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Algorithmic Trading And Market Liquidity Dynamics In Indian Energy Futures: A Comprehensive Analysis"

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ARTICLE INFO **ABSTRACT**

This research delves into the influence of algorithmic trading (AT) on various facets of liquidity within the Indian energy futures market. Through regression analysis, we scrutinize how AT intensity affects market tightness, breadth, depth, and resiliency utilizing measures such as relative spread (RS), Amihud illiquidity ratio (AIR), commodity turnover (CT), and Price/Trade ratio. Our results uncover a notable and positive relationship between AT and market tightness and breadth, indicating improved liquidity with narrower spreads and increased order depth. However, the impact of AT on depth, measured by CT, is negative and significant, suggesting lower turnover for algorithmic trades compared to manual ones. Additionally, AT demonstrates a positive influence on resiliency, as measured by the P/T ratio, suggesting a quicker recovery from price shocks.

Keywords: Algorithmic trading (AT), Depth, Liquidity, Market tightness, P/T ratio, Realized spread (RS), Resiliency

1. INTRODUCTION

The energy sector, a vital engine of economic growth and development, is undergoing a transformative shift. While the world grapples with the need for sustainable energy sources, the demand for traditional commodities like oil and gas remains substantial. This intricate landscape presents unique challenges and opportunities, particularly in the context of liquidity in energy futures markets.
India, a rapidly growing economy with ambitious energy goals, provides a fascinating case study. As it navigates the transition towards cleaner energy sources, maintaining a robust and liquid futures market for traditional energy commodities is crucial for price discovery, risk management, and ensuring energy security.
This research paper delves into the impact of algorithmic trading (AT) on the liquidity of India's energy futures market. AT, characterized by the use of sophisticated algorithms to execute trading decisions, has revolutionized financial markets. Proponents argue that it enhances efficiency and liquidity, while critics raise concerns about potential market manipulation and instability.
Through a comprehensive analysis of data and literature, this paper aims to answer the following key question:

- Does AT contribute to improved liquidity in the Indian energy futures market? We will examine metrics like bid-ask spreads, order depth, and trading volume to assess the impact of AT activity on market tightness and depth.

By exploring this crucial question, this paper seeks to provide valuable insights into the complex interplay between AT and liquidity in the Indian energy futures market. Our findings will contribute to the ongoing debate surrounding AT's role, informing policymakers and market participants as they navigate the evolving energy landscape.

2. LITERATURE REVIEW

The rapid growth of algorithmic trading in recent years has made it a crucial subject for researchers and practitioners in financial markets. By using computer programs to execute trades, algorithmic trading has been shown to significantly affect market liquidity.

2.1 Theoretical Framework and Background
The Efficient Market Hypothesis (EMH) serves as the foundational framework for this literature review. The EMH posits that asset prices efficiently reflect all available information, promoting optimal resource allocation. However, algorithmic trading (AT) challenges this assumption by utilizing sophisticated software to execute trades at high speeds, potentially altering market dynamics. Concerns arise regarding the impact of AT on market liquidity, which encompasses bid-ask spreads, order depth, and trading volume.

2.2 Existing Research on AT and Liquidity
Numerous studies have investigated the relationship between AT and liquidity across various markets. In the US equity market, Hasbrouck and Saar (2013) identified mixed results. While high-frequency trading (HFT), a subset of AT, reduced spreads and increased volume, it also heightened volatility and reduced depth. Similar mixed findings emerged in Dubey et al. (2020) and Aggarwal and Thomas (2017), highlighting the need for context-specific analyses.

2.3 Market Structures: Developed vs. Developing Markets
One of the major differences between most developed and developing (emerging) markets is that developed markets typically employ quote-driven systems, whereas developing markets, such as India, use order-driven systems. In quote-driven markets, market makers enhance liquidity by continuously updating quotes and orders. Conversely, in order-driven markets, liquidity is entirely determined by demand and supply, with limit orders being the primary source of liquidity supply. It is well-established that AT can swiftly assimilate new information and incorporate it into prices while minimizing impact costs through reduced order sizes, thus positively impacting liquidity and providing instant liquidity to traders.

