: *NonCOLOAT* and $NonCOLO_{AT\times HFT}$. $NonCOLO_{AT}$ is the pre-colocation period during which AT was introduced on April 3, 2008. $\mathrm{NonCOLO}_{\mathrm{AT}}$ is a dummy variable that takes the value 1 during the observation period after the introduction of AT and 0 otherwise. Likewise, $NonCOLO_{AT\times HFT}$ is the pre-colocation period during which high-frequency trading (HFT) was also introduced on May 1, 2009. $NonCOLO_{AT\times HFT}$ is a dummy variable assuming a value of 1 for the time period after the introduction of HFT and 0 otherwise. We attempt to understand the relationship between COLO and market volatility. *COLO* is a dummy variable assuming a value of 1 for the time period after the introduction of *COLO* and 0 otherwise, and $COLO_{FAST}$ is also a dummy variable assuming a value of 1 for the time period after the speed enhancement (October 13th, 2015) and 0 otherwise. For comparison, we study the relationship between *COLO* (*COLO* & $COLO_{FAST}$) and market volatility.

Apart from the main variable of interest, we have controlled for the global financial crisis (*GFC*), the colocation scam (COLOSCAM), and the COVID-19 period (*COVID19*). Based on the existing literature, we control for other variables that also impact volatility. For example, market capitalization (Attig et al., 2016), market return (Hendershott et al., 2011), trade size (Hendershott et al., 2011), and the inverse of the closing price (Zhang, 2010). Trade size measures the average daily trade. Since the global financial crisis, the colocation scam (Lokeshwarri, 2022), and Covid-19 (WHO, 2020) conditions are part of our study period, and we assert that these will influence the dependent variables uniquely, we construct dummy variables for the same. To control for potential endogeneity in the regression model, we included one lag of all independent variables, and to assess multicollinearity, we also checked VIFs. Further, to study the robustness of the results, we have substituted the BSE Sensex-30

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with the Sensex-500 and rerun the models. Further, to examine the impact of colocation and its increasing speed on the volatility, we employ multivariate regression analysis (OLS) using daily data of India's fastest exchange, proxied by BSE Sensex-30, from January, 2008 to December, 2023. The basic regression model is as follows:

$$PVOL_{i,t} = \beta_0 + \beta_1 NonCOLO_{AT_{i,t}} + \beta_2 NonCOLO_{AT \cdot HFT_{i,t}} + \beta_3 COLO_t + \beta_4 COLO_{FAST_{i,t}} + e_t. \tag{2}$$

The objective of this study is to examine the effect of colocation on price volatility. Our price volatility indicator is estimated using the following regression to assess and quantify the impact of colocation.

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT*HFT_t} + \beta_3 Log\left(Mcap\right)_{t-1} + \beta_4 RT_{t-1} + \beta_5 Log\left(Volume\right)_{t-1} + \beta_6 TS_{t-1} + \beta_7 ICP_{t-1} + \beta_8 GFC_{Dummy_t} + e_t, \tag{3}$$

where $PVOL_t$ (ratio of price high and low divided by its average) is used to measure the price volatility. $NonCOLO_{AT}$ represents the pre-colocation period wherein *AT* is allowed. $NonCOLO_{AT\times HFT}$ represents the pre-colocation period, which includes both *AT* and *HFT*. The control variables *Log (Mcap)* represents size of the Index, *RT* represents the market returns, Log(*Volume*) represents the amount of trades trading activities during the period, *TS* represents trade size of the market, *ICP* represents the inverse of closing price and GFC_{Dummy} represents global financial crisis period (from July 1 2007 to March 31 2009 (David et al., 2012; Lokeshwarri, 2022). assuming a value of 1 during the period and 0 otherwise.

