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Effect of Co-location in the Johannesburg Securities Exchange (JSE)

Abstract

Co-location on the JSE took place on the 14th of May 2014. This dissertation looks at the impact this event has had on the market. In order to measure the effects of co-location, market quality factors are examined before and after the event to see whether there were any significant changes. A regression is then undertaken to see the correlation between co-location, liquidity and volatility. Our results suggest that co-location benefits market liquidity but we are unable to assess the relationship with volatility. This means that the growing liquidity in the market can be used to attract more institutions and firms wishing to run trading algorithms and strategies. Trades originally meant for dark pools can be now traded on the JSE co-location servers. By moving trades from dark pools to co-location servers at the JSE and encouraging institutions to use these facilities, transparency can be increased. Exchanges should implement kill switches if it is apparent that they are being impaired or flooded with erroneous orders. The deployment of kill switches, circuit breakers and other system compliance will improve investor confidence and market stability. Subsequent research can lead to better understanding by investigating the correlation between co-location and volatility.

Acknowledgements

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ACRONYMS

AltX	Alternative Exchange
ATS	Alternative Trading Systems
CAPEX	Capital Expenditure
CMRC	Capital Markets Cooperative Research Centre
DMA	Direct market access
EOD	End of day
ETF	Exchange Traded Fund
EMH	Efficient Markets Hypothesis
FINX	Financial Index traded on Johannesburg Securities Exchange
FSB	Financial Services Board
GDP	"Gross Domestic Product"
HFT	"High Frequency Trading"
HFTs	High Frequency Traders
IPO	Initial Public Offering
JSE	Johannesburg Securities Exchange
LSE	"London Stock Exchange"
OMX	Options Mäklarna Exchange
NASDAQ	"National Association of Securities Dealers Automated Quotations"
NYSE	"New York Stock Exchange"
SAIFM	South African Institute of Financial Markets

S&P 500	Standard and Poor’s tradable index
SPO	Secondary Public Offer
SPY	Instrument traded tracking the S&P 500 index
Top 40	Top 40 Index traded on Johannesburg Securities Exchange
USA	**“**United States of America”

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Chapter 1: Introduction

This paper examines a host of recent empirical and theoretical research on co-location so that policymakers, researchers, practitioners and other stakeholders can become familiar with the current state of knowledge and some of the outstanding economic issues associated with co-location. It then goes on to investigate whether the recent co-location in May 2014 has improved market quality.

Proximity to markets matters. Market movements are usually observed first by those closest to it. In the past such closeness to the market was gained by acquiring a seat on the exchange. These days, proximity involves subscribing to direct data connections and co-locating trading servers at the exchange. Co-location is when financial institutions are allowed to place their trading servers in the same data centers that house an exchange's computer servers (Brogaard et al., 2013). This is done for a certain fee charged by the respective exchange. A business might choose a co-location over building its own data center for several reasons. The main driver is the capital expenditures (CAPEX) associated with building, maintaining and updating a large computing facility. "Co-location raises issues related to competition between market members, equal access to the market, and the cost of such services, but the regulatory framework that governs these services is explicitly and carefully designed to minimize these issues" (Aitken et al., 2014). The JSE co-location facility allows customers to host their infrastructure in the same vicinity as the infrastructure that drives the markets. This will enable low latency trading strategies through high speed trading and market data access. The latency will be 100 microseconds compared to the existing 2400 microseconds for the surrounding Sandton area, an astounding 24 times faster (Johannesburg Stock Exchange: 2013). Latency is the time it takes for an order to travel from the computer server of a broker to the exchange's trading system and back. This will be the first co-location facility in Africa. Some exchanges that have co-located include NYSE Euronext, NASDAQ OMX and London Stock Exchange (LSE) among others. One of the advantages of co-location is greater latency. There is improved quick trading for all JSE markets. New trading strategies are also developed as a result of co-location. This is because potential execution probability is increased and there is enhanced response to market movement. Another advantage is cost saving which results from reduced cost of bandwidth for JSE clients as they no longer have to put up their own servers to increase speed. Lastly risk mitigation is a product of co-location. An example of this is reduced dependence on telecommunications service providers.

1.1 Johannesburg Securities Exchange

Exchanges are formal marketplaces where financial instruments are bought and sold. They are governed by law and the exchanges' rules and regulations. The advantages of an exchange relative to an over-the-counter market are lower credit risk, anonymity of trading parties, greater market regulation and higher market liquidity (Goodspeed: 2013). Generally equities are exchange traded. The JSE controls trading in South African equities. The exchange clearing house assumes the counterparty credit risk of all trading parties and trading parties generally remain anonymous (Goodspeed: 2013). The exchange has certain legal responsibilities towards the public at large, for example: ensuring an orderly market, distributing information, guaranteeing the transactions on the exchange, facilitating clearing and settlement of transactions and protecting the interests of investors (Goodspeed: 2013). In May 2014 the JSE installed co-location servers and this paper examines the effect this event has had on market quality i.e. liquidity and volatility. The JSE lists approximately 400 companies on its Main Board and Alternative Exchange (AltX) and is well known for its world-class regulation, its access to deep pools of capital and the high participation of foreign investors. Today, the JSE is one of the top 20 stock exchanges in terms of market capitalisation and considered to be a gateway to investing in quality listed African companies. The JSE currently acts as the frontline regulator, setting listings requirements and enforcing trading rules. The Financial Services Board (FSB) supervises the JSE in the commission of its regulatory duties and processes any cases where legislation has been contravened (Goodspeed: 2013). The FSB therefore oversees all trading that takes place on the exchange.

1.2 Effect of Technology on Financial Markets

The advancement of technology has resulted in co-location which has enabled High Frequency Trading (HFT) to take place. Before the advent of technology, most market makers were humans who were usually found on the trading floor of an exchange. Now computerized systems match buy and sell orders according to demand and supply. In the past people interested in purchasing securities would have to phone a broker or arrange to have a consultation. Now all prices are readily accessible and spreads are calculated on a per second basis according to factors such as risk and liquidity. It has given rise to high frequency Traders. "High frequency traders are professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on daily basis" (Securities Exchange Commission: 2010). High frequency traders (HFTs) use co-location services and individual data feeds offered by exchanges and others to minimize network and other types of latencies. HFT is often characterized by the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders. There are very short time-frames for establishing and liquidating positions which are also cancelled shortly after submission. Usually they end the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night). These firms make investments in computer hardware and refine their computer algorithms in order to minimize latency, make quicker trading decisions, and transmit the resulting order messages back to the trading venue. It is important for HFT to locate its computers close to trading venue servers to increase connection speed. Electronic trading venues offer space to HFTs in their data centers, and use of these co-location services is characteristic of HFT. Boehmer, Fong, and Wu (2012) examine international evidence on electronic message traffic and market quality across 39 stock exchanges from 2001-2009. They found that co-location increases algorithmic trading and high frequency trading. The introduction of co-location also improves liquidity and the informational efficiency of prices.

1.3 South African Context

The JSE rents space for servers at its primary site in Sandton. A JSE securities company, which is a JSE member, will rent the server space from JSE. Co-location will provide the fastest access to all JSE markets. Average round-trip co-location network latency will be no more than 100 microseconds. The JSE will measure, monitor and report on co-location network latency and provide this information to co-location customers (Johannesburg Stock Exchange: 2013). Hosting Units will be allocated on a first come first served basis within a limited capacity constraint in the co-location facility. Once the available hosting units in the co-location facility have been rented by customers, there will be no further opportunity for any additional units to be made available. All cables between the hosting units and the co-location network switches will be of equal length, irrespective of the position within the co-location facility. There will be facility environment monitoring which will be performed by the JSE all day (Johannesburg Stock Exchange: 2013). The JSE will provide a facility within the primary data centre which will enable telecommunication service providers to make their telecommunication services available to customers.

