The Impact of Co-location on the Quality of a Satellite Market:

Evidence from the Singapore Exchange

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CERTIFICATE OF ORIGINALITY

I certify that this thesis has not already been submitted for any degree and is not being submitted as part of candidature for any other degree.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

Signature of Candidate

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SYNOPSIS

On 18 April 2011, the Singapore Exchange (SGX) introduced co-location services to its equities and derivatives markets. This infrastructural improvement was part of a $250 million initiative aimed at improving the speed of market access and promoting high frequency trading (HFT). Using intraday data time- stamped in milliseconds, the impact that this microstructure change has on the market quality and the level of high frequency trading of SGX's equity-index futures exchange are assessed. This bourse provides a unique setting to research high frequency trading as it is an offshore satellite exchange where futures contracts written on foreign market indices are traded. It therefore has cross-border linkages with home exchanges that trade the same or similar futures contracts, as they are both driven by the same fundamentals (Covrig, Ding and Low, 2004; Hsieh, 2004).[1] An alternative theory i.e. the order diversion hypothesis posits that dual-listed securities compete for order flow and therefore the cross-listing of futures contracts cause a migration of trading interest from home bourses into satellite bourses. This thesis also assesses whether structural improvements on offshore markets are beneficial or detrimental to home markets.

Increases in the pervasiveness of high frequency trading (HFT) are observed for the Nikkei 225 and MSCI Taiwan index futures contracts. HFT levels in the CNX Nifty and the FTSE China A50 index futures contracts, however, decline following the infrastructural change. The results suggest that co-location services attract more trading interest from high frequency traders on dual-listed stock index futures exchanges if there are cross-border profit opportunities i.e. markets with alternative trading venues that are largely accessible to foreigners. Capital controls and the stringent regulatory framework for overseas investors on the National Stock Exchange of India and the China Financial Futures Exchange restrict foreign participation in these markets. This conjecture is supported by the empirical evidence that suggests that HFT trading takes place across borders. An increase in high frequency trading activity on the alternative venue is shown to increase high frequency trading on Singapore's

[1] Satellite market refers to the exchange that trades futures contracts that are written on foreign market indices. Home market refers to the exchange that trade futures contracts written on domestic market indices.

equity-index futures exchange. This result is consistent across all futures contracts and proxies examined. It suggests that dual-listed futures markets do not compete for HFT order flow but market participants on stock index futures bourses engage in cross-border trading strategies.

The impacts co-location services have on the qualities of the Nikkei 225 and the MSCI Taiwan index futures markedly differ. Co-location services generate more trading activity, improve the liquidity and ease the volatility of the Nikkei 225 index futures market. The quality of the MSCI Taiwan index futures market, however, deteriorates as evident by the decrease in trading activity, decline in liquidity and increase in price volatility. The disparate response to co-location services may reflect the different types of trading prevailing in the futures contracts. Hagströmer and Nordén (2013) put forward the argument that HFTs are a heterogeneous group of traders. How different groups of HFT traders affect the market quality of financial bourses is contingent upon the type of trading strategies utilised. The results of this thesis suggest that the Nikkei 225 index futures market is characterised by liquidity-supplying passive HFTs while the MSCI Taiwan index futures market is characterised by liquidity-demanding active HFTs.

This thesis also finds that liquidity changes on the alternative trading venue explain liquidity changes on Singapore's stock-index futures exchange. A decrease (increase) in the bid-ask spread (depth) of the home market contract leads to a decrease (increase) in the bid-ask spread (depth) of the respective satellite market contract. This finding is consistent with prior literature that document commonality in liquidity across financial bourses (Chordia, Roll and Subrahmanyam, 2000; Domowitz, Hansch and Wang, 2005; Karolyi, Lee and Dijk, 2012) and for the stock index futures markets (Frino, Mollica and Zhou, 2014). Finally, results suggest that low latency trading on Singapore's derivatives exchange is contingent upon underlying market conditions. High frequency trading is found to be negatively related to price volatility across all futures contracts examined. This finding, which is consistent with Brogaard (2010), suggests that low latency traders are less active in the market during volatile conditions.

1. INTRODUCTION

On May 6 2010, the US equity markets saw its second largest point swing of 1010.14 points in the Dow Jones industrial. Amid negative market sentiment, the index had declined by over 300 points by early afternoon. At 2:42pm, the index fell sharply by a further 600 points over a 5 min period to subsequently recover most of its 600 point loss by 3:07pm. This stock market crash, known as the Flash Crash of 2010, brought about wide-spread speculation and investigation over the role high frequency trading systems (HFT) had on this market disruption. A report published jointly by the U.S. Securities and Exchange Commission and the Commodity Futures Trading Commission on 30 September 2010 report that while HFTs did not cause the Flash Crash, their trading activities exacerbated the extreme price movements and liquidity shortages that took place on the day.[2]

The Flash Crash was initiated by a single mutual fund that employed volume but not price or time constraints to execute the sale of 75,000 E-mini futures contracts (SEC and CFTC, 2010). The prevailing market conditions and the algorithms used by this mutual fund caused this sell-off to be completed within 20 minutes, causing a significant drop in prices. HFTs exacerbated this price movement by submitting large quantities of sell orders to reduce their net long positions. Furthermore, the market activities of cross-market arbitrageurs caused the prices of the SPYDR futures contract and individual stocks to plummet correspondingly. At 2:45pm trading on the Chicago Mercantile Exchange was halted. During the period following the trading halt, while some traders eased their liquidity provision many collectively withdrew from the equities market causing a liquidity shortage. The events that took place on May 6, 2010 highlight the susceptibility of exchanges' computerised environment to market destabilisations. Algorithmic and high frequency trading practices were brought to the public's attention and consequently scrutinised by regulatory bodies, academics and policy makers.

[2] 'Findings Regarding the Market Events of May 6, 2010' was published jointly by the U.S Securities and Exchange Commission and the U.S. Commodity and Futures Trading Commission on 30 September 2010.

High frequency trading, the practice of trading at extremely fast speeds, is a controversial area in finance. While a line of research documents its beneficial impact on market quality (e.g. Brogaard, 2010; Hendershott, Jones and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hagströmer and Nordén, 2013), other studies find that it degrades the quality of financial exchanges (Kirilenko, Kyle, Samadi and Tuzun, 2011; Jarrow and Protter, 2012; Boehmer, Fong and Wu, 2012; Lee, 2013). At its extreme, as seen by the Flash Crash of 2010, they potentially contribute to the destabilisation of financial exchanges (SEC and CFTC, 2010). Furthermore, the fairness that a subgroup of traders has faster access to exchanges and real-time market data is questioned (Barrales, 2012; Angel and McCabe, 2013). It raises questions of whether HFTs benefit a segment of the market to the detriment of other participants and therefore creates a two-tiered market. Furthermore, their trading practices have come under scrutiny as having faster market access raises the possibility of inequitable advantages and market manipulation. High frequency trading, the focus of this thesis, is currently the subject of much debate.