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT \cdot HFT_t} + \beta_3 COLO_{AT \cdot HFT_t} + \beta_4 Log\left(Mcap\right)_{t-1} + \beta_5 RT_{t-1} + \beta_6 Log(Volume)_{t-1} + \beta_7 TS_{t-1} + \beta_8 ICP_{t-1} + \beta_9 GFC_{Dummy_t} + \beta_{10} COLOSCAM_{Dummy_t} + \beta_{11} Covid19_{Dummy_t} + e_t, \tag{4}$$

where $COLO_{Dummy}$ is a dummy variable assuming a value of 1 from the introduction date of the colocation service and 0 otherwise for day *t*. Our objective is to examine how the introduction of colocation impacts price volatility through Equation 3. There was a colocation scam period that allowed the co-located brokers unfair access and advantage from December 10, 2012 to May 30, 2014. So, we construct a dummy variable $COLOSCAM_{Dummy}$ that takes the value 1 during the colocation scam period and 0 otherwise. Similarly, Covid19Dummy is a dummy variable used to control for the Covid-19 period (from March,11, 2020 to December 31, 2021) (WHO, 2020). Taking a value of 1 for the Covid-19 period and 0 otherwise.

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT \cdot HFT_t} + \beta_3 COLO_{AT \cdot HFT_t} + \beta_4 COLOFAST_{AT \cdot HFT \cdot COLO_t} + \beta_5 Log\left(Mcap\right)_{t-1} + \beta_6 RT_{t-1} + \beta_7 Log\left(Volume\right)_{t-1} + \beta_8 TS_{t-1} + \beta_9 ICP_{t-1} + \beta_{10} GFC_{Dummy_t} + \beta_{11} COLOSCAM_{Dummy_t} + \beta_{12} Covid19_{Dummy_t} + e_t, \tag{5}$$

where *COLOFAST* is a dummy variable that takes the value 1 starting from the date of increase in the speed of colocation service and 0 otherwise for day *t*. Our objective is to examine how the increase in colocation speed affects price volatility using Equation 5.

3. RESULTS

The main objective is to investigate how volatility has changed since the latency-reduction process was introduced at the BSE, for instance, the introduction of AT, HFT, COLO, and *COLOFAST*. The regression analysis findings are shown in Table 1, which enables us to examine the pre-colocation period (Section A), the post-colocation period (Section B), and the post-colocation-fast period (Section C). The pre-colocation period includes both *AT* and *HFT*, whereas the post-colocation period includes colocation along with *AT* and *HFT*. The further post-colocation-fast period includes latency reduction along with

AT and *HFT*. We understand from the literature that colocation shall supplement high-frequency trading. We have controlled for all possible financial market variables that plausibly impact price volatility, directly or indirectly, during the pre-colocation, post-colocation, and fast-colocation periods.

The results in Table 1 for the pre-colocation period (Section A) show a positive relationship between $NonCOLO_{AT}$ (which includes the *AT* period) and price volatility, which suggests that the introduction of AT destabilized price volatility, and a negative relationship between $NonCOLO_{AT \times HFT}$ (which includes both *AT* and *HFT* and price volatility), which suggests that inclusion of *HFT* in the presence of *AT* improves the volatility in the market. An examination of the dummy variable for the non-colocation period indicates that price volatility increased after the introduction of *AT* by 8 percent on BSE. But after the introduction of *HFT*, there is a 3 percent decrease in price volatility on the BSE. The results in Table 1 for the post-colocation period (Section B) show a positive relationship between COLO and price volatility, suggesting that the introduction of colocation has increased market volatility. Further, Table 1 for the fast-colocation period (Section C) shows a negative relationship between COLOFAST and

Table 1. Price volatility before and after introduction of colocation (Sensex-30)