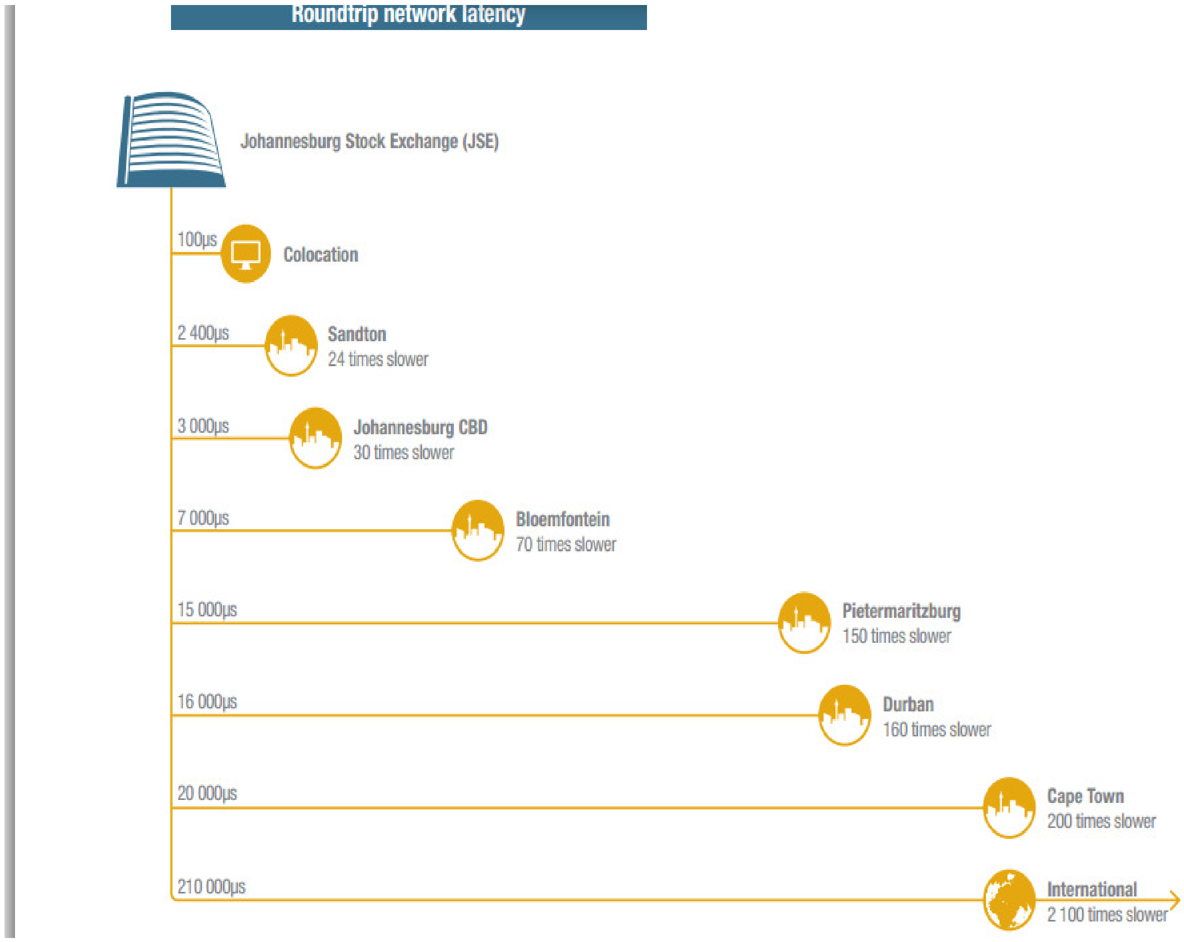


Figure 1.1 Roundtrip Network Latency of the JSE in 2013.

As noted by Jones (2014), the main reason for the JSE wanting to co-locate is that, “faster trading has measurable beneficial impacts on a variety of core market quality metrics including tighter spreads, increased liquidity and more efficient price formation, amongst others, for JSE clients.” The JSE's co-location centre levels the latency playing field for members especially those located geographically far away from the exchange. It has been built on lessons learnt from other markets such as NASDAQ OMX and London Stock Exchange (LSE) among others. It was clear to the JSE that in order to remain a world-class and relevant exchange in a highly competitive industry, it had to remain abreast of technological advances (Pickworth: 2013). Clients demand faster execution speeds and exchanges need to offer these in order to compete. Most of the demand for higher speeds was by United Kingdom (UK)-based firms, but local software providers and data vendors were also keen on the benefits of co-location, such as less bandwidth costs and reduced reliance on network service providers (Williams: 2014). Credit Suisse Securities Johannesburg, Fixnetix, Iress Financial Markets, Peregrine Equities and SunGard Financial Systems were among the first to sign up. The JSE makes money from the volume of transactions, so high frequency traders are good for business. Algorithms buy and sell faster than a blink, boosting overall trading volumes. Higher volumes, in turn, help attract investors, creating a virtuous circle that benefits the exchanges.

1.4 Crashes Caused by High Frequency Trading

Some of the times, the technology has had negative influences on the market and disrupted trading activities. The following are examples of crashes that have occurred.

1. Knight Capital Group

It is one of the largest market-makers in U.S. equities. Executes orders from retail investors as per arrangement, with many brokerage firms in the USA. On August 1, 2012, Knight Capital introduced a new trading algorithm that was implemented without sufficient testing (Kirilenko et al., 2014). The group incurred losses of $440 million as a result of the rogue algorithm

2. The Facebook IPO

NASDAQ had serious computer problems during the debut of Facebook shares. These problems appeared to be the result of computer software that was incapable of handling the pace of order submissions and cancellations by humans and computer algorithms. This cost investors and their broker-dealers tens of millions of dollars, of which NASDAQ is still sorting out compensation.

1.5 Events since Co-location

When the JSE launched its co-location centre in May 2014, it accounted for about 5% of equity activity. In October 2014, co-location activity had accounted for 18%-20% of the JSE’s equity trading. There was a record in the same month, with daily average volume reaching close to 400,000 (Jones: 2015). Stock transactions also rose 19 percent at the exchange in 2014. This shows that HFT has already had an impact on the equity market since co-location took place. This paper examines whether this increase in trading volume has in fact been beneficial to market quality factors such as volatility and liquidity.

Chapter 2: Empirical Literature on High Frequency Trading

2.1 Introduction

This chapter starts by explaining how a stock exchange works and the characteristics that make a good stock market. It then gives a brief description of the trading process. In order to critically understand high frequency trading it is important to first discuss the Microstructure of the Equity Market and Order-flow. The second section of the chapter explains these concepts. The final part of the chapter focuses on the literature regarding HFT and Co-location.

A stock exchange is defined as a place –physical or virtual –where buyers and sellers (the users or members of the exchange) can meet and trade under rules that are mandated by a regulator such as the Financial Services Board (FSB) in South Africa, the Securities Exchange Commission in the United States and the Financial Services Authority in the United Kingdom (Goodspeed: 2013). In general a good stock market should have timely and accurate price and volume information on past share transactions as well as prevailing supply and demand for shares. Liquidity should also be present. It is the degree to which a share can be quickly and cheaply turned into cash. Liquidity requires marketability, which is a share's ability to be sold quickly. Prices are not supposed to change from one transaction to another in the absence of substantial new information. A stock exchange must exhibit the ability to absorb large trade volumes without a significant impact on prices. In a good exchange, transaction costs as a percentage of the value of the trade are low and share prices adapt quickly to new information so that current market prices are fair in that they reflect all available information on the share. Co-location can only take place over an exchange and for this reason the research will focus on shares traded on an exchange. South Africa has one National Stock Exchange which is the Johannesburg Stock Exchange (JSE). Stock exchanges tend to be either order or quote-driven. In an *order-driven market,* buyers and sellers submit bid and ask prices of a particular share to a central location where the orders are matched by a broker. The JSE Ltd and most US securities exchanges are order-driven. In a *quote-driven* market, individual dealers act as market makers by buying and selling shares for themselves. NASDAQ is a quote-driven market.

Table 2.1: Characteristics of Johannesburg Stock Exchange

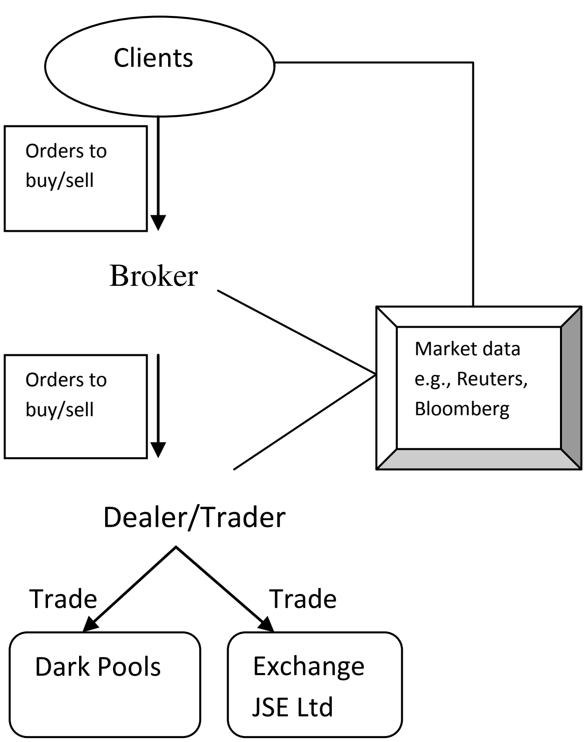
	South Africa
National exchange	Johannesburg Stock Exchange (JSE Ltd)
Turnover (%) (2011)	42.1
Listed companies	395
Market capitalization (USD billion end 2011)	789.1
Broad stock market index	FTSE/JSE All share index
Trading system	Order and quote driven
Trading methodology	Continuous

Source: World Federation of Exchanges, 2011 Annual Report

2.1.2 JSE Trading Process

Most trading in shares is intermediated by brokers, dealers or broker-dealers, which are members of the exchange and trade on behalf of their clients. The trading process is shown in figure 2.2 below.

Figure 2.2 Trading Process



The JSE has an automated trading system. Client orders are entered to the trading system by the clients' appointed JSE or broker members-dealers. The orders are stored by brokers in the central order book, which is anonymous so that JSE members do not know the identity of their counterparts.