The general consensus is that high frequency trading has a beneficial impact on market liquidity and price discovery. Prior to the advent of direct market access, liquidity provision was predominately carried out by market makers who had contractual agreements with exchanges to quote binding bid and offer prices. Developments in electronic trading that facilitated other traders to directly access the limit order book saw the role of liquidity provision extend to high frequency traders (HFT). Studies that examine the impact of low latency trading on market liquidity find evidence of narrower bid-ask spreads and improved market depth (Brogaard, 2010; Riordan and Storkenmaier, 2012; Hasbrouck and Saar, 2013; Menkveld, 2013). Furthermore, arbitrage trading strategies that are employed by low latency traders reduce transient price disturbances and therefore improve price discovery (Brogaard, 2010; Hendershott and Riordan, 2014; Hasbrouck and Saar, 2013). There is less agreement, however, in empirical literature regarding its effects on price volatility. While studies such as Hasbrouck and Saar (2013) and Hagströmer and Nordén (2013) report marked declines, Boehmer, Fong and Wu (2012) and

Kirilenko, Kyle, Samadi and Tuzun (2011) show that high frequency trading and, more broadly, automated trading lead to an increase in volatility. This thesis assesses price, liquidity and trading activity variables to determine the effects a microstructure change, aimed at attracting HFT activity, have on the market quality of a satellite bourse.

High frequency trading is potentially detrimental during adverse market or trading conditions. As opposed to designated market makers who have an obligation to post firm quotes, HFTs have discretion over the timing and location of their trades. Brogaard (2010) finds that on the U.S. equities market, moderate declines in high frequency trading levels arise when volatility increases. If trading levels are contingent upon the market environment, changes in HFT activity during periods of unfavourable conditions may degrade the quality of financial bourses. It is found that the collective withdrawal of traders contributed to the liquidity shortage in the equities market during the Flash Crash (SEC and CFTC, 2010; Kirilenko, Kyle, Samadi and Tuzun, 2011). Furthermore, due to the magnitude and speed of trading that takes place, HFT systems may exacerbate risks by accelerating the propagation of trading errors or illegal trades. The greater correlation between computer-initiated orders than human-initiated orders (Chaboud, Chiquoine, Hjalmarsson and Vega, 2014) suggests the greater susceptibility of risk transmissions. By regressing high frequency trading proxies on price volatility, Brogaard's finding (2010) that HFT participation rates are contingent upon market conditions, is reassessed in the context of Singapore's equity-index futures exchange.

The fairness of low latency trading remains a highly contentious issue. High frequency trading is found to be profitable with approximately $3 billion of trading profits generated annually on NASDAQ (Brogaard, 2010). However, whether these trading profits are derived from fair, equitable means is debatable. Proponents argue that traditional investors benefit from the positive externalities of HFTs and therefore the practice of trading at high speeds is not necessarily unfair (Angel and McCabe, 2013). Narrower bid-ask spreads due to greater HFT presence reduce the implicit cost of trading for other market participants (Hendershott, Jones and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hasbrouck and Saar, 2013). Furthermore, the arbitrage activities of low latency traders reduce mispricings and improve the efficiency at which prices are determined (Brogaard, 2010; Hendershott and Riordan, 2014; Chaboud, Chiquoine, Hjalmarsson and Vega, 2014). High frequency trading is, therefore, not necessarily unfair to long-term investors as they derive benefits from improvements to the quality of markets (Hasbrouck and Saar, 2013).

Critics of high frequency trading put forward the argument that trading venues where a segment of the market has faster access to the limit order book and real-time market data is inherently unfair. It gives a subgroup of traders speed advantages over other market participants and therefore profit opportunities to the detriment of slower traders (Jarrow and Protter, 2012; McInish and Upson, 2011). Furthermore, low latency traders impose adverse selection costs to competing traders (Biais, Foucault and Moinas, 2013). Critics of HFT also argue that the fast market access may be used for market manipulation. Predatory algorithmic strategies such as spoofing and order triggering artificially inflates or deflates prices. These strategies generate profits for high frequency trading systems at the expense of slower traders who buy or sell assets at less favourable prices (Angel and McCabe, 2013). Empirical research conducted by Brogaard (2010), however, finds that front-running, a type of predatory trading strategy is not systematically employed by HFTs on the US equities market.

The level of high frequency trading across financial markets varies due to differences in their market microstructure and regulatory framework. In the United States and Western Europe, high frequency trading accounts for a substantial proportion of their equity activity.[3] Algorithmic trading is thought to be responsible for as much as 73% of trading volume in the United States in 2009 (Hendershott, Jones and Menkveld, 2011). These markets are conducive to HFT activity as they have become highly fragmented. To capture the market share of a particular stock, trading venues compete for order flow by

[3] According to Brogaard (2010), the trade participation rate of HFT firms for his sample of NASDAQ and NYSE-listed stocks is 74%. In a more recent study conducted by Carion (2013) with the same dataset, HFT traders contribute to 68.3% of the dollar trading volume.

lowering transaction fees. Low trading costs and multiple venues at which price discrepancies can be profited from are reasons for its pervasiveness in the US and Europe. Trading in these areas is becoming increasingly fragmented due to the establishment of alternative trading venues such as Chi-X and BATS. According to a report published by the U.S. Securities and Exchange Commission, the New York Stock Exchange's market share of equity trading was significantly higher in January 2005.[4] Approximately 79.1% of its listed shares' aggregate trading volume was transacted on the exchange. By October 2009, the bourse's market share had declined to 25.1%.

The overall prevalence of HFT in the equity markets of the Asia-Pacific region, however, has remained low, with the exception of Japan and Australia.[5] This is due to a lack of competing exchanges and comparatively higher transaction costs, making high frequency trading strategies unprofitable.[6] Despite low participation rates in equity markets, it has a larger presence in Asia's derivatives bourses due to their lower levies and less stringent regulatory environment.[7] In Korea, as opposed to the equities market, taxes are not imposed on transactions on the KOSPI 200 index futures market. Consequently, greater HFT activity takes place on the futures market in Korea than on the equities market. According to Lee (2013), 24% of trading activity and 32% of quoting activity on the Korean stock index futures market are attributable to low latency activity. He suggests that index futures markets may be a popular trading venue for high frequency traders due to their greater liquidity (Lee, 2013). Similarly, HFT activity on Singapore's derivatives market, the institutional setting of this thesis, accounts for approximately 30% of their trading volume while on its equities market levels are minimal. The fragmentation of stock-index futures trading across multiple bourses is likely to be a contributing factor for its sizeable HFT levels on SGX's derivatives market.

