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A Brief Discussion of Algorithmic Trading and Co-movement in Returns and Market Quality

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1. Introduction

High-frequency traders (HFTs) dominate message traffic and trading in most markets. The explosive growth in HFT activities has raised concerns about the effect of the underlying low latency and algorithmic trading (AT) on financial markets. Much of the extant literature on AT focuses on individual securities. In our study, we investigate the impact of latency on co-movement (i.e., the degree of correlation) in order flow, returns, and a range of liquidity measures. For example, if HFTs increase co-movement in liquidity, then a liquidity shock to one stock is more likely to reduce liquidity in other stocks as well. This type of correlation can, in the worst case, lead to systemic events such as the 2007 "Quant Crisis." Systemic crises arising from idiosyncratic shocks can be costly for market participants; it could prove challenging for regulators to come up with effective responses to such crises. In this paper, we examine how the rise in algorithmic trading affects co-movements in variables that measure returns, trading activity, and market quality.

If faster trading leads to greater co-movement in trading strategies and perhaps in liquidity, then the associated increase in the correlation of order flow and liquidity could magnify systemic shocks to liquidity and, thus, increase systemic risk in financial markets. At best, greater co-movement in liquidity, returns, or order flow will create externalities that can conceivably magnify the costs of trading. For example, if algorithmic traders often trade contemporaneously in the same direction for multiple securities (i.e., co-movement in order flow is high) or trading costs tend to increase at the same time for multiple securities (co-movement in liquidity is high), the trading costs are greater compared to those in markets with less correlated trading patterns. Conversely, a recent review paper notes that lower latency may encourage faster trading without fundamentally changing either the

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strategies employed by traders or the underlying economics of financial markets.[5] Under this view, lower latency might not have any impact on co-movement in liquidity or order flows. Which view is right?

2. Our Study

We provide the first direct evidence for the impact of low-latency trading on co-movement in order flows and market conditions. We use a natural experiment at the National Stock Exchange of India (NSE).[6] Direct Market Access (DMA) was introduced in Indian markets in April 2008. This allowed institutional clients to directly access the exchange's trading system using their brokers' infrastructure, but without their manual intervention. This step is important because it allows algorithmic traders to access the market without the delay caused by routing through a brokerage. To further reduce external latency, the NSE introduced co-location services in January 2010. With co-location, market participants can rent servers situated within the NSE's premises. Our analysis focuses on this step, which is designed to support and facilitate low-latency strategies. Market participants have eagerly embraced these innovations; within 15 months of launching the co-location facilities, 60% of incoming orders at the NSE were from co-located servers.[7] We use order-level NSE data that cover certain periods before and after the introduction of co-location facilities. Our data identify the originator for each incoming message as either AT (algorithmic trader) or non-AT.

In our analysis, we focus on the introduction of co-location facilities and measure whether co-movement differs before and after the introduction of co-location facilities. With systems to handle algorithmic trading already in place through DMA, it is likely that market participants do not require long acclimatization periods after the adoption of colocation. For our pre-event sample, we use two weeks of data from two months before the introduction of co-location. For our post-event sample, we obtain data for two weeks from two distinct time periods: two months and four months after the event.

Our sample contains 150 stocks that were selected from a universe of over 1400 stocks

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[5] See Chordia, T., Goyal, A., Lehmann, B.N., and Saar, G. (2013), "High frequency trading," *Journal of Financial Markets*, **16**(4): 637–645.

[6] World Federation of Exchanges (2012) reports that the NSE is the largest exchange globally when ranked by number of trades in equity shares. During 2011–2012, a total of 1.4 billion trades were executed at the NSE compared to 1.37 billion trades at the NYSE Euronext (US) and 1.26 billion trades at NASDAQ OMX. In terms of the value of shares traded, the NSE is ranked lower (27th position).

[7] Source: "The changing landscape of India's equity markets," *Live Mint*, April 26, 2011.

that were traded at the beginning of our pre-event period. We first select 50 stocks that are members of the NSE's key benchmark index, S&P CNX Nifty. It is a market capitalization weighted index that is adjusted for free-float. It contains 50 stocks that represent 24 sectors of the economy. These "index stocks" form the first group in our analysis. We then select another 100 stocks from those that are traded in the derivatives segment.[8]

3. Results

We find that co-movement in returns, volatility, and liquidity experiences a significant decline around co-location. Taken together, our findings are not consistent with the notion that an increase in AT strategies worsens the co-movement of returns, volume, or liquidity. Overall, our study complements prior analyses that examine the impact of faster trading on market quality. We show that order flow, liquidity, and volatility have common factors that appear to be driven by AT. Contrary to anecdotal evidence, an increase in AT reduces the importance of these common factors.

While co-movement and the market impact of low-latency/high-frequency trading on market quality have independently attracted attention in recent years, there is little evidence on how the intensity of low-latency trading is related to the co-movement in order flow, returns, volatility, and liquidity. We provide the first direct evidence for this using a new dataset obtained from a natural experiment at the NSE. We can cleanly identify algorithmic order flow at the order level and exploit a co-location event that makes algorithmic trading strategies more effective. Contrary to some prior (indirect) results, we find that order flow from algorithmic traders is less correlated than the order flow of other traders is. Correspondingly, a reduction in latency around the introduction of co-location facilities leads to a significant reduction in order flow co-movement for both trader categories. The co-movements in other relevant firm-specific attributes such as returns, volatility, and liquidity also show a significant decline around this event.

4. Conclusion

Our findings are not consistent with the notion that increased low-latency trading increases systemic risk by accentuating co-movement in order flows and liquidity. Instead,

[8] The NSE has laid out clear guidelines for adding stocks to the derivatives segment; the dominant criterion is liquidity. To be specific, the NSE computes "quarter sigma" for each stock; a stock's quarter-sigma order size refers to the order size (in value terms) that is required to cause a change in the stock price equal to one-quarter of its standard deviation. A stock is eligible for the F&O segment only if this amount is above a certain minimum threshold (currently set at INR 500, 000).

we show that more intense algorithmic trading is associated with less intense co-movements. These results are consistent with the view that low-latency trading is merely fast trading, without any fundamental changes in either the strategies employed by these traders or the underlying economics of financial markets.

The important open question is: Why and through which channels can algorithmic trading strategies reduce co-movements? Clearly, if algorithmic traders followed strategies that merely mimic one another or are derived from a common model, we should observe more co-movement in order flow, not less. We suggest instead that the results are driven by fiercely competitive trading. For example, if alpha is limited in scale, then correlated order flow signals a reduced scale limit. Traders who observe that their strategy is correlated with that of other traders should modify their strategy to increase the scale of potential alpha and, thus, maximize the potential size of assets in this strategy. If traders are competitive in this way and modify their strategies in response to co-movement, we should expect declines in co-movement as algorithmic trading becomes more intense.

These results have a clear message for regulators and market operators: trading protocols and the regulatory playing field should further encourage competition among traders. Competition for returns and for liquidity provision appear to minimize co-movements, in addition to the known effects of competition on transaction costs and other measures of market quality.