2.2 Microstructure of Equity Market

Microstructure analysis is designed to yield insights into the effect of market design (structure and regulation) on market performance. "Equity market microstructure addresses issues that involve the placement and handling of orders in a securities market, and their translation into trades and transaction prices in a marketplace" (Brogaard: 2012). Microstructure models recognize that some information relevant to share prices is not publicly available. It recognizes that market participants differ in ways that affect prices and that trading mechanisms differ in ways that affect prices (Lyons: 2005). Microstructure studies have facilitated the development of trading strategies and algorithms for asset managers and broker/dealer intermediaries and this has been evident in the current development of computer driven algorithmic trading. Efficient Markets Hypothesis (EMH) was widely accepted by financial economists as a hallmark of modern portfolio theory. According to (Fama: 1991), "A market is informationally efficient if no participant is able to achieve excess risk adjusted returns by trading on currently available information." Many of the EMH tests have considered one major part of the information set – market information (e.g., recent quotes, trading volume, and transaction prices). If prices properly reflect all known information, then they must change randomly over time; hence the term "random walk" (Schwartz: 2004). Earlier studies, based on daily data, generally supported the random walk hypothesis. However, with the advent of records of all trades and quotes, correlation patterns have been detected. This observation, along with superior knowledge of the impact of trading costs on returns behavior, is casting a new light on market efficiency. Microstructure analysis sheds light on how new information is incorporated into security prices. In a zero cost environment, share values would be continuously and instantaneously updated with the release of new information. In actual markets, however, information must be received and assessed, traders' orders must be placed and processed, and executions must be delivered and accounts cleared and settled. Costs, both explicit (e.g., commissions) and implicit (e.g., market impact), are incurred throughout this chain of events. Highlighted in much microstructure literature are the costs that some participants incur when, in an asymmetric information environment, other participants receive information first and trade on it to the disadvantage of the uninformed. Asymmetric information is not the only reality, however. In light of the size, complexity, and imprecision of much publicly available information, one might expect that investors in possession of the same information set will form different expectations about future risk and return configurations (Schwartz: 2004). This situation is referred to as "divergent expectations." Asymmetric information and divergent expectations together reflect a rich set of forces that impact the dynamic behavior of security prices. Participant orders cannot be translated into trades at zero cost (markets are not perfectly liquid), and trades typically are not made at market clearing (i.e., equilibrium) prices. Trading decision rules (algorithms) are needed because the costs of implementing portfolio decisions can sharply lower portfolio performance (Hasbrouck: 2002). In fact, much algorithmic trading is designed to control trading costs, rather than to exploit profitable trading opportunities.

2.2.1Price discovery and Quantity Discovery

Price discovery refers to participants collectively searching for equilibrium prices and quantity discovery refers to the difficulty that participants who would be willing to trade with each other actually have finding each other and trading when markets are fragmented (Biondi: 2010). This difficulty is accentuated because some participants (primarily institutional investors) do not immediately reveal the total size of their orders (doing so would unduly drive up their market impact costs). The link between market structure and price discovery depends on the environment within which participants are operating. At one end of the spectrum, investors can be equally informed and form homogeneous expectations based on the information. At the other end, they can be differentially informed and form divergent expectations with regard to commonly shared information. "When investors are not equally informed, and when they form different expectations based on common information, prices must be discovered in the marketplace and the exchange provides this economic service" (Biondi: 2010).

Regarding quantity discovery, handling the orders of large institutional customers is a challenge. It is not at all uncommon for an institution to want to buy or to sell shares of a company that exceed the average daily trading volume. Executing an order of this size can easily drive prices away from the trader before the job has been completed. The adverse price move is a market impact cost. Institutions attempt to control their market impact costs by trading patiently and, as much as possible, invisibly. To this end, a number of alternative trading systems (ATSs) have been formed in recent years, and dark (i.e., non-transparent) liquidity pools have emerged. Trading is driven by informational change, liquidity needs, and noise trading and the information motive for trading is the first mover of the three. All participants in possession of the same information form equivalent expectations concerning future risk and return configurations. When information changes, however, participants may not all receive the news at the same time dividing traders into two groups – the informed and the uninformed. Informed participants will never trade with each other and consequently, liquidity and noise traders must be present for a market to function (Schwartz: 2004). The hallmark of the microstructure approach is order-flow. This will now be discussed in detail.

2.2.2 Order-flow

Order flow is transaction volume that is signed. Order-flow measures actual transactions, where each transaction is signed positively or negatively depending on whether the initiator of the transaction is buying or selling (Lyons: 2002). Order-flow conveys information about fundamentals because it contains the trades of those who analyse fundamentals. It gives the idea that prices go up when there are more buyers than sellers. In this sense, it is a transmission mechanism. For example; Fig 2.3, shows information processing has two stages. The first stage is the analysis or observation of fundamentals by non-dealer market participants (mutual funds, hedge funds, individuals with special information, etc.). The second stage is the dealer's interpretation of the first-stage analysis. The dealer's interpretation comes from reading the order-flow. Dealers then set price on the basis of this interpretation.

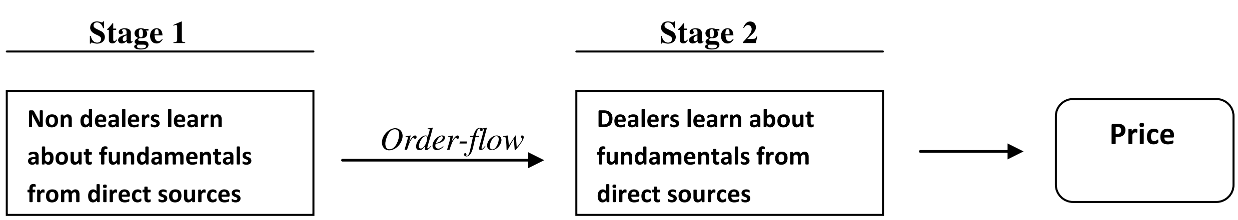


Figure 2.3 Two stages of information processing

The dealer's dependence on learning from order flow arises in these models because the information being learned is not publicly known. When information is publicly known, dealers do not need to learn from order flow. In practice, though some information relevant to shares is publicly known, some is not, so learning from order flow can be important. “Order-flow in equity markets is persistent in the sense that orders to buy tend to be followed by more orders to buy and orders to sell tend to be followed by more orders to sell” (Lyons: 2002). Positive serial autocorrelation of signed order-flow has been observed in many different markets. Positive autocorrelation was observed in the Paris Bourse by Biais, Hillion and Spatt (1995), in foreign exchange markets by Danielsson and Payne (2012), and in the NYSE by Ellul (2007). Two important concepts in order-flow are order splitting and order herding. Order splitting occurs when single investors split desired large trades into smaller pieces and execute them gradually. The strategic motivations for order splitting were originally derived by Kyle (1985), who showed that an informed trader with a monopoly on private information would trade gradually in order to reduce impact. Herding occurs when investors imitate others or act together in response to a signal such as a press release or price change. There are many strategic reasons why agents might herd, including reputational considerations, delayed response to public information or slow diffusion of private information (Zhang: 2012). Lee and Subrahmanyam (2004), studied daily autocorrelations in order-flow imbalances on the Taiwan Stock Exchange. They found that splitting and herding influence the observed persistent autocorrelation of order-flow to a great extent.

2.3 High Frequency Trading and Co-location

The beneficiaries from co-location appear to be a new breed of high frequency traders who implement low-latency strategies, which are strategies that respond to market events in the millisecond environment. While estimates vary due to the difficulty in ascertaining whether a trade is part of High frequency trading (HFT), recent estimates suggest HFT accounts for 50-70% of equity trades in the U.S., 40% in Canada and 35% in London (Chang, 2010; Grant, 2011; O’Reilly, 2012). HFT is usually characterized by a large number of orders with smaller order quantities and speedy cancellations that tend to have short position-holding periods with almost no overnight position. There are many potential benefits of HFT. The main positive is that HFT can intermediate trades at lower cost. Those lower costs from automation can be passed on to investors in the form of narrower bid-ask spreads and smaller commissions (Jones: 2013). It can help ensure that related assets remain consistently priced due to increased liquidity (Chaboud et al., 2009). It can also help traders cope with market fragmentation by fostering competition between trading mechanisms, including exchanges and other platforms. Brogaard (2010) finds that, rather than increasing stock volatility due to more frequent trading, HFT reduces stock volatility. Many HFT strategies are not new. They are simply familiar trading strategies updated for an automated environment. For example, many HFTs make markets using the same business model as traditional market-makers, but with lower costs due to automation. In fact, HFT market-makers have largely replaced human market makers. Other HFT strategies conduct cross-market arbitrage, such as ensuring that prices of the same share trading in both New York and London are the same. In the past, human traders would carry out this type of arbitrage, but the same trading strategy can now be implemented faster and at lower cost with computers (Jones: 2013).

“While HFT causes better market quality on average, some commentators have argued that HFT could make markets more fragile, increasing the possibility of extreme market moves and episodes of extreme illiquidity” (Kyle: 2011).The potential negative is that the speed of HFT could put other market participants at a disadvantage. The resulting adverse selection could reduce market quality. There is also the potential for an unproductive arms race among HFT firms racing to be fastest. Biais and Woolley (2011) also note the potential costs of HFT which includes manipulation in various ways, such as adverse selection and imperfect competition. Adverse selection can take place in the sense that non-HFT trades are slower and less well informed than HFT trades, thereby leading to a reduced market participation among the non-HFT traders (i.e., HFT trades impose a negative externality of adverse selection on non-HFT traders). Imperfect competition exists among HFT traders and non-HFT traders due to the large fixed costs of establishing high frequency trading. While the average effect of HFT on market quality is positive, there is substantial skewness in this kind of trading. This suggests that many firms either do not experience it or are subject to negative consequences. Several theoretical and empirical models analyse high frequency trading’s effects on market quality measures, including execution costs, liquidity, volatility and informational efficiency. While theoretical models mostly predict negative (or mixed) consequences of having fast traders in the market, the average effects estimated in empirical results tend to be positive.