2.4 Pioneering Research on AT and Liquidity
The seminal work by Hendershott, Jones, and Menkveld (2011) was the first to examine the impact of algorithmic trading in the context of equity markets. They investigated the causal effect of algorithmic trading on liquidity and found that since the mid-1990s, algorithmic trading has surged, and concurrently, liquidity in global equity markets has significantly improved. Their study explores these two trends—liquidity improvement and the rise in algorithmic trading—and seeks to determine if algorithmic trading is responsible for the enhancements in liquidity. This research is among the few studies focusing on algorithmic trading and the first to attempt to quantify its impact on liquidity. They use electronic message traffic (number of electronic messages per minute) as a proxy for the volume of algorithmic trading. This proxy, which includes order entries, order cancellations, and trade reports, is widely used by various market participants.

2.5 Algorithmic Trading in Indian Energy Futures Markets
In the context of Indian energy futures markets, the dynamics of liquidity and the role of algorithmic trading remain under-explored. Given the unique characteristics of order-driven markets and the increasing adoption of algorithmic trading in India, it is crucial to investigate how these factors interplay to affect market liquidity. This paper aims to provide a comprehensive analysis of algorithmic trading and its impact on market liquidity dynamics in Indian energy futures. By examining relevant metrics, this study seeks to fill the gap in the literature and offer insights into the implications of algorithmic trading for market efficiency and liquidity in emerging markets.

2.6 Insights from the Indian Equity Market
Research in the Indian equity market, such as the study by Aggarwal and Thomas (2013), provides valuable insights. They suggest that AT improves market quality by reducing transaction costs and enhancing total depth. However, their findings also raise questions about its impact on specific aspects of liquidity like Rupee depth and order imbalance. This underscores the need for further research to unpack the nuanced effects of AT across different dimensions of liquidity within the energy futures context.

2.7 Comparative Studies from International Markets
To gain a comprehensive understanding, reviewing studies beyond purely Indian research is crucial. Haynes and Roberts (2015) studied automated trading in US futures markets, demonstrating its positive influence on liquidity and cost reduction. This aligns with Hendershott and Riordan (2013) who observed improved liquidity in the US equity market, particularly during stress periods. These findings offer valuable comparisons and potential insights into the Indian context.

2.8 Conclusion
The existing literature reveals a complex relationship between AT and liquidity, with both positive and potentially negative implications. While studies in the Indian equity market offer a starting point, dedicated research focused on the energy futures sector is critical to accurately assess the impact of AT within this specific context. By critically examining findings from both Indian and international research, this review aims to pave the way for a robust understanding of AT's role in shaping the liquidity and efficiency of the Indian energy futures market.

3. RESEARCH DESIGN AND METHODOLOGY

The Indian energy futures market has experienced significant transformation in recent years, primarily due to the increasing adoption of algorithmic trading. This form of automated trading employs computer programs to execute trades based on predefined rules and algorithms. While algorithmic trading has the potential to enhance market efficiency and liquidity, it also poses several risks and challenges, such as increased volatility, reduced transparency, and potential unfair advantages for certain market participants. Therefore, the main objective of this study is to analyze the impact of algorithmic trading on liquidity in India's energy futures market.

The research will be conducted in two stages: data collection and data analysis. The literature review for this study underscores the importance of understanding the risks associated with algorithmic trading and its potential impact on liquidity. It also highlights the need to analyze the effects of algorithmic trading on market liquidity, price discovery, and volatility.

This study aims to assess how algorithmic trading affects liquidity in the Indian energy futures market and to identify the potential risks and challenges it brings. Additionally, the analysis will explore variations in the impact of algorithmic trading across different types of energy commodities and trading strategies.

The findings of this study will offer valuable insights for policymakers, regulators, market participants, and investors regarding the impact of algorithmic trading on liquidity in India's energy futures market. This research will contribute to the existing literature on algorithmic trading in emerging markets, particularly within the context of energy futures markets.