Variables	(A) Pre-Colocation	(B) Post-Colocation	(C) Fast-Colocation
Intercept	0.07***	0.10***	0.07***
	(0.00)	(0.00)	(0.00)
$NonCOLO_{AT}$	0.08***		
	(0.00)		
$NonCOLO_{AT \times HFT}$	−0.03 **		
	(0.02)		
COLO		−0.004***	
		(0.00)	
COLOFAST			−0.011**
			(0.03)
Log $(Mcap)_{t-1}$	−0.008***	−0.009***	−0.007***
	(0.00)	(0.00)	(0.00)
RT_{t-1}	−0.02	−0.02	−0.03
	(0.25)	(0.24)	(0.12)
Log *(Volume)t-1*	0.008 ***	0.007 ***	0.008 ***
	(0.00)	(0.00)	(0.00)
TS_{t-1}	−1.76***	−1.80***	−1.69***
	(0.00)	(0.00)	(0.00)
ICP_{t-1}	−20.56**	−44.19**	−26.37**
	(0.03)	(0.03)	(0.03)
GFC	0.005***	0.009***	0.007***
	(0.00)	(0.00)	(0.00)
COLOSCAM		(−0.005)	(−0.001)
		(0.10)	(0.31)
COVID19		0.003***	0.003***
		(0.00)	(0.00)
F-stat	323.52***	367.44***	278.60***
	(0.00)	(0.00)	(0.00)
R-Squared	0.31	0.31	0.30

Note: *, **, and *** indicate significance levels for 10%, 5%, and 1%, respectively. p-values are in parentheses. Column (A) presents the regression analysis of price volatility during the pre-colocation period for the BSE Sensex-3.

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price volatility, which suggests that the consecutive adoption of financial market innovations or add-ons that increase transaction speed at BSE makes prices more stable.

The following specification is estimated:

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT \cdot HFT_t} + \beta_3 Log\left(Mcap\right)_{t-1} + \beta_4 RT_{t-1} + \beta_5 Log\left(Volume\right)_{t-1} + \beta_6 TS_{t-1} + \beta_7 ICP_{t-1} + \beta_8 GFC_{Dummy_t} + e_t, \quad (6)$$

where $PVOL_t$ is the price volatility (proxied by daily price high-low volatility). The pre-colocation period (*NonCOLO*) includes the *AT* and *HFT*. The $NonCOLO_{AT}$ included in the estimated specification is a indicator variable such that the AT period is equal to 0 prior to the introduction of AT on April 1, 2008, and equal to 1 following the introduction of AT and $NonCOLO_{AT \cdot HFT}$ included in the estimated specification is a binary variable which represents the HFT period along with AT period, equal to zero prior to the introduction of *HFT* on May 1, 2009, and equal to 1 following *HFT* introduction. Column (B) presents a regression analysis of the economic relationship between colocation services and price volatility. The following specification is estimated:

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT \cdot HFT_t} + \beta_3 COLO_{AT \cdot HFT_t} + \beta_4 Log\left(Mcap\right)_{t-1} + \beta_5 RT_{t-1} + \beta_6 Log(Volume)_{t-1} + \beta_7 TS_{t-1} + \beta_8 ICP_{t-1} + \beta_9 GFC_{Dummy_t} + \beta_{10} COLOSCAM_{Dummy_t} + \beta_{11} Covid19_{Dummy_t} + e_t, \quad (7)$$

where price volatility is proxied by daily price high-low. The *COLO* represents the colocation period, which takes a value of zero before the introduction of colocation facilities on November 15, 2010, and one after the introduction of colocation. Further, Column (C) of Table 1 presents regression analysis on the relationship between the increasing speed of colocation services and price volatility, for the given regression model:

$$PVOL_t = \beta_0 + \beta_1 NonCOLO_{AT\,t} + \beta_2 NonCOLO_{AT \cdot HFT_t} + \beta_3 COLO_{AT \cdot HFT_t} + \beta_4 COLOFAST_{AT \cdot HFT \cdot COLO_t} + \beta_5 Log\left(Mcap\right)_{t-1} + \beta_6 RT_{t-1} + \beta_7 Log\left(Volume\right)_{t-1} + \beta_8 TS_{t-1} + \beta_9 ICP_{t-1} + \beta_{10} GFC_{Dummy_t} + \beta_{11} COLOSCAM_{Dummy_t} + \beta_{12} Covid19_{Dummy_t} + e_t, \quad (8)$$