High Frequency Trading Strategies

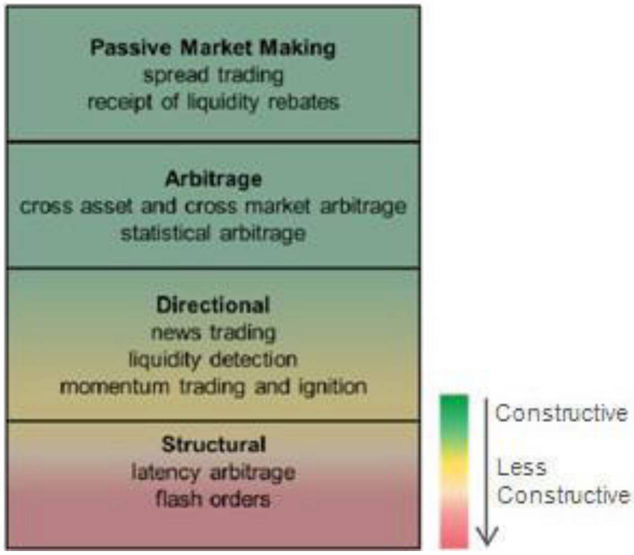


Figure 2.4 High Frequency Trading Strategies
Source: BlackRock

Market-makers: Market-makers simultaneously post limit orders on both sides of the electronic limit order book. They provide liquidity to market participants who want to trade immediately. Market-makers aim to buy at the bid price and sell at the ask price, thereby earning the bid-ask spread. They bear the risk that they trade with, and lose money to, an informed counterparty. Thus, they have an incentive to make sure that their limit orders to buy and sell incorporate as much current information as possible, so as to limit their losses to informed counterparties (Jones: 2013). HFT market-makers have largely replaced traditional human market-makers, in part because they are less likely to be picked off by an informed counterparty, and in part because the use of technology results in a lower cost structure for HFT market-makers.

Arbitrage trading: A classic example is index arbitrage. S&P 500 futures are traded in Chicago on the Chicago Mercantile Exchange, while SPY is the ticker symbol for the largest exchange-traded fund (ETF) that tracks the S&P 500 index. The two instruments are very similar, and their prices should move one-for-one. If the futures price goes up due to the arrival of buy orders, but the ETF price does not move up at the same instant, high frequency traders would quickly buy SPY, sell S&P 500 futures contracts, and lock in a small profit on the price differential between the two instruments. Naturally, these profit opportunities require rapid computer processing capability and the quickest possible link between the electronic market in Chicago and the electronic equity markets.

Directional trading: Some HFT firms electronically parse news releases, apply textual analysis, and trade on the inferred news. These news providers sell summary measures of the news to HFT firms, saving the firms from having to perform their own analysis and saving them precious milliseconds (Zhang: 2012). Other HFT firms trade based on order flow signals and momentum. For example, if a large buy order executes at the prevailing ask price, a HFT strategy might infer that the order submitter has substantial positive information. The high frequency trader might then respond by buying shares itself.

However, how much of the price formed constitutes the true value of a security? Is the price a true reflection of the company's fundamentals? It therefore becomes an empirical question to determine whether these high-frequency trading algorithms in the aggregate, harm or improve the market quality perceived by long-term investors.

2.3.1 Volatility

"Volatility is the degree of variation of a trading price series over time, as measured by the standard deviation of returns" (Goodspeed: 2013). Volatility is important to traders and issuers. Greater volatility makes limit orders more costly, and may discourage some traders from supplying liquidity. Certain types of volatility could be desirable. For example, prices change faster in response to new information, and volatility could be higher, when markets are more efficient. It is thus conceivable that the greater efficiency that is associated with more Algorithmic Trading also produces higher volatility. Co-location refers to locating a trader's order submission algorithm physically close to a trading center's computer. Given that Algorithmic Trading improves informational efficiency, it is plausible that the elevated volatility associated with more algorithmic trading reflects faster price adjustments to new information. In this case, the higher volatility could be desirable, because it reflects new information rather than noise. Brogaard (2010) came up with a HFT data set. He used a unique dataset from NASDAQ OMX that distinguishes HFT from non-HFT quotes and trades. The NASDAQ dataset consists of 26 traders that have been identified as engaging primarily in high frequency trading. His results showed that HFTs contribute more to price discovery and reduce volatility. Hasbrouck and Saar (2012) explored the nature and impact of low-latency (algorithmic) trading on the NASDAQ exchange during June 2007, a 'nominal' market period, and October 2008, a volatile, uncertain period. They identified periods of high market activity due to algorithms and relate these to longer-term market quality metrics such as spread, effective spread and depth of liquidity. They observe in both periods "that higher low-latency activity implies lower posted and effective spreads, greater depth, and lower short-term volatility." Zhang (2012) reports that there is a positive correlation between stock price volatility and HFT, being more distinctive when the markets are under stress, for example, when there are rapid volatility swings or unexpected price fluctuations. However, he did not rule out the possibility of a sudden and severe market condition in which high-frequency traders contribute to a market failure. The experience of the "flash crash" in May of 2010 demonstrates that such fragility is certainly possible when a few big players step aside and nobody remains to post limit orders. Co-location eventually leads to the impossibility of achieving equal access in financial markets. Avramovic (2012) released a follow-up report for Credit Suisse on the impact of HFT on market quality and found that bid-ask spreads declined and depth at the inside quote increased. She also looked at historical long-term and short-term (intraday) volatility and found that long-term volatility has remained within historical norms while short-term volatility has declined over recent years. The conclusion was that, with regard to high frequency traders, "markets are not worse for their presence". Chaboud et al. (2009) used a dataset that separately identified computer generated trades from human generated trades and showed that an increase in automated trading may be associated with less market volatility, and that automated traders tend to increase liquidity provision after exogenous market events such as macroeconomic data announcements.

2.3.2 Liquidity

Liquidity is an important, desirable feature of financial markets. Some researchers have raised the concern that the liquidity provided by HFTs may be illusory. "Since HFTs have no affirmative obligation to provide liquidity, their trading is opportunistic in nature, and the liquidity they create may disappear quickly when it is most needed on the market" (O'hara: 2011). For example, Kirilenko et al. (2014) documents that during the Flash Crash of May 6, 2010, many HFT traders withdrew from the market while others turned into liquidity demanders. Using data from Toronto Stock Exchange, Korajczyk and Murphy (2015) found that HFTs initially trade against institutional investors' large orders and quickly turn to competing with them by trading in the same direction later. They also report that HFTs reduce liquidity provision when institutional trades are too large. Initial expectation is that HFT facilitates the entry of additional liquidity suppliers thereby increasing competition. Hendershot et al. (2011) investigated the empirical relationship between high frequency trading and liquidity. They used a normalized measure of NYSE electronic message traffic as a proxy for HFT which included electronic order submissions, cancellations, and trade reports. It was found that for large-cap stocks, an increase in algorithmic liquidity supply narrows both the quoted and effective spread. The same increase in algorithmic trading had no great impact on small cap stocks. It could be the case that algorithms are less commonly used in these smaller stocks, so high frequency trading has little effect on these stocks' market quality. Jarnecic and Snape (2010) used data provided by the London Stock Exchange (LSE). The authors used a similar regression framework as Brogaard in order to isolate the impact of HFT on various market metrics. They found that HFT participants tend to provide liquidity when spreads are wide, demand liquidity when spreads are narrow, that they are more likely to "smooth" out liquidity over time and are unlikely to exacerbate stock price volatility. Lepone (2011) summarized the results of a series of research conducted by the Australian organization, Capital Markets Cooperative Research Centre (CMCRC). These papers examined the impact of HFT on market quality for exchanges based in Singapore, Australia, the United States of America and the United Kingdom. Their data allowed them to identify trading participants and classify them into HFT and non-HFT groups. Following a methodology similar to Brogaard (2010), each of these papers measured the impact of HFT on market quality metrics. The findings showed a consistent pattern of improved market quality coinciding with growing HFT participation. They also demonstrated that HFT is active during all volatility conditions and "become the primary providers of liquidity" in periods of high uncertainty. Riordan and Storkenmaier (2011) reported on how a 2007 upgrade to the Deutsche Bourse's Xetra trading system focused solely on latency reduction, positively affected market quality. After latency reductions in the exchange's trading systems, liquidity increased across market capitalization and trade sizes, and adverse selection and permanent price impact were dramatically reduced. Brogaard et al. (2013) showed that the optional speed upgrade at NASDAQ OMX in September 2012 was associated with improved liquidity and that the improvements benefited both fast and slow traders. Malinova, Park and Riodan (2013) also found that high frequency trading significantly lowers spreads and reduces trading costs for non HFT traders.