[4] This report is titled, "Concept Release on Equity Market Structure" and was published by the U.S. SEC in 2010.
[5] A report conducted by the Schroders report that the proportion of HFT in the Asia-Pacific markets (excluding Australia and Japan) is 12% of the total value traded.
[6] Market participants in Hong Kong and South Korea incur a stamp duty tax of 0.1% and 0.3% respectively.
[7] Foreign HFT participation in China and India's derivatives markets are low due to capital controls that restrict onshore access by foreigners.

Singapore's derivatives market provides a unique setting to research high frequency trading as it is an offshore satellite bourse where futures contracts written on foreign market indices are traded. The same or similar equity-index futures contracts are also listed on domestic trading venues. Extant literature suggests that the listing of a security across multiple exchanges may be beneficial or detriment to the market quality of competing markets. An offshore trading venue could potentially reduce the demand for an asset on a domestic bourse (Domowitz, Glen and Madhavan, 1998). When cross-listed securities markets compete for the same order flow, a microstructural improvement on one of the rival markets may cause an outflow of orders on the competing trading venue, consequently deteriorating its market quality. Alternatively, greater intermarket competition may reduce bid-ask spreads or prompt alternative markets to make policy changes to attract order flow (Foucault and Menkveld, 2008). Furthermore, as identical financial instruments listed on multiple exchanges are driven by the same fundamentals, they are informationally-linked (Booth, Lee and Tse, 1996; Hua and Chen, 2007; Chen and Gau, 2009). Arbitrage profit opportunities exist when prices deviate from their relative values (Board and Sutcliffe, 1996). The multiple listing of an asset may positively impact the market quality of all exchanges due to cross-border trading activities (Board and Sutcliffe, 1996).

Given the unique characteristics of cross-listed securities bourses, this thesis aims to address the following research questions:

i) Does the introduction of co-location services increase the incidence of high frequency trading on an off-shore market?

ii) Does market quality improve subsequent to the implementation of co-location facilities on equity-index futures exchanges?

iii) How does a microstructure improvement on an off-shore bourse impact the market quality of its related domestic bourse?

iv) Do high frequency traders reduce their participation levels during periods of greater volatility?

The remainder of this thesis is structured as follows. Chapter 2 provides a review of prior literature regarding algorithmic trading, high frequency trading and cross-listed securities markets. Chapter 3 presents an outline of the institutional details of Singapore's equity-index futures exchange. Chapter 4 describes the data and the research design employed in this thesis. Chapter 5 presents the results of both the univariate and multivariate analysis. Chapter 6 concludes by discussing the key findings of the research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Algorithmic and High Frequency Trading

2.1.1 Description of Algorithmic and High Frequency Trading

Algorithmic trading or automated trading (AT) refers to the use of computerised systems and algorithms to make and execute trading strategies on bourses with electronic access. Pre-programmed algorithms analyse market data to determine the optimal time to enter the market and other variables including the type, price and quantity of the orders to be submitted. Algorithmic trading is classified into two broad categories: agency algorithmic trading and proprietary algorithmic trading (Hagströmer and Nordén, 2013). Agency trading refers to the purchase and sale of securities initiated by agents on behalf of their clients. It is employed by buy-side institutional investors to mitigate the market risk and execution costs of their clients' orders. To minimise the impact that a large trade has on a security's price, it is often divided into smaller parcels and traded over a period of time or routed to multiple trading venues. Algorithms are customarily used in this instance to compute when and where each parcel should be executed for the best price possible. Proprietary algorithmic trading, on the other hand, is undertaken by technologically advanced financial institutions to generate profits by directly trading with their own capital. A class of proprietary algorithmic traders are high frequency traders (Hasbrouck and Saar, 2013).

High frequency trading (HFT) is a subset of algorithmic trading where the submissions, amendments and cancellations of automated trading instructions take place at rapid speeds. Through proprietary trading strategies, advanced computerised systems and fast access to financial markets, positions are established or liquidated within fractions of a second, typically milliseconds. While other types of trading seek to generate a significant abnormal return for every transaction executed, HFTs aim to capitalise on marginal profit opportunities and to accumulate profits by trading frequently. Various trading strategies are implemented by HFT systems to identify and trade on incremental profit opportunities in the market. They include arbitrage trading, market making, order discovery strategies and order triggering strategies. These types of trading are not recent developments but existing, traditional strategies executed at high speeds using low latency technology (Angel and McCabe, 2013). Further discussions on HFT strategies are provided in Section 2.1.2. In response to the growing prevalence of high speed trading in financial markets, policy makers have upgraded the microstructure of exchanges. The implementation of co-location facilities is a structural change made by exchanges to increase the speed at which traders can access the limit order book and therefore to generate more trading interest from HFTs. This innovation in low latency technology will be discussed in Section 2.1.3.

As high frequency trading is a recent development in electronic trading, there has yet to be a universally accepted definition of it. The U.S. Securities and Exchange Commission characterises HFTs as proprietary entities that involve:[8]

- the use of extraordinarily high speed and sophisticated computer programs for generating, routing and executing orders;
- the use of co-location services and individual data feeds offered by exchanges and others to minimise network and other type of latencies;
- very short time-frames for establishing and liquidating positions;
- the submission of numerous orders that that are cancelled shortly after submissions;
- ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions overnight).

Definitions of high frequency trading (HFT) provided in literature are congruous to the definitions outlined by the U.S Securities and Exchange Commission and other regulatory bodies.[9] Firstly, a

[8] This definition of high frequency traders was provided by the U.S. Securities and Exchange Commission in a 2010 publication titled “Concept Release on Equity Market Structure.”