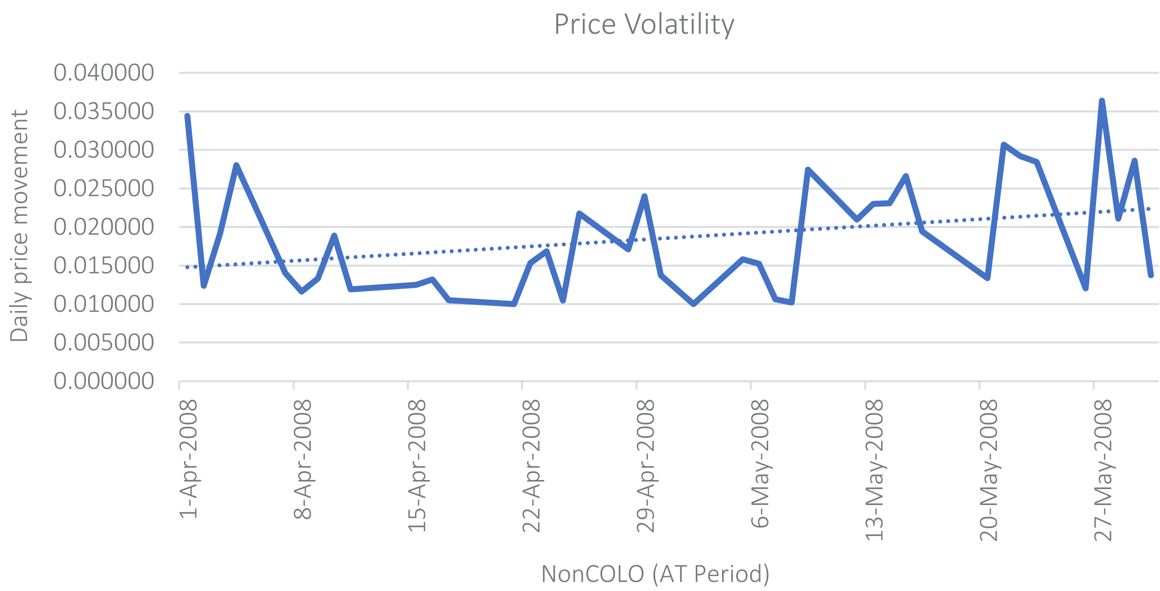

Figure 1. Price volatility during the $NonCOLO_{AT}$ period (Sensex-30)

where *COLOFAST* represents latency reduction after the introduction of colocation service at BSE, assuming a value of 0 before the latency reduction in the post-colocation period on October 13, 2015, and 1 after the implementation of latency reduction at BSE. VIF values are below 5, indicating no severe multicollinearity. To control for potential endogeneity in the regression model, we include the one-period lagged values of all employed variables.

3.1. Robustness tests

Additional analyses were performed to assess the robustness of this study's results. Figure 1 depicts upward movement in price volatility in the Sensex-30 index in the $NonCOLO_{AT}$ period (April 1, 2008 to April 30, 2008). This supports the main result and analysis of the paper that there is fickleness in the Indian capital market after the introduction of *AT* but before the introduction of *HFT*. Figure 2 demonstrates the relationship between price volatility and the *NonCOLOAT* × *HFT* period (December 1, 2009 to December 31, 2009), indicating a decline in price volatility after the introduction of high-frequency trading in the Indian securities market. Figure 3 depicts the association between price volatility and the *COLO* period (January 1, 2010 to January 29, 2010). It demonstrates that the introduction of colocation has positively supplemented high-frequency trading, resulting in improved price volatility in the Indian securities market. Further, Figure 4 demonstrates the association between price volatility and *COLOFAST* period (October 13, 2015 to November 12, 2015).

Figure 1 presents daily observations of price movements during the $NonCOLO_{AT}$ period (April 1, 2008 to April 30, 2008) for the Sensex-30 index. The data include one month from the introduction of AT.

Figure 2 presents daily price movements of the Sensex-30 during the $Non\text{-}COLO_{AT \times HFT}$ period (December 1, 2009 to December 31, 2009). The data include one month from the introduction of high-frequency trading.