2.3.3 Price Manipulation less during HFT

The beneficial role of high frequency traders in price discovery is consistent with theoretical models of informed trading, e.g., Kyle (1985). In these models informed traders go against transitory pricing errors and trade in the direction of permanent price changes. HFTs predict price changes occurring a few seconds in the future. The short-lived nature of HFTs' information raises questions about whether the informational efficiency gains outweigh the direct and indirect adverse selection costs imposed on non-HFTs. Some institutional investors have expressed serious concerns that HFTs may adversely impact their trading profits. There is a view that high frequency traders are the modern-day version of market makers with highly engineered computer systems. If technology expedites the execution of trades and/or improves the efficiency of market making, HFT should benefit other market participants, including institutional investors. Some commentators have expressed concern that high frequency trading might increase the prevalence of market manipulation (Biasis and Woolley: 2011). High frequency trading, by virtue of the speed of entering orders and execution of transactions, has the potential scope for facilitating manipulation more easily in a number of ways. Firstly, HFT can be used to enter purchase orders at successively higher prices to create the appearance of active interest in a security, which is also termed as ramping/gouging. Another example is giving up priority, which refers to deleting orders on one side of the market as they approach priority and then entering the order again on the same side of the market. Cummings et al. (2012) directly examined the link between HFT and one very important and specific form of manipulation: end-of-day price dislocation using 'closing' or 'end-of-day' [EOD] prices. They examined closing price manipulation from 22 stock exchanges around the world from January 2003 – June 2011 and noted when there were unusual changes in market trading patterns over the period. Overall, their findings implied that High frequency trading makes it more difficult for market manipulators to manipulate EOD closing prices. Frino and Lepone (2012) looked at HFT trading on the LSE and Euronext Paris to study whether HFT participates in manipulative behavior. Using message traffic as a proxy for HFT, and using two different proxy measures for market manipulation, "Dislocation Price Alerts" and "Ticking", the authors found no link between HFT activity and market manipulation. Specifically, the authors found a negative relationship between HFT activity and Dislocation Price Alerts (implying that HFT actively reduces these events) and no statistical relationship between HFT activity and Ticking. If HFTs are indeed better informed due to their speed in processing information, there is also an upside, because their trading contributes to price discovery. Stock prices are more efficient because they reflect information more quickly, and this can be valuable to all investors. For example, as discussed earlier index arbitrage activity by HFT ensures that the price of a basket of stocks reflects the prices of the underlying stocks. An investor who wants to hold a broad market index such as the S&P 500 can purchase SPY (the biggest ETF that tracks the S&P 500) secure in the knowledge that the price of the ETF closely reflects the trading price of the underlying stocks. This suggests that the price discovery due to HFT and other arbitrageurs is quite valuable to investors. End of day price manipulation is not as pronounced under HFT as current regulatory concerns might suggest. This is counter to recent concerns expressed in the media. However this does not rule out the fact that HFT can lead to other forms of manipulation.

2.3.4 Systematic Return Risk and Liquidity Risk

There is scarce evidence on HFT's direct effect on systematic risk which is the non diversifiable part of every stock's total risk. Laube and Malcenieks (2013) were the first to examine this relationship. They investigated whether during the time period of 2007-2009, European equity markets experienced a change in systematic risk due to high frequency trading activity, which was measured by looking at the change in commonality in stock returns (systematic return risk) and commonality in liquidity (systematic liquidity risk). High frequency traders contribute to systematic risk. When High Frequency Traders operate in high volumes, non-high frequency traders may misinterpret these signals, and this can cause speculative trading. Also market overreaction to news can take place when HFTs are actively participating. Trading algorithms also have a possibility to contain small errors, which can lead to chaos in the market. Donefer et al. (2011) carried out a regression on a sample of stocks from different exchanges. The results from their regression for the whole sample suggested that an increase in HFT leads to a rise in both commonality in stock returns and liquidity. Their conclusion showed that countries that displayed the highest commonality in returns were also among those with the greatest commonality in liquidity (Sweden, UK, Germany, Spain, and France), confirming that most active markets with co-location facilities have higher systematic return and liquidity risk.

“Based on the vast majority of the empirical work to date, HFT, automated trading and competing trading venues have substantially improved market liquidity and reduced trading costs for all investors” (Jones: 2013). Share prices are almost surely higher as a result of this reduction in trading costs, benefiting long-term investors. Higher share prices also have favorable implications for firms’ cost of equity capital. With a lower cost of capital, firms are likely to invest more, with likely increases in the gross domestic product (GDP) and other measures of economic activity. In specific terms, HFT has sharply increased competition in market making, and bid-ask spreads are much narrower as a result. Stock prices are more efficient as a result of HFT activity. Overall, there is no evidence of any adverse effect due to HFT in the average results. Perhaps the only concern supported by the data is that HFT may not help to stabilize prices during unusually volatile periods.

Chapter 3: Empirical Evidence on Co-location in the JSE

3.1 Introduction

This chapter analyses the effect co-location has had on the JSE since the launch of the co-location facility on May 14 2014. The first section in this chapter tries to identify the impact of co-location on the JSE Equity Market by comparing the change in volatility, before and after co-location, in the three main indices which are the All Share Index, Top 40 Index (Top 40) and Financial Index (FINX). Price data is taken from Bloomberg over the period November 2013 to May 2015. Summary statistics are then depicted before and after co-location to test whether volatility actually increased. The second section identifies the impact co-location has had on liquidity. Data is taken monthly from the JSE Market statistics and statistical summary statistics are undertaken in Gretl using one lag difference. The third section identifies factors affecting co-location trades which are liquidity, volatility, interest rate and exchange rate. A regression is then run to see the correlation between co-location trades and each of those factors. Lastly the significant variables are then taken as the dependent variables and a regression is done to determine effect of co-location trades on the significant variables.

Other empirical studies which have been done include Hagströmer and Norden (2012), who used data from NASDAQ-OMX Stockholm containing a sample of 120 randomly selected stocks from 2008 to 2009. It was found that HFT's are responsible for roughly 42% of trading volume in large stocks and 18% in small stocks. These numbers show that HFT is concentrated in large liquid stocks and less in small less liquid stocks. One reason is that HFTs value the ability to exit positions quickly, making more frequently traded stocks more attractive. Another reason might be narrower bid-ask spreads in large stocks facilitating liquidity. In this paper co-location is regarded as the event that infers high frequency trading, as is the case with similar studies on the topic .Volatility is tested only on the large liquid stocks which make up the three main indices. In this case the co-location go live date is 14 May 2014.

3.2 Volatility

"Volatility is the degree of variation of a trading price series over time, as measured by the standard deviation of returns" (Goodspeed: 2013). Simply, volatility is the up-and-down movement of the market. Volatility obtained before co-location is compared to volatility after co-location in order to compare the two periods. Co-location is associated with high frequency trading which can lead to great price volatility. By comparing the volatility before and after, we are able to see whether there was a significant change in the volatility rather than taking it all as one period. The descriptive statistics show the mean, median, minimum and maximum values, and the standard deviation values just to name a few. Volatility is important for market participants and regulators. Market tends to fluctuate more and by a larger extent during more volatile periods. In general normal traders base their strategies on buying the stocks of fundamentally strong companies. Higher volatility means more risks because prices are unstable. This risk causes market makers to widen their bid/ask spreads, increasing the cost of trading for both institutional and retail traders whose risk management techniques will need to be adjusted based on changes in volatility (Brogaard: 2013). However some short term traders prefer volatility because it presents them with more profitable opportunities. For high frequency traders, some trading algorithms work only with low volatility while others need high volatility. Regulators and the government will prefer volatility on the exchange to be low because the market will be more stable and this attracts more investors. It is important to understand how volatility reacts to co-location because it is a factor that will have a large effect on the rest of the market.

Using Gretl statistical software, summary statistics before co-location are obtained for the three main indices which are All Share Index, Top 40 Index and Financial Index. The volatility is obtained from the standard deviation value in the summary statistics table. Volatility before co-location for the All Share Index, Top 40 and FINX respectively is 0.0069, 0.0075 and 0.0075 respectively. The average volatility is thus 0.0073.

Table 3.1 Before Co-location
Summary Statistics, using the observations 2013-11-04 - 2014-05-11 [Closing Prices]

Variable	Mean	Median	Minimum	Maximum
ld_All Share	0.0007	0.0008	-0.0270	0.0181
ld_TOP_40_	0.0008	0.0013	-0.0297	0.0199
ld_FINX	-0.0011	-0.0007	-0.0252	0.0241
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
ld_All Share	**0.0069**	9.6859	-0.4961	0.7410
ld_TOP_40_	**0.0075**	10.0411	-0.5136	0.8302
ld_FINX	**0.0075**	6.7053	-0.0304	0.9896
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
ld_All Share	-0.0107	0.0111	0.0097	1
ld_TOP_40_	-0.0119	0.0119	0.0104	1
ld_FINX	-0.0138	0.0117	0.0092	1

Table 3.2 After Co-location
Summary Statistics, using the observations 2014-05-14- 2015-11-05 [Closing Prices]

Variable	Mean	Median	Minimum	Maximum
ld_All Share	-0.0003	-0.0014	-0.0219	0.0316
ld_TOP40	-0.0005	-0.0014	-0.0236	0.0354
ld_FINX	-0.0004	-0.0007	-0.0197	0.0216
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
ld_All Share	**0.0087**	26.8416	0.4479	1.5412
ld_TOP40	**0.0096**	19.2954	0.5289	1.5734
ld_FINX	**0.0089**	21.1835	0.2594	-0.1376
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
ld_All Share	-0.0143	0.0168	0.0106	1
ld_TOP40	-0.0168	0.0179	0.0119	1
ld_FINX	-0.0145	0.0166	0.0118	1

After co-location during the period from May 2014 to May 2015, volatility for the All Share Index, Top 40 and FINX respectively is 0.0088, 0.0096 and 0.0089 respectively. The average volatility increases from 0.0073 to 0.0091. For all indices there is an increase with the biggest change coming in the Top 40 Index. Hasbrouck and Saar (2012) utilized publicly-available

NASDAQ order level data and developed measures that allowed them to characterize the influence of high frequency trading on liquidity and short-term volatility .They found HFT was negatively correlated with short-term volatility, meaning volatility decreased with an increase in HFT which was positive for the markets. Brogaard (2010) in his study also found that intraday volatility was significantly reduced. Groth (2011) found that HFT does not significantly increase volatility. In our case the volatility has increased which is bad for the market. This is in contrast to most empirical studies which have shown the opposite effect. One reason might be that HFT traders are not yet fully present in the market to bring about the changes experienced in other markets. Secondly, other exchanges such as NYSE, LSE etc are more developed. The last reason might be that there is no real correlation between volatility and high frequency trading. Chaboud, Chiquoine, Hjalmarsson, and Vega (2009) in their study found no casual relationship between HFT and volatility.