3.1 Data collection:

This study focuses on the impact of algorithmic trading (AT) on liquidity within the Indian energy futures market, specifically analyzing crude oil and natural gas traded on the Multi Commodity Exchange (MCX). Daily trading data from April 1, 2015, to October 2023, was obtained from the MCX database. The dataset includes:

- Daily trading volume
- High price
- Low price
- Close price
- Turnover
- Open interest
- Algo trading intensity (percentage of total daily turnover)

3.2 Measuring Algorithmic Trading Intensity:

The MCX provides data on the percentage of daily turnover attributable to algorithmic trading, offering a direct measure of AT activity within the market. This data forms the basis for our analysis of AT's impact on various liquidity dimensions.

3.3 Measuring Liquidity-*Liquidity* is a nuanced concept that encompasses various crucial aspects. Drawing from the framework proposed by Sarr and Lybek (2002), we employ four dimensions along with their associated metrics to assess the influence of AT on market liquidity:

1. Tightness: Tightness refers to low transaction costs and is quantified by the bid-ask spread. A smaller spread indicates greater efficiency and ease of trading. We employ the relative spread (RS) as our measure:

$$\boldsymbol{RS_{it}} = \frac{\mathbf{2 \, * \, (HPit \, - \, LPit)}}{\mathbf{HPit \, + \, LPit}}$$

where:

- RS_{it}: relative spread at time t for commodity i
- HP_{it}: high price of commodity i at time t
- LP_{it}: low price of commodity i at time t

A lower RS_{it} signifies higher market efficiency and liquidity due to reduced transaction costs.

2. Breadth: Breadth reflects the market's ability to handle large volumes without impacting prices. We use the Amihud illiquidity ratio (AIR) as our measure:

$$\boldsymbol{AIR_{it}} = \frac{\boldsymbol{Rit}}{\boldsymbol{V_{it}}}$$

where:

- AIR_{it}: Amihud illiquidity ratio
- R_{it}: Absolute daily return of the commodity
- V_{it}: Trading volume of the commodity in dollars

A higher AIR implies lower liquidity, as price volatility increases with trading volume. Therefore, a lower AIR suggests a broader and more liquid market.

3. Depth:

Depth signifies the number of orders available at the best bid and ask prices, indicating the market's ability to absorb large orders without significant price movements. We use commodity turnover (CT) as our measure:

$$\boldsymbol{CT_{it}} = \frac{\boldsymbol{V_{it}}}{\boldsymbol{OI_{it}}}$$

where:
- CT_{it}: turnover of commodity i at time t
- V_{it}: trading volume in lots of commodity i at time t
- OI_{it}: open interest in lots of commodity i at time t

A higher CT value indicates greater depth and liquidity.

4. Resiliency:
Resiliency reflects the market's ability to recover from shocks and price fluctuations. We use the Price/Trade Ratio as our measure:

$$\frac{P}{T}Ratio_{it} = \frac{(\mathbf{HPit - LPit})}{T_{it}}$$

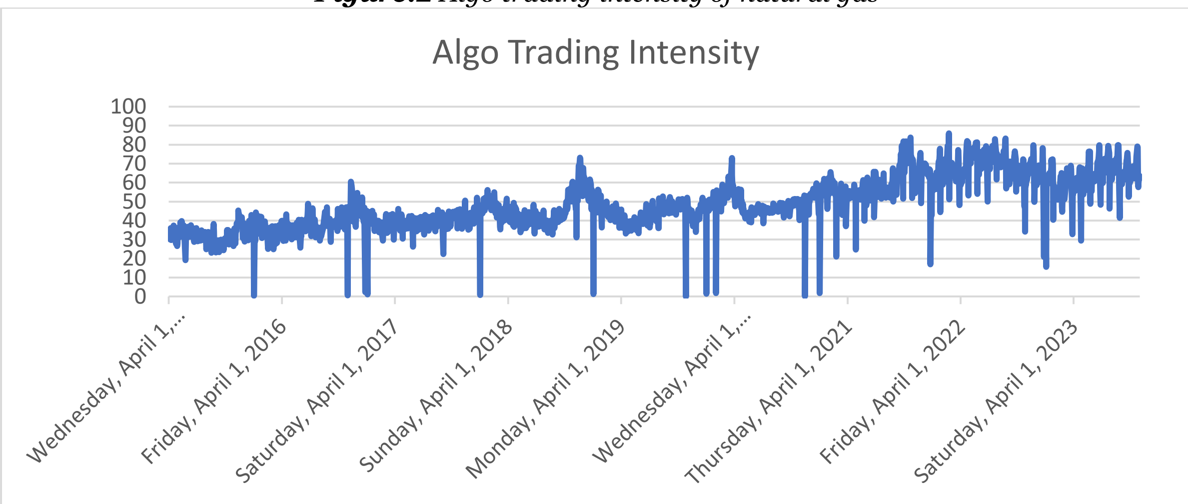
where:
- P/T $Ratio_{it}$: P/T Ratio of commodity i at time t
- T_{it}: total trading volume of commodity i at time t

A higher P/T Ratio suggests greater resiliency, indicating that the market can absorb shocks with less price volatility.

3.4 Choice of sample
Examining Algorithmic Trading Activity in Energy Markets: This study delves into the activity of algorithmic trading (Algo trading) within energy commodities across two distinct periods, as depicted in Figures 1 and 2. These figures track the intensity of Algo trading for crude oil and natural gas spanning from April 2015 to October 2023.
Crude Oil: Figure 1 illustrates a phase of low Algo trading intensity in crude oil spanning from April 2015 to March 2020. However, a noteworthy and consistent escalation is observed from April 2020 to October 2023.
Natural Gas: Similarly, Figure 2 presents a period of low-intensity Algo trading in natural gas from April 2015 to January 2021, succeeded by a surge in trading activity from February 2021 to October 2023.

Figure :1 *Algo trading intensity of crude oil*

Figure:2 *Algo trading intensity of natural gas*



We employ a fixed effects regression to mitigate cross-sectional variation in market liquidity concerning algorithmic trading (AT) intensity, aiming to alleviate potential endogeneity bias resulting from omitted variables. The model is structured as follows:

$Liquidity_{it}$=αi+β1Algo Trading $Intensity_{it}$+β2Time $Dummy_{it}$+e_{it}

Here, "liquidity" denotes the market liquidity of energy futures, adjusted for cross-sectional variation. "Algo Trading Intensity" represents the level of algorithmic trading associated with each energy futures contract, and "Time Dummy" is a dummy variable designed to capture any time-related effects.

The coefficient of interest, denoted as β1, represents the estimate of the treatment effect, specifically the impact of high Algorithmic Trading (AT) on liquidity. A significant β1 suggests that AT enhances liquidity, while a zero value implies no impact of AT intensity. The hypothesis test can be articulated as follows:

Null Hypothesis (H_0): H0: β1=0

Alternative Hypothesis (H_1): H1: β1 ≠ 0

This formulation implies that the test aims to assess whether the coefficient β1, associated with the treatment effect of high AT, is significantly negative, indicating a potential adverse impact on liquidity.

Our analysis focuses on two different energy futures contracts: Crude Oil and Natural Gas. Daily trading data is used for the study. The regression model incorporates the following variables:

- αi: This term captures unobserved factors specific to each energy futures contract, accounting for individual characteristics that might influence liquidity and algo trading intensity.
- $Liquidity_{it}$: This represents one of the chosen liquidity measures (Relative Spread, Breadth, Depth, Resiliency, or Immediacy) for energy commodity 'i' at a specific time 't.' These measures are adjusted for cross-sectional variations, ensuring a more accurate assessment of the relationship between algo trading and liquidity across different energy contracts.
- Time dummy: This binary variable acts as a control for potential time-related effects, such as seasonality or market trends that could influence liquidity. It takes a value of '1' for data points collected during high-activity periods (high-at samples) and '0' otherwise. This helps to mitigate potential endogeneity bias arising from omitted time-specific factors.