Figure 3 presents daily observations of the price fluctuations during the *COLO* period (November 15, 2010 to December 15, 2010) for the Sensex-30 index. The data include one month from the introduction of colocation.

Figure 4 presents daily observations of the price fluctuations during the *COLOFAST* period (October 13, 2015 to November 13, 2015) for the Sensex-30 index. The data include one month from the implementation of the fast colocation service.

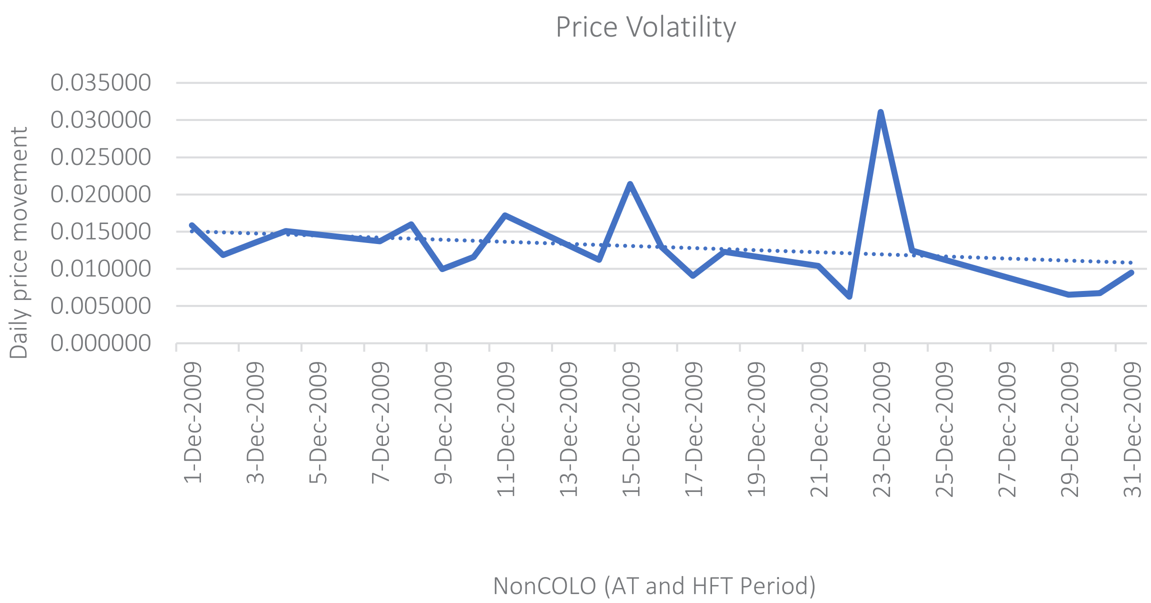

Figure 2. Price volatility during the *NonCOLOAT×HFT* period (Sensex-30)

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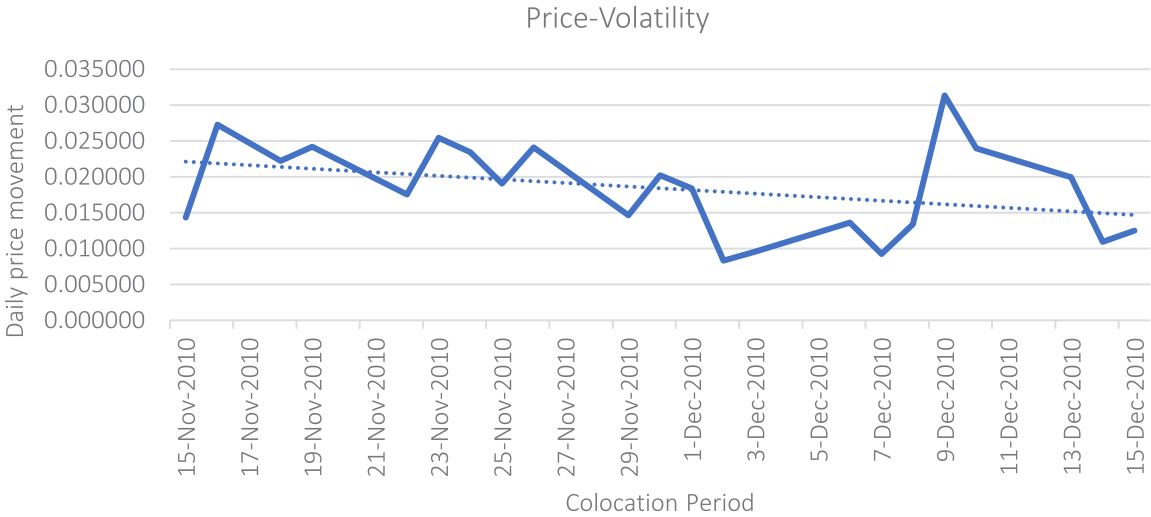