3.3 Liquidity

"Liquidity describes the degree to which an asset or security can be quickly bought or sold in the market without affecting the asset's price" (Goodspeed: 2013). If an exchange has a high volume of trade the price a buyer offers per share (the bid price) and the price the seller is willing to accept (the ask price) will be fairly close to each other. Investors, then, will not have to give up unrealized gains for a quick sale. When the spread between the bid and ask prices grows, the market becomes more illiquid. Liquidity data is obtained monthly from the JSE Market statistics. In our study, liquidity obtained before co-location is compared to liquidity after co-location in order to compare the two periods. Co-location is associated with high frequency trading which can lead to greater liquidity as a result of the HFTs acting as market makers. By comparing the liquidity before and after, we are able to see whether there was a significant change in the liquidity rather than taking it all as one period. Liquidity is important for market participants and regulators. The liquidity and corporate finance literature provides abundant evidence that liquidity is beneficial in many corporate settings. "It facilitates the entrance of informed traders, enhances the effectiveness of equity-based compensation to managers, reduces the cost of equity financing, mitigates trading frictions investors encounter when trading and lowers the immediate transaction costs for firms conducting large share repurchases" (Brogaard: 2013). High liquidity makes it easier for traders and companies to sell shares easily. The market will also be more attractive to investors who will know they can easily leave the market when things go south or when they have made profit. Regulators will want an environment where liquidity is high so that transactions can easily be conducted. A bad situation is one where the share price rarely moves and there are few buyers and sellers. This will mean the price can be manipulated with large orders by traders who want to move the share price in a specific direction. It is important to understand how liquidity is affected by co-location because other potential investors and companies might want to invest on the JSE and they will want to know how easily they can close out their positions on the market.

Summary statistics were obtained from Gretl before and after co-location to assess impact of co-location.

Table 3.3 Before Co-location

Summary Statistics, using the observations Nov-2013–May 2014 [Monthly Liquidity]

Variable	Mean	Median	Minimum	Maximum
Liquidity	0.0029	0.0027	-0.2403	0.03338
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
Liquidity	0.2239	76.0105	0.4474	-0.9848
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
Liquidity	undefined	undefined	0.4055	0

The mean liquidity before co-location was 0.0029 using first log difference.

Table 3.4 After Co-location

Summary Statistics, using the observations May 2014– May 2015 [Monthly Liquidity]

Variable	Mean	Median	Minimum	Maximum
Liquidity	0.0171	-0.0457	-0.3380	0.4727
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
Liquidity	0.2058	12.0186	0.8039	0.7325
Variable	**5% Perc.**	**95% Perc.**	**IQ range**	**Missing obs.**
Liquidity	undefined	undefined	0.1183	0

After co-location the mean liquidity increased to 0.0171 using first log difference. Hendershot et al. (2011) investigated the empirical relationship between HFT and liquidity. They developed a time-series evolution of HFT and liquidity for a sample of NYSE stocks over the five years from

February 2001 through December 2005.It was found that for large-cap stocks, an increase in algorithmic trading narrows both the quoted and effective spread by 0.53 basis points and had no great impact on small cap stocks. This means high frequency trading was positively correlated with liquidity. Brogaard et al. (2013) showed that the optional speed upgrade at NASDAQ OMX in September 2012 was associated with improved liquidity and that the improvements benefited both fast and slow traders. This study closely resembles that paper as they also used an event to incur high frequency trading and the result in this paper of increased liquidity is similar to Brogaard and other empirical studies done. This is good news for traders and regulators as it means shares can be bought and sold more easily. Malinova, Park and Riodan (2013) found that HFT significantly lowers spreads and reduces trading costs for non HFT traders. The increase in liquidity in our study should be taken as positive for the JSE market.

3.4 Regression

In order to see the effect of co-location we run a regression to see whether co-location is correlated with liquidity and volatility. There are two other factors identified which can also impact co-location which are the interest rate and exchange rate. Lastly a dummy variable is included in the regression to see the effects of the policy changes which were in the form of interest rate rises by the central bank between July 2014 and November 2015. Volatility is calculated from the JSE Top 40 Index. This is because as stated before, HFT is concentrated in large liquid stocks and less in small less liquid stocks. The Top 40 Index represents the 40 largest companies by capitalization and I believe these are the stocks mostly affected by co-location. Daily closing prices and returns for the Top 40 Index are taken from July 2014 to November 2015 and the prices and returns are used to compute the standard deviation. This is then multiplied by the square root of the number of trading days in that month to obtain the monthly standardized volatility. The log differences of Trades, liquidity and volatility are obtained from Gretl and we see from the diagram below that Trades and liquidity seem to be closely related.

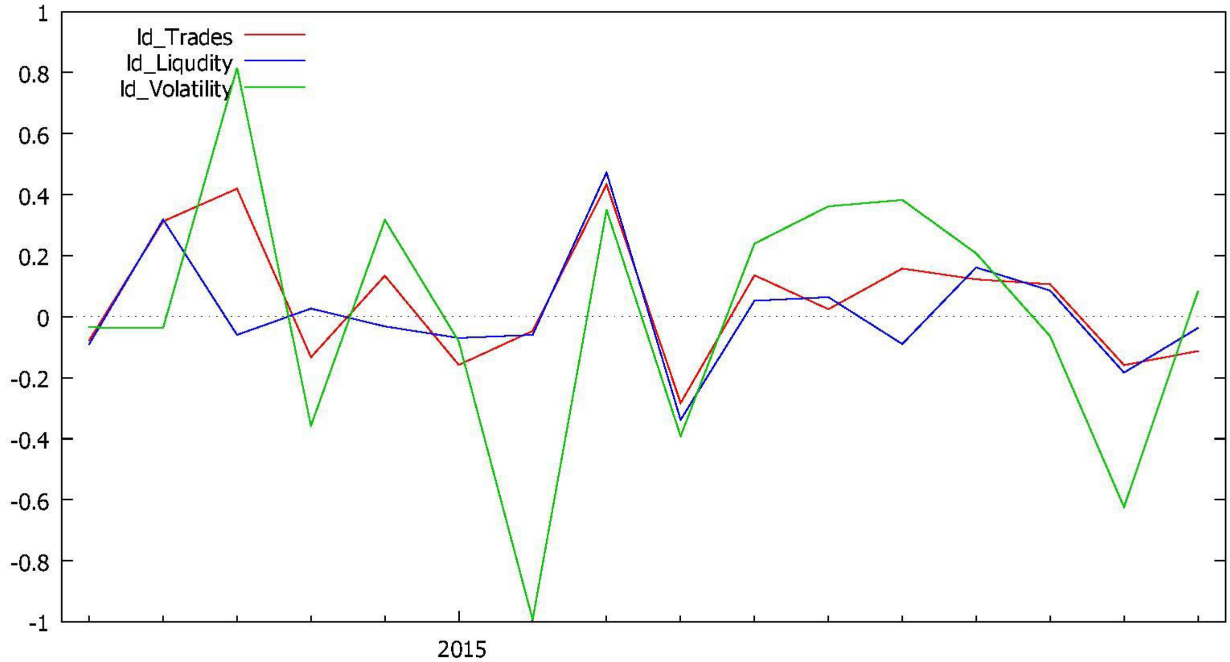


Fig 3.1 Log differences of Trades, liquidity and volatility. Courtesy of Gretl.

The log differences of the other two factors which are interest rate and exchange rate are obtained and we see from the diagram below that trades and the exchange rate seem to be closely correlated. Interest rate was constant throughout much of 2014 but we see that after the rate hike in July 2015, trades went down and only started to rise in October 2015.

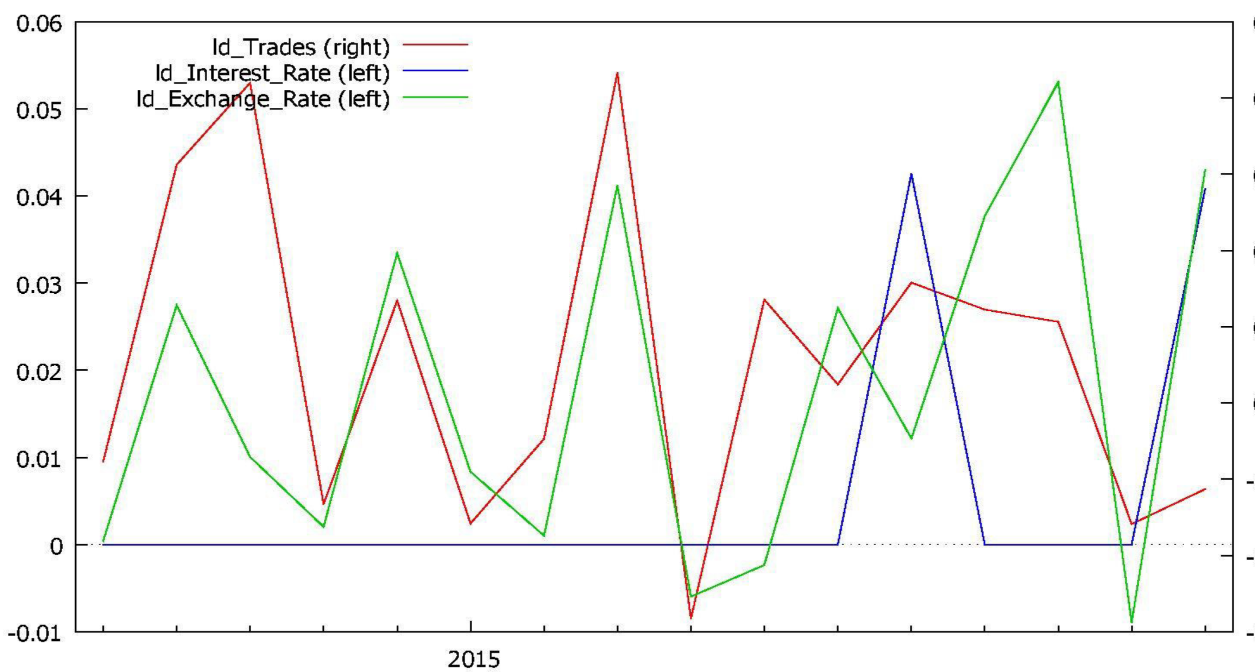


Fig 3.2 Log differences of Trades, Interest Rate and Exchange Rate. Courtesy of Gretl.