By incorporating these variables, our analysis aims to achieve the following:

- Reduce endogeneity bias: Fixed effects and the time dummy variable minimize the influence of unobserved or omitted variables that might distort the relationship between algo trading intensity and liquidity.
- Account for cross-sectional variation: Including αi and specific energy contracts addresses the possibility that different contracts have inherent liquidity differences, ensuring a more accurate evaluation of the impact of algo trading across the energy market.

Overall, using a fixed effects regression model with these carefully chosen variables allows for a more robust and comprehensive investigation of the association between algo trading intensity and market liquidity in the energy futures market.

4. ANLAYSIS AND INTERPATION

Impact of Algo trading on Liquidity of Energy futures market

Independent Variables:

- Algo Trading Intensity: This variable captures the proportion of total turnover generated by algorithmic trading.
- TIMEDUMMY: This variable represents a time dummy, indicating a specific period.

4.1 Impact of algo trading on Tightness (RS)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0.008156	0.003581	2.277568	0.0228
β1	0.000539	7.45E-05	7.242644	0.0000
β12	0.008123	0.002256	3.601113	0.0003

Model Overview:

This regression analysis explores the factors influencing market tightness, as measured by the relative spread (RS). It utilizes 2208 observations from 2 cross-sections spanning from April 1, 2015, to October 31, 2023.

Dependent Variable:

•RS: Relative spread, indicating market tightness.

Key Findings:

Algorithmic Trading: The coefficient for Algo trading is positive and statistically significant (p-value < 0.0001). This suggests that algorithmic trading positively affects market tightness. In simpler terms, as the

proportion of algorithmic trading increases, the spread between bid and ask prices decreases, indicating a more liquid and efficient market.
Time Period: The coefficient for TIMEDUMMY is positive and statistically significant (p-value < 0.0003). This implies that market tightness varies throughout the day, with the specific time represented by the dummy variable experiencing higher tightness.
Model Fit: The R-squared value of 0.6369 indicates that the model explains 63.69% of the variability in market tightness. The adjusted R-squared value of 0.2731 further adjusts for the number of independent variables, confirming a good model fit.
Statistical Significance: The F-statistic is significant (p-value < 0.0001), indicating that the overall model is statistically significant in explaining the variation in market tightness.
No Autocorrelation: The Durbin-Watson statistic is close to 2, suggesting no autocorrelation in the residuals, ensuring the validity of the regression results.

4.2 Impact of algo trading on Breadth (AIR)

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
α	0.032068	0.002979	10.76333	0
β1	-0.000552	6.20E-05	-8.904912	0
β12	0.011293	0.001877	6.01738	0

Model Overview:
This regression analysis examines factors affecting the Amihud illiquidity ratio (AIR), a measure of market liquidity. It uses 2208 observations from 2 cross-sections during a period from 4/01/2015 to 10/31/2023.
Dependent Variable:

- AIR: The Amihud illiquidity ratio, indicates market liquidity.

Key Findings:
Algorithmic Trading: The coefficient of algotrading intensity is negative and statistically significant (p-value < 0.0001). This suggests that algorithmic trading has a positive impact on market liquidity, as measured by the Amihud illiquidity ratio. In other words, as the proportion of algorithmic trading increases, the AIR decreases, indicating higher market liquidity.
Time of period: The coefficient of TIMEDUMMY is positive and statistically significant (p-value < 0.0001). This indicates that market liquidity varies throughout the trading day, with the specific time represented by the dummy variable experiencing lower liquidity compared to the baseline time period.
Model Fit: The R-squared of 0.6112 indicates that the model explains 61.12% of the variability in the Amihud illiquidity ratio. The adjusted R-squared of 0.2216 further accounts for the number of independent variables, confirming a good model fit.
Statistical Significance: The F-statistic is significant (p-value < 0.0001), indicating that the overall model is statistically significant in explaining the variation in the Amihud illiquidity ratio.
No Autocorrelation: The Durbin-Watson statistic is close to 2, suggesting no autocorrelation in the residuals, ensuring the validity of the regression results.