Figure 3. Price volatility during the *COLO* period (Sensex-30)

Latency reduction has positively supplemented high-frequency trading and colocation, resulting in improved price volatility in the Indian securities market. Figures 1, 2, 3, and 4 support the results of the present study and indicate robustness.

In the next step of the additional robustness analysis, we rerun the multivariate regression and replace the Sensex-30 data with the Sensex-500 data. Table 2 summarizes the findings of the regression analysis performed on the Sensex-500. The primary results for the Sensex-30 are consistent with those for the Sensex-500. As a consequence, the findings from the supplementary study are reliable and qualitatively comparable to the findings from the first investigation.

4. DISCUSSION

The findings of this study reveal that the link between colocation, HFT, and market volatility is complex and is a function of the trading regime. Both stabilizing and destabilizing factors mark the relationship. The coefficient on *NonCOLOAT* is large and highly significant. This indicates that non-colocated algorithmic trading increases vola-

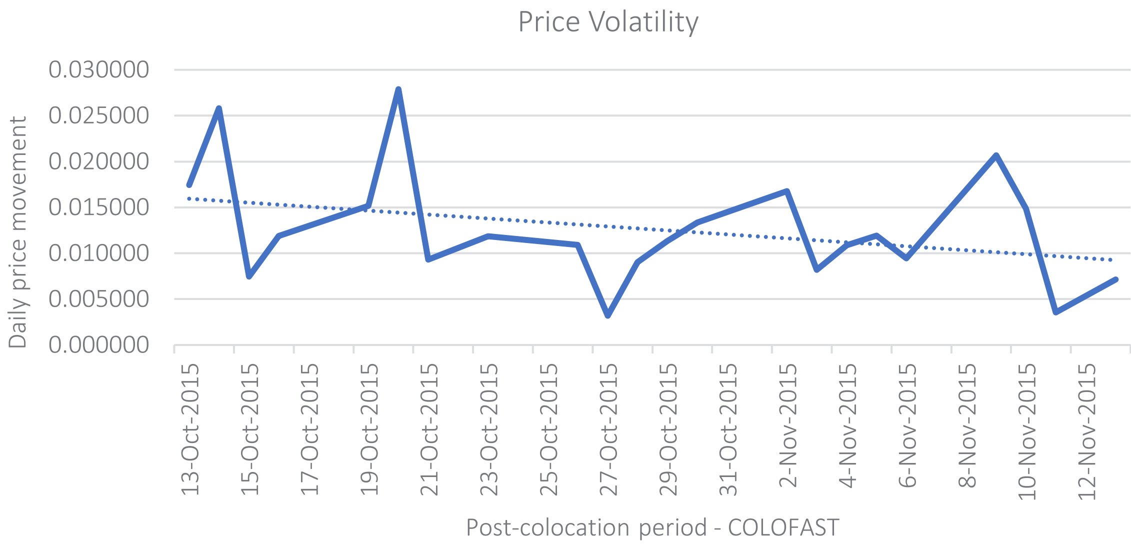

Figure 4. Price volatility after the latency reduction period (Sensex-30)