3.4.1 Results of Regression

Table 3.5 Results of Regression

Summary Statistics: 2014:07-2015:11 (T = 17) Dependent variable: Trades

	Coefficient	Std. Error	t-ratio	p-value	
const	889990	4.92645e+06	0.1807	0.85992	
Liquidity	3.88797e+06	1.33069e+06	2.9218	0.01389	**
Volatility	1.13722e+07	3.18187e+06	3.5741	0.00436	***
Interest_Rate	-1.39228e+08	1.10786e+08	-1.2567	0.23488	
Exchange_Rate	630642	155863	4.0461	0.00193	***
DummyPolicyChange	61277.7	203758	0.3007	0.76922	

Mean dependent var	2416334	S.D. dependent var	755432.0
Sum squared resid	5.08e+11	S.E. of regression	214855.5
R-squared	0.944387	Adjusted R-squared	0.919109
F(5, 11)	37.35921	P-value(F)	1.54e-06
Log-likelihood	-229.1430	Akaike criterion	470.2860
Schwarz criterion	475.2853	Hannan-Quinn	470.7830
rho	-0.396281	Durbin-Watson	2.531399

If we wanted to predict the number of co-location trades we would use the equation:

Trades = 889990 + **(3.88797e+06*Liquidity) + (1.13722e+07*Volatility) + (-1.39228e+08*Interest Rate) + (630642 * Exchange_Rate)**

Statistical significance is very important. This is shown by the stars or asterisks to the far right for each variable. Three stars is the "best", two is "good", and one is just "okay". If there are no stars, the variable is said to be insignificant. These stars/asterisks are based on the number in the column titled "p-value". This is the probability value for the statistical test. A p-value of 1% (0.01) or lower gives three stars, a p-value greater than 1% (0.01) but less than 5% (0.05)gives two stars, and a p-value greater than 5% (0.05) but less than 10% (0.10) gives one star. If the p-value is higher than 10% (0.10) the variable is said to be "insignificant". We see that interest rate and DummyPolicyChange are the only insignificant variables. Volatility and exchange rate are the most significant, with liquidity lower but still giving a good significance. As stated earlier in the chapter, it is unclear whether volatility is positively or negatively correlated with co-location trades. This is because some strategies require high volatility while others will work with low volatility. From Fig 3.1 we can clearly see that volatility tends to have its own path. The exchange rate is positively related to co-location trades. The higher nominal exchange rate means that foreign currencies will appreciate in relation to the rand and this will mean investors will find it cheaper to invest in shares. Lastly liquidity is positively related with co-location trades because investors and traders find high liquidity more attractive. It is easier to buy and sell and strategies can be implemented at lower costs.

The R-squared tells us how good the model is at fitting the data. In this case it is high at 0.94439. This means that liquidity, volatility, exchange rate, interest rate and the dummy variable predicts about 94.4% of the variation in the number of trades. Now we want to know individually, how the co-location trades affect liquidity and volatility. To do this we run a regression of co-location trades with liquidity and volatility with the dependent variables being liquidity and volatility respectively.

3.4.2 Liquidity Regression Results

Table 3.6 Liquidity Regression Results

Summary Statistics: 2014:07-2015:11 (T = 17) Dependent variable: Liquidity

	Coefficient	Std. Error	t-ratio	p-value	
const	0.240871	0.031137	7.7359	<0.00001	***
Trades	6.17169e-08	1.23313e-08	5.0049	0.00016	**

Mean dependent var	0.390000	S.D. dependent var	0.058952
Sum squared resid	0.020827	S.E. of regression	0.037262
R-squared	0.625457	Adjusted R-squared	0.600488
F(1, 15)	25.04886	P-value(F)	0.000157
Log-likelihood	32.86823	Akaike criterion	-61.73646
Schwarz criterion	-60.07003	Hannan-Quinn	-61.57081
rho	-0.281927	Durbin-Watson	2.509583

The regression results show that the R-squared is 0.62547. This means that co-location trades predict about 62.5% of the variation in liquidity. The p-value also shows us that co-location variable is significant. Now linking the first part of the chapter which showed that after co-location the mean liquidity increased to 0.0171, this shows that there is a relatively strong link between co-location trades and overall liquidity. The regression has shown that co-location does in fact affect overall liquidity. The reason why co-location might increase liquidity is because the high frequency trading involved in co-location has been shown to decrease spreads and improve price discovery. Riodan (2011) found that higher system speeds led to increased liquidity and improved price discovery. Hendershot (2012) found that that the increase in automated trading caused a reduction in effective spreads, thereby reducing costs to investors. As stated in the first part of the chapter, the increase in liquidity in our study should be taken as positive for the JSE market and the regression has shown that the relationship between co-location trades and liquidity is significant.

3.4.3 Volatility Regression Results

Table 3.7 Volatility Regression Results

Summary Statistics: 2014:07-2015:11 (T = 17) Dependent variable: Volatility

	Coefficient	Std. Error	t-ratio	p-value	
const	0.0212778	0.0148068	1.4370	0.17124	
Trades	1.14959e-08	5.86401e-09	1.9604	0.06879	*

Mean dependent var	0.049056	S.D. dependent var	0.019230
Sum squared resid	0.004710	S.E. of regression	0.017719
R-squared	0.203959	Adjusted R-squared	0.150890
F(1, 15)	3.843260	P-value(F)	0.068791
Log-likelihood	45.50450	Akaike criterion	-87.00899
Schwarz criterion	-85.34257	Hannan-Quinn	-86.84335
rho	0.471794	Durbin-Watson	1.054597

The regression results show that the R-squared is 0.203959. This means that co-location trades predict about 20.4% of the variation in volatility. The p-value also shows us that the co-location trades variable is significant although at a low level. Now linking the first part of the chapter which showed that after co-location the volatility increased to 0.0091, this shows that there is a weak link between co-location trades and volatility. The regression has shown that co-location trades do not affect overall volatility to a large extent. This is in line with other studies that have found no strong relationship between HFT and volatility. Hendershot (2009) found that automated trades made prices more efficient but did not contribute to higher volatility. Janeric (2010) stated that HFT improved liquidity and was unlikely to increase volatility. The tests and regression has shown that it is difficult to infer the effect of co-location trades on volatility.

Chapter 4: Implications of Study

4.1 Introduction

This dissertation examined a host of recent empirical and theoretical research on co-location so that policymakers, researchers, practitioners and other stakeholders can become familiar with the current state of knowledge and some of the outstanding economic issues associated with co-location.

In this concluding chapter, I start by highlighting briefly what each of the previous chapters covered. Chapter 1 introduced the issue of co-location and set the tone for the rest of the study by explaining high frequency trading and the main issues in the study. Chapter 2 formed the heart of the study and focused on explaining the microstructure of the equity market. It then gave a literature review on the topic of co-location and high frequency trading. In the process, issues like volatility and liquidity were discussed. Chapter 3 gives the findings of tests before and after co-location and shows the contrasts and differences with previous empirical studies. Regression analysis is then undertaken to determine effect of co-location on market quality.

The rest of the chapter focuses on presenting findings and stating the implications of the study. I present my findings on the JSE since this is the main contribution of the study and explain how it will affect market participants. The issue of co-location is important to market participants and regulators because it will change some market quality factors such as liquidity and volatility.

4.2 Overview of Previous Chapters

Chapter 1 introduced the reader to co-location. It gives a description of the JSE, discusses the effect technology has had on the markets and gives a South African context .Lastly it talks about the crashes that have occurred "supposedly" because of high frequency trading. Co-location is when financial institutions are allowed to place their trading servers in the same data centers that house an exchange's computer servers (Brogaard et al., 2013). The advancement of technology has resulted in co-location which has enabled HFT to take place. Before the advent of technology, most market makers were humans who were usually found on the trading floor of an exchange. It was clear to the JSE that in order to remain a world-class and relevant exchange in a highly competitive industry, it had to remain abreast of technological advances (Pickworth: 2013). Clients demand faster execution speeds and exchanges need to offer these in order to compete. However it has been claimed that there are some disadvantages associated with high frequency trading and it has been linked to some crashes such as the Knight Capital and Facebook IPO crash.

Chapter 2 presented a literature review on the topic of co-location and high frequency trading. It also gave a microstructure of the equity market that explains key concepts such as order-flow. Equity market microstructure addresses issues that involve the placement and handling of orders in a securities market, and their translation into trades and transaction prices in a marketplace (Brogard: 2012). Order-flow forms a part of this, and conveys information about fundamentals because it contains the trades of those who analyse fundamentals. In this sense, it is a transmission mechanism and lays the basis for understanding how the market works. The literature review given is quite extensive on empirical studies which have been done to show effect of co-location and high frequency trading on the market.