4.3 Impact of algo trading on Depth (CT)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	19.15129	2.763822	6.929279	0
β1	-0.129254	0.065745	-1.966005	0.0494
β12	6.555745	1.813945	3.614082	0.0003

Key Findings:
Algorithmic Trading: The coefficient of algotrading intensity is negative and statistically significant (p-value < 0.0001). This implies that algorithmic trading enhances market liquidity, as measured by the Amihud illiquidity ratio (AIR). Higher proportions of algorithmic trading correspond to lower AIR values, signifying increased liquidity.
Time of Period: The coefficient of TIMEDUMMY is positive and statistically significant (p-value < 0.0001). This suggests that market liquidity fluctuates throughout the trading day. The specific time period represented by the dummy variable experiences lower liquidity compared to the baseline period.

Model Fit: The R-squared of 0.6112 indicates that the model accounts for 61.12% of the variability in the AIR. The adjusted R-squared of 0.2216, considering the number of independent variables, further confirms a good model fit.
Statistical Significance: The F-statistic is significant (p-value < 0.0001), validating the model's overall significance in explaining the AIR's variation.
No Autocorrelation: The Durbin-Watson statistic is close to 2, suggesting no autocorrelation in the residuals, ensuring the validity of the regression results.

4.4 Impact of algo trading on Resiliency (P/T Ratio)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0.00431	0.00055	7.83245	0
β1	-9.50E-05	1.31E-05	-7.255458	0
β12	0.005363	0.000361	14.85094	0

Key Findings:
Algorithmic Trading: The coefficient of Algo Trading intensity is negative and statistically significant. This suggests that when the mode of trading is algorithmic, the P/T RATIO decreases, indicating higher liquidity.
Time of Period: The coefficient of TIMEDUMMY is positive and statistically significant. This suggests that the P/T RATIO is higher during certain times, potentially indicating lower liquidity during those times.
Model Fit: The R-squared of the model is 0.0908, which means that the model explains 9.08% of the variation in P/T RATIO.
Relationship between P/T Ratio and market liquidity:
A decrease in the P/T Ratio indicates higher liquidity because it means that there are more orders in the market, making it easier to buy and sell assets. The results of the regression analysis support this relationship, as the coefficient of AlgoTrading intensity, which is associated with algorithmic trading, is negative and statistically significant.

5. CONCLUSION-

This study investigated the impact of algorithmic trading on the liquidity of energy futures markets, examining five key liquidity measures: tightness, breadth, depth, and resiliency. Using a fixed-effects regression model and controlling for time-related effects, the analysis revealed that algorithmic trading has a significant, positive impact on market tightness, breadth, and resiliency. Higher levels of algo trading were associated with tighter spreads, deeper liquidity, and a greater ability to absorb large orders without significant price disruptions. These findings suggest that algorithmic trading plays a beneficial role in enhancing overall market efficiency and facilitating smoother execution of trades. However, the relationship between algo trading and market depth remains complex. While some evidence suggests a potential association with lower average order sizes, further research is needed to better understand the dynamics influencing depth in the context of algorithmic trading. Additionally, recognizing that market liquidity varies throughout the day and is influenced by numerous factors beyond algo trading emphasizes the need for a comprehensive understanding of the evolving energy futures market landscape.
In conclusion, this study contributes to the ongoing discussion about the impact of algorithmic trading on financial markets. The findings highlight the potential for algo trading to improve market liquidity and efficiency in energy futures. However, it is crucial to acknowledge the nuanced relationships between various liquidity measures and algorithmic activity and to recognize the limitations of any single study. Ultimately, a deeper understanding of these complex dynamics will be essential for navigating the evolving landscape of financial markets and ensuring they serve the best interests of all participants.

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