Table 2. Price volatility before and after introduction of colocation (Sensex-500)

Variables	(A) Pre-Colocation	(B) Post-Colocation	(C) Fast-Colocation
Intercept	0.08***	0.13***	0.11***
	(0.00)	(0.00)	(0.00)
$NonCOLO_{AT}$	0.005***		
	(0.00)		
$\boldsymbol{NonCOLO_{AT\times HFT}}$	−0.003 **		
	(0.01)		
COLO		−0.007***	
		(0.00)	
COLOFAST			−0.013**
			(0.03)
Log $(Mcap)_{t-1}$	−0.23***	−0.01***	−0.008***
	(0.00)	(0.00)	(0.00)
RT_{t-1}	−0.02**	−0.24***	−0.23***
	(0.02)	(0.00)	(0.00)
Log (Volume)t-1	0.008 ***	0.012 ***	0.007 ***
	(0.00)	(0.00)	(0.00)
TS_{t-1}	−4.05***	−6.10***	−4.61***
	(0.00)	(0.00)	(0.00)
ICP_{t-1}	−2.12*	−6.10***	−7.09***
	(0.09)	(0.00)	(0.00)
GFC	0.006***	0.009***	0.007***
	(0.00)	(0.00)	(0.00)
COLOSCAM		−0.003***	−0.064
		(0.00)	(0.85)
*COVID*19		0.004***	0.014***
		(0.00)	(0.00)
F-stat	309.09***	293.32***	281.28***
	(0.00)	(0.00)	(0.00)
R-Squared	0.30	0.31	0.30

Note: *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively. Values in parentheses are the p-values. Columns A, B, and C present the regression analysis of price volatility for the BSE Sensex-500 sample. The regression model specifications for all the columns are the same as those reported in Table 1.

tility in the pre-colocation period. This coefficient also implies greater volatility. This is in line with the study by Clapham et al. (2023), which found that latency-induced frictions stemming from execution delays and information asymmetry among traders can increase price volatility. This is comparable to the findings of Hasbrouck and Saar (2013) and Menkveld (2016), who suggest that slow order-flow adjustment and poor absorption of new information led to volatility due to sluggish traders. The interaction (*NonCOLOAT×HFT* = −0.03**) indicates that HFTs reduce volatility. High-frequency traders (HFTs) provide continuous liquidity and tight spreads, thereby minimizing short-run price volatility (Brogaard et al., 2015; McGowan, 2010). This contrasts with skeptics such as Pagnotta and Philippon (2018) and Zhang (2010), who believe that high-frequency trading could increase volatility through predatory behavior and order cancellations, thereby destabilizing the order book.

The liquidity stabilization hypothesis has a small but statistically significant negative effect on volatility in the post-colocation period (COLO = −0.004***). This is in line with Brogaard et al. (2015), who find that improvements in colocation at NASDAQ OMX Stockholm resulted in smaller bid-ask spreads and higher market depth, which in turn led to lower volatility under normal market conditions. For the same reason, Caivano (2015) and Brogaard et al. (2018) show that faster access to the matching engine enables better management of inventory and order book updates, thereby reducing price overshooting and volatility. These findings are in accordance with Menkveld (2016), who finds that high-frequency traders in close proximity tend to be net liquidity providers

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during calm periods by minimizing transient mispricings and smoothing price swings. This, however, runs counter to the findings of Breckenfelder (2019) and Pagnotta and Philippon (2018) that HFTs could increase volatility, particularly in stressful circumstances or when HFTs withdraw liquidity collectively. Although we do not explicitly characterize regime-dependent effects in our specification, the insignificance of the COLO coefficient suggests that colocation dampens volatility in a non-generic way and is likely state-dependent, as Chordia et al. (2013) illustrate. Sharp movements that force fast traders to enter or exit positions can exacerbate intraday declines.