Finally, Chapter 3 conducted empirical analysis on the effect of co-location on the JSE and also ran a regression to determine the effect of different factors on co-location. The volatility before was compared to the volatility after co-location and it was found that the average volatility had increased. In addition to volatility, the liquidity was compared for the two periods showing that it had increased after co-location. Interest rates and the exchange rate were also identified as having an impact on co-location and a regression was run to see how much these two factors were correlated to co-location. Co-location trades obtained from the JSE were taken as the dependent variable and volatility, liquidity, interest rates and exchange rate were the regressors. A dummy variable was also included in the regression to see the effects of the policy changes which were in the form of interest rate rises by the central bank between July 2014 and November 2015. Interest rate and DummyPolicyChange were found to be the only insignificant variables. Volatility and exchange rate were the most significant variables affecting co-location trades, with liquidity lower but still giving a good significance.

4.3 Findings

This section discusses the findings from the empirical tests done in Gretl before and after co-location as well as the regression analysis, all done in Chapter 3. Findings are divided into two parts. The first section presents the findings on the factors affecting co-location and how significant the test results were. The second section discusses the results of the regression analysis done to determine effect of co-location on liquidity and volatility.

4.3.1 Factors Affecting Co-location

Chapter 3 gave great insight into the factors affecting co-location and was useful in determining whether co-location improves market quality factors such as volatility and liquidity. The factors which affect co-location trades are exchange rate, interest rate, volatility and liquidity. In the empirical analysis, it was found that the interest rate is insignificant. The most significant variables were the exchange rate, volatility and liquidity (in that order). From the results of empirical analysis, if we wanted to predict the number of co-location trades we would use the equation:

Trades = 889990 + **(3.88797e+06*Liquidity) + (1.13722e+07*Volatility) + (-1.39228e+08*Interest Rate) + (630642 * Exchange_Rate)**

The exchange rate is positively related to co-location trades. The higher nominal exchange rate means that other foreign currencies will appreciate in relation to the rand and this will mean investors will find it cheaper to invest in shares. Mao and Ka (1990), found that an appreciation in the currency of export-dominant economies tends to negatively influence the domestic stock markets of those economies. Traders are aware of the factors affecting the rand and whether they are the result of short-term sentiment or longer-term structural factors. The latter will result in a drastic decline in both direct investment as well as portfolio Investment. This will most likely cause the JSE shares to fall and reduce overall trades.

It is unclear whether volatility is positively or negatively correlated with co-location trades. This is because some strategies require high volatility while others will work with low volatility. There is a strong relationship between volatility and market performance. Volatility tends to decline as the stock market rises and increase as the stock market falls. When volatility increases, risk increases and returns decrease. In a 2011 report, Crestmont Research examined the historical relationship between stock market performance and the volatility of the market. Their research tells us that higher volatility corresponds to a higher probability of a declining market. Lower volatility corresponds to a higher probability of a rising market. This means that high frequency programmers will take this into account when buying and selling stocks. The higher level of volatility that comes with bear markets has a direct impact on portfolios (Kirilenko et al., 2011). At the same time that some portfolios will be falling in value, high frequency traders will be taking advantage of this high volatility to short sell shares and benefit from the large drops.

Liquidity is positively related with co-location trades because investors and traders find high liquidity more attractive. It is easier to buy and sell and strategies can be implemented at lower costs. Liquidity is characterized by a high level of trading activity and small spreads between the bid and offer price. This means that during periods of high liquidity, high frequency traders will be more keen to place their trades because it is cheaper .It also reduces the probability of a liquidity risk should they wish to exit the position earlier than expected. Liquidity risk induces investors to trade fewer times and submit larger quantities in early periods. If liquidity is low it may be advantageous to postpone orders to see whether liquidity improves. This is why during period s of low liquidity, trades are less.

4.3.2 Effect of Co-location on Liquidity and Volatility

In order to know how co-location trades affect liquidity we ran a regression of co-location trades with liquidity. The regression showed that co-location does in fact affect overall liquidity and predicts about 62.5% of the variation in liquidity. The reason why co-location might increase liquidity is because the high frequency trading involved in co-location has been shown to decrease spreads and improve price discovery. Empirical analysis in Gretl also showed that liquidity increased in the pre to post co-location period. The increase in liquidity in our study should be taken as positive for the JSE market. As mentioned in Chapter 3, liquidity has a lot of advantages for the market participants. It facilitates the entrance of informed traders, enhances the effectiveness of equity-based compensation to managers, reduces the cost of equity financing, mitigates trading frictions investors encounter when trading and lowers the immediate transaction costs for firms conducting large share repurchases (Brogaard: 2013). Our results are in line with previous papers like Malinova, Park and Riodan (2013), who found that HFT significantly lowers spreads and reduces trading costs for non HFT traders.

In order to know how co-location trades affect volatility we ran a regression of co-location trades with volatility. The regression showed that there is a weak link with co-location trades predicting only about 20.4% of the variation in volatility. Gretl empirical tests saw volatility increase after co-location compared to the period before. The tests and regression has shown that it is difficult to infer the effect of co-location trades on volatility. This is in line with other studies that have found no strong relationship between HFT and volatility. Hendershot (2009) found that automated trades made prices more efficient but did not contribute to higher volatility. Chiquoine, Hjalmarsson, and Vega (2009) in their study found no casual relationship between high frequency trading and volatility. Volatility is important for market participants and regulators. Market tends to fluctuate more and by a larger extent during more volatile periods. Overall volatility will rise when traders are concerned about risk or are becoming very fearful. Conversely, volatility will fall when investors are very confident or bullish. This matters to traders because an increase in volatility causes a rise in options. Unfortunately the empirical analysis was unable to establish a link between volatility and co-location. This means that at the end of this paper we are still unsure on the impact of co-location on volatility.

4.4 Implications of Study

As stated in chapter 1, the JSE makes money from the volume of transactions, so high frequency traders are good for business. Higher volumes, in turn, help attract investors, creating a virtuous circle that benefits the exchanges. The results have shown that liquidity is now higher than before co-location. This means that the growing liquidity in the market can be used to attract more institutions and firms wishing to run trading algorithms and strategies. Dark pools are a term for private exchanges or forums for trading securities. Unlike stock exchanges, dark pools are not accessible by the investing public. Dark pools are present in the South African financial market. They are intended to help asset managers trade large blocks of shares without moving the market against them but exhibit a lack of transparency. “Dark pools are an invaluable execution tool for large orders and stocks which may be more difficult to trade due to wide spreads or low liquidity” (Goodspeed: 2013). Trades originally meant for dark pools can be now traded on the JSE co-location servers. By moving trades from dark pools to co-location servers at the JSE and encouraging institutions to use these facilities, transparency can be increased. Trades will be executed at fast speeds to reduce the risk of market price moving against the firm. It will also be an added advantage because liquidity in dark pools is usually low. Regulators in the USA have won about $150 million from Credit Suisse and Barclays for behavior in their dark pools.

High frequency trading models can be made to comply with agreed upon order-to-trade ratios to avoid abuse. Monitoring order-to-trade ratios would add to market stability, enable better controls for message traffic and help to distinguish between those that are truly adding liquidity and those that are not acting in the best interest of the market. The data feeds that are available publicly and privately should be in sync so that one market participant does not have an undue information advantage over another. The South Africa Financial Services Board (FSB) has been the result of thoughtful regulation which promotes competition, innovation and transparency. Policy makers should continue to take steps to further enhance transparency and the stability of the market. Exchanges and regulators need to establish a robust framework to police and identify abuses, and to act on manipulative practices when found on the market.

In the current market environment, several opportunities to improve stability exist. Exchanges should implement kill switches if it is apparent that they are being impaired or flooded with erroneous orders. The JSE currently only has a circuit breaker to halt continuous trading if prices fall by 5% for leader stocks and South Africa/UK dual listed shares. The deployment of kill switches, circuit breakers and other system compliance will improve investor confidence and market stability. Better testing environments for strategies and liquidity programs should also be available. In our highly complex market network, “freak events” will also occur. Practitioners and industry need to have contingency plans in place for containing the damage when such events happen. The weakness of this study is that only one market quality factor was identified to be affected by co-location. Other factors such as volatility were shown to have a low significant relationship. Subsequent research can lead to better understanding of co-location by investigating the correlation between co-location and volatility. Further analysis could also include an investigation into how co-location and the high frequency traders affect institutional investors and retail traders.

4.5 Conclusion

Technology has revolutionized trading in financial markets. Most evidence suggests that the increased use of technology has led to improvements in liquidity, but little empirical evidence exists on the channels for such improvements. This dissertation shows that the co-location event at the JSE in May 2014 is associated with improved liquidity. Empirical analysis was conducted before and after co-location and regression analysis was undertaken. Our findings were that there is a positive correlation between co-location and overall liquidity which is good for the JSE. Co-location appears to improve liquidity for all market participants primarily through the high frequency traders acting as market makers and lowering spreads.

However it is still unclear as to how co-location trades and high frequency trading affects volatility. This finding indicates that future research on co-location and high frequency trading should emphasize impact on volatility. Hopefully in the near future, empirical studies can be undertaken to analyse how volatility is affected so that market participants can be aware. This would also help markets to be structured in a way that produces the most efficient prices.

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