[9] Documents released by other regulatory bodies including the Committee of European Securities Regulators (2010), the Australian Securities and Investment Commission (2010), the Authority for the Financial Markets (2010) and the European Commission (2010) provide definitions of high frequency trading.

distinctive characteristic of HFTs is the extremely fast speed at which they move into and out of positions in the market. Speed is a defining factor for low latency market participants as profits are generated by being faster than competing traders. This speed is known as latency. According to Hasbrouck and Saar (2013), latency is defined as the time it takes to learn about an event, generate a response and have the exchange act on the response. The latency at which high speed traders execute orders is extremely low and markedly lower than other market participants (Chaboud, Chiquione, Hjalmarsson and Vega, 2014; Hagströmer and Nordén, 2013; Hasbrouck and Saar, 2013). For example, a major HFT market participant on Chi-X and Euronext has access to an effective trading speed of 1ms (Menkveld, 2013). Disparities in latencies across groups of market participants are documented in literature (Hagströmer and Nordén, 2013; Hasbrouck and Saar, 2013). In August 2011, compared to a minimum latency of 0.96ms that non-HFTs trade at, the minimum trading speed of HFTs is 0.36ms on the NASDAQ-OMX Stockholm (Hagströmer and Nordén, 2013). Similarly, the most sophisticated high speed traders have access to latencies of 2-3ms on NASDAQ. Response times for humans, however, are substantially slower at approximately 200ms (Kosinski, 2012; Hasbrouck and Saar, 2013).

High frequency trading is also characterised by very brief holding periods and the liquidation of investment positions prior to a trading day's close. On NASDAQ-OMX, the average duration of limit orders for non-HFTs is 20,434ms in August 2011. In comparison, significantly shorter holding periods of 2,774ms are reported for HFT market participants during the same month (Hagströmer and Nordén, 2013). Furthermore, average limit order duration is found to be a function of market conditions and trading strategy types. An analysis of HFT holding periods find that it is significantly shorter during periods of greater volatility. The need to update quotes faster and more frequently when there are large variations in prices may be a reason for the shorter limit order durations. Furthermore, low latency traders such as market making HFTs that adopt a more passive trading strategy have longer holding periods. These market participants do not rely on active trading and therefore their trading strategies are characterised by longer limit order durations (Hagströmer and Nordén, 2013).

High frequency traders liquidate most of their inventory positions prior to a trading session's close.[10] Empirical studies that examine the trading behaviour of HFTs at a markets close find evidence of overnight exposure minimisation. On the Chi-X and Euronext, a major HFT market maker liquidates his entire inventory position on 69.8% of trading days (Menkveld, 2013). Similarly, a significant 42% of low latency traders on the KOSPI 200 index futures market end the trading day with a zero inventory position. The net inventory levels of the remaining 56% are marginally negative or positive (Lee, 2013). The trading strategies of HFTs on the NASDAQ-OMX Stockholm is also characterised by low overnight positions (Hagströmer and Nordén, 2013). However, they find that net positions at the markets close are, on average, non-zero. This may be attributable to cross-market HFT trading activities that take place across multiple trading venues and multiple trading sessions. Finally, an analysis of investment positions during the trading day shows that while high frequency traders alternate between long and short net positions numerous times during a trading session, other market participants seldom change their net positions (Brogaard, 2010).

Another prominent characteristic of HFTs is their quoting intensity. While other types of trading aim to generate significant abnormal returns for every trade executed, the purpose of high frequency trading is to capitalise on marginal profit opportunities in the market and to accumulate profits by trading frequently. HFT strategies are usually order-intensive and characterised by large quantities of order submissions, amendments and cancellations. Consequently, order to trade ratios are widely employed in literature to differentiate HFT market activity from non-HFT market activity (Brogaard, 2010; Hendershott, Jones and Menkveld, 2011; Boehmer, Fong and Wu, 2012; Frino, Mollica and Webb,

[10] Investment positions held overnight incur clearing and capital expenses.

2014). Evidence of high quoting intensity is found on the KOSPI 200 index futures market where order cancellations constitute 33% of quoting activity (Lee, 2013). An examination of quoting intensity on the NASDAQ-OMX Stockholm finds that order to trade ratios of HFTs are significantly higher during volatile market conditions (Hagströmer and Nordén, 2013). This suggests that contrary to the findings of Brogaard (2010), high speed traders do not reduce their presence during uncertain market conditions. Trading strategies that are commonly implemented by high speed market participants are explored further in Section 2.1.2.

High frequency trading involves the use of co-location or proximity services to buy or sell highly liquid securities (Gomber, Arndt, Lutat and Uhle, 2011). Hendershott, Jones and Menkveld (2011) show that on the New York Stock Exchange, active and liquid stocks generate the most trading interest from HFTs. Furthermore, Lee (2013) suggests that the greater liquidity of futures markets and consequently the ease at which market participants can establish and liquidate positions are reasons for its attraction among HFTs. However, Hagströmer and Nordén (2013) suggest that the preference for liquid securities differ across groups of high frequency traders. Liquidity suppliers such as market makers profit from the bid-ask spread while liquidity demanders such as opportunistic traders pay the differential in prices. Securities with narrow bid-ask spreads therefore incentivise liquidity consumptions but makes the provision of liquidity more expensive. The converse holds for securities characterised by wider bid-ask spreads. Hagströmer and Nordén (2013) shows that on the NASDAQ-OMX Stockholm, market making is significantly higher in stocks that have wider bid-ask spreads. Therefore, different HFT trading strategies require different levels of market liquidity. Finally, as speed is defining factor for high frequency traders, co-location or proximity services are utilised to remain competitive. This innovation in market microstructure will be discussed further in Section 2.1.3.

2.1.2 Types of High Frequency Trading Strategies

Hagströmer and Nordén (2013) suggest that high frequency market participants are a heterogeneous group of traders. While market makers are predominately liquidity suppliers, opportunistic traders such as arbitrageurs or directional traders primarily consume liquidity. Consequently, the impact that they have on the market quality of financial exchanges differ. This highlights the importance of understanding the nature of trading strategies commonly utilised by high frequency traders. Most HFT trading strategies are not newly developed but are existing, traditional mandates executed at high speeds using low latency technology (Angel and McCabe, 2013). An empirical analysis of the range of strategies implemented by HFTs on the U.S. equities market finds that they focus on a smaller set of trading strategies than non-HFTs (Brogaard, 2010). HFT trading are categorised into three subgroups: market making, arbitrage trading and directional trading. This section of the thesis provides a description of the different types of trading.

Market makers facilitate trading in a security by continuously providing firm bid and ask quotes throughout the trading day. Their business model is to trade in large volumes and to generate incremental profits from the bid-ask spread. Prior to the advent of direct market access, liquidity provision was predominately carried out by market makers who had contractual agreements with exchanges to quote binding bid and offer prices. Developments in electronic trading that facilitated other traders to directly access the limit order book saw the role of liquidity provision extend to HFTs. Prior literature find that market-making HFTs constitute a significant proportion of an exchanges low latency activity (Hagströmer and Nordén, 2013; Menkveld, 2013). A majority of high frequency trades in Swedish large capitalisation stocks are transacted by market makers. Specifically, market makers account for 7.15% and 62.8% of the exchange's HFT trading volume during normal and volatile market conditions, respectively (Hagströmer and Nordén, 2013). Furthermore, a major high frequency trader who has captured a significant 64.4% and 8.1% market share of Chi-X and Euronext, respectively functions primarily as a multi-venue market maker.