The speed colocation standard (COLOFAST = –0.011**) for premium colocation services is also more effective at taming volatility, with substantial repercussions for systemic risk and equity in market conflicts. This is consistent with Hasbrouck and Saar (2013) and Brogaard et al. (2015), who have shown that the speed advantage of the quickest traders enables them to supply continuous liquidity and cushion the effects of order-flow shocks, minimizing volatility. This is consistent with Riordan and Storkenmaie (2012), who find that the lowest-latency enterprises have the largest increase in liquidity. This is consistent with our finding that COLOFAST has a larger (in absolute terms) coefficient than COLO. However, this is at odds with the "systemic risk" notion of Zhang (2010) and Kirilenko et al. (2017), who claim that premium colocation leads to a split market, with gains siphoned off by high-speed traders, and can destabilize markets during periods of volatility. Our results indicate that lower, rather than higher, volatility is associated with faster colocation services under typical settings. This contrasts with Breckenfelder (2019), who found that "pure" HFT firms increase their trading activity by 0.5-0.8 standard deviations in response to higher volatility. These results are consistent with the arguments of McGowan (2010) and Hendershott et al. (2011) that the long-run benefits of high-frequency trading for market quality outweigh the short-run costs. Another explanation is that COLOFAST captures the cumulative impact of the larger liquidity supply that overrides any disruptive speculative conduct. Nevertheless, high-frequency trading can also increase volatility when orders are canceled concurrently, and liquidity is used aggressively (Caivano, 2015; Clapham et al., 2023). The implications are that the results may not be valid under stressful conditions.

CONCLUSION

The SEBI introduced the colocation facility at the BSE on November 15, 2010, as part of its broader initiative to modernize the Indian securities market and enhance trading efficiency. Subsequently, BSE further strengthened its technological infrastructure by establishing a state-of-the-art Data Center, significantly reducing trading latency and improving the performance of its colocation services. These advancements enabled BSE to emerge as India's fastest stock exchange, achieving an execution speed of approximately 6 microseconds. The continuous enhancement of trading infrastructure reflects SEBI's commitment to promoting a technologically advanced, efficient, transparent, and globally competitive capital market. This study analyzes the effects of colocation and low latency on market volatility. Further, this study evaluates whether the introduction of colocation and reduced latency at the BSE has contributed to improved price stability and market efficiency in the Indian stock market. This study presents empirical findings that demonstrate a noticeable rise in daily price fluctuation (volatility) following the implementation of AT (*NonCOLOAT*). In addition, this study presents empirical evidence demonstrating a decrease in the frequency of daily price movements after the implementation of high-frequency trading (*NonCOLOAT × HFT*). Moreover, the enhanced transaction speed and the implementation of colocation services have significantly improved market efficiency, particularly by reducing volatility. The robustness tests using the Sensex-500 index confirm the consistency of these findings, indicating that technological innovations have strengthened the quality and resilience of the Indian securities market. The study concludes that technological advancements in algorithmic trading, high-frequency trading, colocation, and latency reduction have collectively enhanced the efficiency and stability of the Indian stock market. Although the introduction of algorithmic trading initially increased price volatility, the integration of HFT and subsequent improvements in colocation infrastructure significantly reduced volatility and improved market quality. In summary, our analysis indicates that reducing latency has improved trading efficiency, as reflected in lower price volatility on India's fastest BSE. The results obtained for Sensex-500 were similar. Our sample includes the introduction dates of all three financial market innovations (AT, HFT, and Colocation) and the recent latency-reduction process at the BSE. This allows us to study the effect on price volatility. In summary, the implementation of latency-reduction techniques, such as high-frequency trading (HFT), colocation, and Colo-fast, has been shown to enhance market efficiency and stability.

AUTHOR CONTRIBUTIONS

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Project administration: Harsh Raj Pathak.
Software: Harsh Raj Pathak.
Supervision: Md Sikandar Azam.
Validation: Zakir Hossen Shaikh.
Writing – original draft: Harsh Raj Pathak, Zakir Hossen Shaikh, Md Sikandar Azam.
Writing – review & editing: Harsh Raj Pathak, Zakir Hossen Shaikh, Md Sikandar Azam.

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