A comparison of trading strategies show that market making HFTs is characterised by greater quoting intensity and faster trading speeds than other categories of low latency traders. In August 2011, the minimum latency of market makers is found to be 0.1ms on NASDAQ-OMX Stockholm. Opportunistic traders, conversely, experience a minimum latency of 0.6ms over this period (Hagströmer and Nordén 2013). This heterogeneity in latencies may be attributable to the different nature of the trading strategies. Opportunistic HFTs adopt active trading strategies and therefore face less risk of being adversely selected. Market-making HFTs, however, partake in passive trading and therefore face additional risks of trading with faster, more informed market participants. The ability to update quotes faster is therefore more critical for market making HFTs. Consequently this group of traders may trade at faster speeds. The competition among liquidity providers may also be a reason for the lower latency.

Arbitrage strategies involve identifying and trading on temporary price discrepancies that arise across related assets or financial markets. When a mispricing has been detected in the market, arbitrageurs sell the overvalued asset and purchased the undervalued asset. These trading activites place upward pressure on the undervalued asset and downward pressure on the overvalued asset, thereby correcting the mispricing. As financial markets are extensively monitored by many traders, arbitrage opportunities are temporary and short-lived. Consequently, due to the succinct time periods at which profitable mispricings materialise in financial markets, HFT strategies and low latency technologies are required to establish positions at high speeds. Studies find that high frequency arbitrageurs are more active in volatile market conditions (Brogaard, 2010; Hagströmer and Nordén, 2013). The greater deviations in prices may give rise to greater profitable mispricings and therefore generate more trading interest from HFTs. However, Chaboud, Chiquione, Hjalmarsson and Vega (2014) document that the advent of algorithmic trading has led to a significant decline in triangular arbitrageur opportunities in foreign exchange markets confirming that arbitrage opportunities are limited.

Directional trading involves the analysis of current available information to anticipate future market movements. The type of information used to infer market or company activity determines the legality of this trading strategy. In most jurisdictions, the use of price sensitive, non-public information breaches insider trading regulations. In Singapore, Sections 218 and 219 of the Securities and Futures Act prohibit insider trading on Singapore's capital markets. However, order anticipations strategies based on public information are arguably ethical (Angel and McCabe, 2013). The following section will discuss both the legal and illegal types of directional trading implemented by HFTs.

The arrival of new, material information regarding a security's price causes the market's consensus of its value to be revised. Prices usually decrease or increase following the arrival of unexpected negative or positive news, respectively. News reaction strategies involve the analysis of publicly available information including news releases, company announcements or analysts' forecasts to predict and trade on expected price movements. Before the information is fully reflected in the securities' price, profit opportunities arise for fasts traders. Previous studies find that the information is impounded into prices soon after its arrival (Ederington and Lee, 1993; Fleming and Remolona, 1997). A more recent study by Carrion (2013) show that the efficiency at which market information regarding order flow and market-wide returns is incorporated into prices is higher due to high frequency traders. In highly efficient markets where the speed of price adjustment is fast, market participants require low latency technology for news reaction strategies.

Order discovery strategies are utilised by HFTs to detect latent liquidity or trading activity in financial markets. This strategy involves "pinging" the market through the submission and cancellation of orders for the purpose of uncovering large institutional orders that have yet to be filled. When a high frequency trader infers that a large block trade is taking place, he then trades in the same direction as a block trade in anticipation of significant price movements. A large buy order places upward pressure on a securities price. To minimise its impact, it is often divided into smaller packages and traded over a period of time or routed to alternative trading venues. HFTs that detect the existence of a block trade submit buy orders to profit from the expected increase in price. As opposed to front running, anticipatory trading strategies that detects latent market activity based on public information is beneficial to financial markets as they improve the efficiency at which prices are determined (Angel and McCabe, 2013).

A controversial area in the practice of trading at high speeds is the possibility of market manipulation through predatory trading strategies. Predatory strategies utilise insider information or market manipulation to generate illegal trading profits. This type of trading inflates or deflates prices or trading volumes to induce other market participants to buy or sell at less favourable conditions. In Singapore, market manipulation is outlawed under the Section 197 of the Securities and Futures Act, which prohibit:

(a) creation of a false or misleading appearance of active trading in any securities on a securities exchange in Singapore;
(b) creation of a false or misleading appearance with respect to the market for the price of any securities on a securities exchange in Singapore;
(c) affecting the price of securities by way of purchase or sale that do not involve a change in the beneficial ownership of those securities;
(d) affecting the price of securities by means of any fictitious transactions of devices.

Order triggering strategies, spoofing, wash sales and quote stuffing are types of illegal market manipulation. These types of unconstitutional trading activities artificially inflate or deflate prices or trading volumes to the detriment of slower traders. Order triggering strategies involve the deliberate manipulation of prices to induce other market participants to trade. HFTs may short sale a security and consequently cause its price to decline. Other market participants may view this decline as an indication of adverse changes in a securities' fundamentals and therefore may choose to sell the security. This causes a further decline in its price which in turn may trigger stop orders or liquidate margin accounts. The HFT then covers the short position and generate a profit from the artificially deflated prices.

Spoofing refers to the submission of orders with the intention of cancelling prior to its execution. Wash sales involve the simultaneous purchase and sale of a security to create the false impression of buying and selling pressures. Finally, quote stuffing refers to the submission and cancellation of large quantities of orders to slow competing traders down and therefore reduce their competitive edge. Previous studies suggest that while market making and arbitrage activity improve market quality, predatory trading practices have a detrimental impact on financial exchanges. The disparate impact that different trading strategies have on the quality of financial bourses is explored in Sections 2.2.1 and 2.2.2.

2.1.3 Co-location Facilities

HFTs that implement low latency strategies profit by analysing and trading on information faster than competing traders. Consequently, the speed of access is a defining factor in their trading. In recent years, policymakers have made changes to the microstructure of exchanges to improve traders' speed of access and therefore attract greater HFT activity. This innovation in exchange technology allows latency sensitive market participants to situate their trading systems in the data centre and within close proximity of centralised trading and data engines. This is achieved through the rental of rack space in the data centre. Co-location facilities improve round-trip network latency of trades and therefore enable market participants to move into and out of positions faster. On certain financial markets, including the Singapore Exchange, proximity services are offered at multiple speeds. Exchanges are therefore able to price discriminate among traders (Brogaard, Hagströmer, Nordén and Riordan, 2013).[11] Furthermore, the ability to directly subscribe to real-time data feeds located in an exchange's data centre enables co-located HFTs to access information incrementally faster than the rest of the market.

Previous studies find that the distance a trader is located from an exchange's centralised systems is a function of his trading profits (Hau, 2001; Ivković and Weisbenner, 2005; Garvey and Wu, 2010). According to Garvey and Wu (2010), the disparities in trading profits associated with geographic

[11] On the Singapore Exchange, three tiers of co-location services are offered with round-trip network latencies differing across the three tiers.

location may arise from differences in latencies. This in turn leads to differential execution costs of market orders for traders located inside and outside the city of New York. Market orders originating from inside New York are transacted at a price 1.9c more expensive than the quoted price prevailing at the time of submission. Market orders that originate from outside New York, however, incur an average loss of 4.1c. The findings of this study suggest that latency advantages have a material impact on trading profits.

Physical proximity has always been an important factor in trading. Prior to the advent of co-location services, the more latency sensitive market participants rented office space near exchanges (Frino, Mollica and Webb, 2014). On the Singapore Exchange, proximity hosting services were available to market participants prior to the introduction of co-location services. Proximity hosting is a type of network service which allows market participants to place their trading systems in facilities operated by third parties and located near exchanges. Co-location facilities did, however, substantially improve network latency in Singapore's capital markets. Brokers who connected to leased lines and SGX's proximity hosting service face a round-trip latency of 6,000ms to 13,000ms and 800ms to 1,250ms, respectively. The implementation of co-location services saw latencies reduce to 100ms.

Empirical researches find that the introduction of co-location services increases the pervasiveness of high frequency trading activity (Frino, Mollica and Webb, 2014) and leads to improvements in market liquidity (Frino, Mollica and Webb, 2014; Boehmer, Fong and Wu, 2012; Brogaard, Hagströmer, Nordén and Riordan, 2013). There is a lack of agreement in literature, however, regarding the impact that co-location services have on price volatility. While Boehmer, Fong and Wu (2012) find evidence of volatility increases, Frino, Mollica and Webb (2014) and Brogaard, Hagströmer, Nordén and Riordan (2013) report no significant changes. This technological upgrade on Australia's futures market is found to generate greater high frequency trading activity in interest-rate futures contracts. Low latency trading activity in the equity-index futures contract, however, decline significantly. Frino, Mollica and Webb (2014) attribute this to a tax on cash market equity message traffic that was introduced around the time of the infrastructural change. High frequency trading in the cash market is more expensive due to the tax, the profitability of cross-market arbitrage activities is reduced and consequently high frequency trading levels decline.

Liquidity improvements arising from the introduction or upgrade of co-location facilities is documented in literature (Frino, Mollica and Webb, 2014; Boehmer, Fong and Wu, 2012; Brogaard, Hagströmer, Nordén and Riordan, 2013). On the ASX, bid-ask spreads narrow and market depth increase significantly for interest rate futures contracts. Equity-index futures contracts also experience improvements in liquidity, despite an evident decline in HFT levels. They conjecture that co-location services improve the speed at which HFTs and other market participants are able to supply liquidity and therefore have a positive impact on spreads and market depth. Boehmer, Fong and Wu (2012) use the introduction of co-location services as an instrumental variable to assess the causality of algorithmic trading on the liquidity of equities market. They find that liquidity improvements are most pronounced for stocks characterised by high price or low volatility. Conversely, less expensive or more volatile stocks experience mild increases in liquidity. Greater algorithmic trading on small capitalisation stocks, however, deteriorates market liquidity.

10G Premium Co-location Services was introduced on NASDAQ-OMX which enable existing co-located HFTs to upgrade to faster trading speeds. Brogaard, Hagströmer, Nordén and Riordan (2013) study this microstructure change and suggest that there are two opposing impacts on liquidity that arise from the availability of lower latency. Market participants who trade at faster speeds have the capacity to adjust more quickly to market events. Consequently, they have an informational advantage over slower traders and impose adverse selection costs to their competitors. This is consistent with theoretical models of Biais, Foucult and Moinas (2013) and Martinez and Rosu (2011). Faster trading speeds, conversely, encourage liquidity provision and improve the management of inventory, thereby have a positive impact on market liquidity. Overall, bid-ask spreads narrow and market depth increase following the upgrade of co-location services. The results suggest that while there are negative impacts on liquidity of slower, competing traders, the market benefits from overall improvements in liquidity.

While empirical studies show that the introduction of co-location services improve liquidity, there is less agreement regarding its impact on price volatility. Boehmer, Fong and Wu (2012) find that volatility is exacerbated by greater proliferation of algorithmic trading on global equities markets. Brogaard, Hagströmer, Nordén and Riordan (2013) and Frino, Mollica and Webb (2014), however, find no evidence of volatility changes in Swedish large capitalisation stocks or Australian futures contracts, respectively. Boehmer, Fong and Wu (2012) test for the source of the volatility increase and find that it is not associated with the greater efficiency at which prices are determined in the market i.e. faster price discovery. They conclude that the evident increase in volatility is not derived from positive sources. Brogaard, Hagströmer, Nordén and Riordan (2013) show that the greater willingness and ability of high speed traders to hold inventory are reasons for the resilience of price volatility from co-location service upgrades. If more inventories are held by a group of traders, large market orders that consume liquidity can be absorbed without correspondingly large price impacts. Therefore, the non-permanent component of volatility may be reduced. Furthermore, improvements in inventory management capacity may also contribute to a decrease in price pressures and thereby also reduce the non-permanent component of volatility (Hendershott and Menkveld, 2013; Brogaard, Hagströmer, Nordén and Riordan (2013). How algorithmic and high frequency traders affect the liquidity and volatility of financial markets are explored further in Sections 2.2.1 and Sections 2.2.2.

2.2. Impact of Algorithmic and High Frequency Trading on Market Quality

The impact that high frequency trading and, more generally, algorithmic trading has on the market quality of financial exchanges are subject to ongoing research. The general consensus in empirical literature is that they have a positive impact on market liquidity (Brogaard, 2010; Hendershott, Jones and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hasbrouck and Saar, 2013). Heterogeneity in liquidity impacts, however, arise across different characteristics of securities (Hendershott, Jones and Menkveld, 2011; Boehmer, Fong and Wu, 2012; Riordan and Storkenmaier, 2012), market conditions (Hasbrouck and Saar, 2013), trading strategies (Hagströmer and Nordén, 2013) and financial exchanges (Lee, 2013). The impacts of algorithmic and high frequency trading systems on price volatility are less conclusive. While a line of studies find evidence of volatility increases (Boehmer, Fong and Wu, 2013; still Kirilenko, Kyle, Samadi, Tuzun, 2011), other researches suggest it has a mitigating effect on price volatility (Brogaard, 2010; Hagströmer and Nordén, 2013; Hasbrouck and Saar, 2013). Finally, other studies find volatility levels to be insensitive to algorithmic and high frequency trading (Lee, 2013; Chaboud, Chiquione, Hjalmarsson and Vega, 2014 and Frino, Mollica and Webb, 2014).

Prior to the advent of direct market access, liquidity provision was predominately carried out by market makers who have affirmative obligations to quote binding bid and offer prices.[12] Developments in electronic trading that facilitate other traders to directly access the limit order book saw the role of liquidity provision extend to HFTs. The greater competition among a larger group of liquidity providers may narrow bid-ask spreads and therefore improve market liquidity (Hendershott, Jones and Menkveld, 2011). Improvements in liquidity attributable to algorithmic and high frequency trading are extensively documented in literature. Hendershott, Jones and Menkveld (2011) show that increased levels of automated trading following the introduction of autoquoting on the New York Stock Exchange significantly reduced quoted and effective bid-ask spreads. The reduction in spreads, however, is found

[12] Market making scheme are not in place on the Singapore Exchange.

to be driven by a decline in the adverse selection component of the spreads' costs. Similarly, Menkveld (2013) shows that the market activity of a major HFT trader on the Chi-X and Euronext is pivotal to the 50% reduction in the bid-ask spreads in Dutch stocks. Finally, Hasbrouck and Saar (2013) find that a one standard deviation in their proxy for low latency activity leads to a 26% and 32% decrease in bid-ask spreads during volatile and normal market conditions, respectively.

Studies find that the increased algorithmic and high frequency trading levels have different liquidity impacts across different characteristics of securities. Hendershott, Jones and Menkveld (2011) find that liquidity improvements are concentrated in large-capitalisation stocks. Similarly, Boehmer, Fong and Wu (2012) examine the introduction of co-location facilities on international equities markets. This microstructure event is used as an instrumental variable to examine the causality of algorithmic trading on market liquidity. Analogous to Hendershott, Jones and Menkveld (2011), greater increases in liquidity levels are observed for high price or low volatility stocks. Less expensive or more volatile stocks experience mild increases in liquidity. Small capitalisation stocks, however, report deterioration in liquidity attributable to greater automated trading. They suggest that in a more volatility market, limit orders are more expensive and this may discourage liquidity provision. Elevated levels of volatility are more prevalent in stocks that are small, low-priced or volatile. Conversely, Riordan and Storkenmaier (2012) assess how a technological enhancement on the Deustche Bourse that reduces network latency from 50ms to 10ms affects the bid-ask spreads of stocks. They find that liquidity improvements are most evident in small and medium-sized stocks. Analogous to Hendershott, Jones and Menkveld (2011), reductions in quoted and effective spreads arise from a decline in adverse selection costs. Both papers conjecture that increased automated or high-speed trading reduce the competition for liquidity provision. However, Hendershott, Jones and Menkveld (2011) note that although liquidity suppliers are capturing some of the surplus for themselves, as evident by the increase in realised spreads, the market power of computerised systems appear to decline.

The magnitudes of liquidity changes from low latency market activity are shown to differ across market conditions. Hasbrouck and Saar (2013) examine how increased low latency trading affects the quality of financial exchanges under different market conditions on NASDAQ. Two sample periods are examined. During October 2007, prevailing market conditions are normal. The market conditions of June 2008 are characterised by uncertainty and high volatility. They find an increase in the low latency trading leads to improvements in market quality during both sub-periods. Bid-ask spreads significantly decline, best depth and total market depth increase and short-term volatility ease. The magnitudes of the changes in market quality variables are greater during June 2008. During this period, bid-ask spreads narrow, depth increase and short-term volatility ease to a greater extent than during normal market conditions. They conjecture that low latency provide positive externalities more during stressed conditions.

Hagströmer and Nordén (2013) suggest that differences in the type of trading strategies of HFTs have differential impact on market quality. Liquidity suppliers such as market makers profit from the bid-ask spread while liquidity demanders such as opportunistic traders pay the differential in prices. Securities with narrow bid-ask spreads therefore incentivise liquidity consumptions but makes the provision of liquidity more expensive. The converse holds for securities characterised by wider bid-ask spreads. Hagströmer and Nordén (2013) shows that on the NASDAQ-OMX Stockholm, market making is significantly higher in stocks that have wider bid-ask spreads. Carrion (2013) finds analogous results to that of Hagströmer and Nordén (2013). They find that HFTs engage in more liquidity provision during periods of low liquidity but consume liquidity during periods of high liquidity. That is, on NASDAQ, effective spreads are narrower by 0.7 basis points when the low-latency traders consume liquidity but 0.3 basis points wider when the low-latency market traders provide liquidity. Furthermore, liquidity-demanding and liquidity-supplying traders may have a different impact on bid-ask spreads and market depth levels (Hendershott, Jones and Menkveld, 2011). They suggest that greater competition among liquidity providers should improve bid-ask spreads. If liquidity-demanding automated traders, however, prevail in the market, their trading activities may improve or deteriorate spreads.

Chaboud, Chiquione, Hjalmarsson and Vega (2014), suggest that there is greater correlation between computer-generated orders than human-initiated orders. The greater degree of correlation between the market activities of computerised systems may be attributable to their pre-programming. There may be more common components in their responses to market events among automated traders. Greater pervasiveness of algorithmic and high frequency trading in financial markets may, therefore, exacerbate price volatility. Another reason for AT and HFT-induced volatility increases is provided by Boehmer, Fong and Wu (2012). Prior studies find that the efficiency at which prices are determined in markets improve due to algorithmic and high frequency trading activities (Brogaard, 2010; Hendershott and Riordan, 2014; Hasbrouck and Saar, 2013). Boehmer, Fong and Wu (2012) argue that an exacerbation of volatilities may arise from greater speeds of price adjustment i.e. improved price discovery. They examine an extensive sample of 40 equity markets over a nine-year period and find that algorithmic trading are positively correlated to volatility levels. Furthermore, exacerbations in volatility are more pronounced for stocks that are characterised by small market capitalisation, low price and high volatility. They find that observed increase in volatility, however, is not derived from improved price discovery.

During extreme market conditions, high frequency traders are found to exacerbate volatility. An examination of the Flash Crash on May 6 2010 shows that although high frequency traders did not cause the event, their aggressive trading activities contributed to the volatility in the market that day. (Kirilenko, Kyle, Samadi, Tuzun, 2011). High frequency traders are found to have aggressively traded in the price direction of the E-mini index futures contract and therefore amplified variations in prices. Results provided by Kirilenko, Kyle, Samadi, Tuzun (2011) suggest that during adverse market conditions, high frequency traders may have a detrimental impact on market volatility.

Conversely, Brogaard (2010), Hagströmer and Nordén (2013) and Hasbrouck and Saar (2013) present evidence of volatility improvements arising from greater algorithmic and high frequency trading. Hagströmer and Nordén (2013) examine trading in the 30 large-capitalisation Swedish stocks and finds that market-making HFTs have a mitigating impact on price volatility. In markets concentrated by market making-HFTs, an increase in high-speed trading reduces price volatility. Hasbrouck and Saar (2013) find analogous results on the NASDAQ. Increased low latency activity ease price volatility during both normal market conditions and volatile market conditions. The decline in price volatility is greater in magnitude during periods of greater uncertainty and volatility and for small-capitalisation stocks during this period. Hasbrouck and Saar (2013) suggests that during periods characterised by greater variation in prices, arbitrage HFT strategies are more profitable. Increased prevalence of arbitrage activities that trade away price deviations and therefore revert prices back to equilibrium has a mitigating impact on volatility.

Finally, a line of studies find no evidence of volatility changes attributable to automated or high frequency trading (Chaboud, Chiquione, Hjalmarsson and Vega, 2014; Brogaard, Hagströmer, Nordén and Riordan, 2013; Lee, 2013; Frino, Mollica and Webb, 2014). Chaboud, Chiquione, Hjalmarsson and Vega (2014) find that a more significant proportion of price variations arise from human-initiated orders as opposed to computer-generated trades. Brogaard, Hagströmer, Nordén and Riordan (2013) show that the greater willingness and ability of high speed traders to hold inventory are reasons for the resilience of price volatility from co-location service upgrades. If more inventories are held by a group of traders, large market orders that consume liquidity can be absorbed without correspondingly large price impacts. Therefore, the non-permanent component of volatility may be reduced. Furthermore, improvements in inventory management capacity may also contribute to a decrease in price pressures and thereby also reduce the non-permanent component of volatility (Hendershott and Menkveld, 2013; Brogaard, Hagströmer, Nordén and Riordan (2013). Finally, Lee (2013) suggest that in a market characterised by high liquidity, low latency and low levels of volatility, price volatility is resilient to changes in high frequency trading levels. More generally, they find that HFTs do not materially impact the quality of active, liquid markets.

2.3. Cross-listed Securities

The dynamics of related financial bourses have generated much interest among academics (e.g. Garbade and Silber, 1979; Koontz, Garcia and Hudson, 1990; Board and Sutcliffe, 1996; Domowitz, Glen and Madhavan, 1998; Pennings and Leuthold, 2001). With the increasing globalisation of financial markets and the greater efficiency of intermarket information flows, exchanges have become more related. Given the backdrop of greater interconnectedness across bourses, this section of the literature review examines cross-listed securities markets. An analysis of the short run price behaviour of cross-listed assets finds that it is a function of intermarket trading and information flows (Garbade and Silber, 1979). Information flows and the relative rates of price discovery are pertinent issues in cross-listing studies (Fleming, Ostdiek and Whaley, 1996; Hauser, Tanchuma and Yaari, 1998; Xu and Fung, 2002; Covrig, Ding and Low, 2004; Hsieh, 2004) as identical financial instruments listed on multiple exchanges are driven by the same source of information. Intermarket trading, another determinant of short run price behaviour, is described in literature as either competing (Domowitz, Glen and Madhavan, 1998; Chowdhry and Nanda, 1991; Parlour and Seppi, 2003) or mutually beneficial (Lau and McInish, 2002; Frino, Harris, Lepone and Wong, 2013). If cross-listed exchanges compete for the same order flow, as theorised by the Order Flow Diversion Hypothesis, the establishment of alternative venues or a microstructural improvement on one of the financial bourses may potentially cause a migration of trading interest or a change in intermarket dynamics.

A line of study contends that trading across cross-listed security bourses is competing in nature. Exchanges that trade the same financial instrument are substitute markets that compete for the same order flow (Domowitz, Glen and Madhavan, 1998; Chowdhry and Nanda, 1991; Parlour and Seppi, 2003). However, while cross-listed equity index securities are written on the same underlying asset, they differ by microstructural and regulatory factors and therefore are not perfect substitutes (Board and Sutcliffe, 1996). The Order Flow Diversion Hypothesis (Domowitz, Glen and Madhavan, 1998) supports the view that cross-listed financial exchanges are differentiated by market-specific factors and that a more conducive market structure attracts trading interest at the expense of alternative trading venues. This suggests that the existence or the establishment of an alternative market places downward pressure in the demand for that asset on an incumbent exchange. Differences in contract specification such as delivery month, margin requirements, contract size, trading hours and tick size may be material in determining the relative demand for trading across cross-listed equity-index futures markets. Regulatory regimes such as price limits, accessibility to foreigners, trading halts and position limits also potentially differentiate exchanges that trade cross-listed financial instruments (Board and Sutcliffe, 1996). Finally, the location of financial exchanges potentially affects the level of trading interest. The greater proximity of home markets to the source of information and local knowledge may influence a market participant's trading decision (Webb, Muthuswamy and Segara, 2007).

Differential trading costs across competing markets is found to be a significant determinant of the relative trading and rates of price discovery that takes place on these exchanges (Roope and Zubruegg, 2002; Chou and Lee, 2002; Hsieh, 2004). According to the Trading Cost Hypothesis (Fleming, Ostdiek and Whaley, 1996), informed traders gravitate towards markets that are characterised by lower trading costs to maximise their profits from trading on their information. Consequently, the market with the more competitive trading cost should reflect information first i.e. lead in price discovery. Furthermore, a reduction in trading costs on one of the cross-listed security exchanges should change the relative efficiency at which price is determined across these markets. According to Garbade and Silber (1979), disparities in price discovery efficiencies give rise to dominant and satellite markets. Price leadership takes place on the dominant bourse whereas satellite markets depend on dominant markets as a primary source of information (Garbade and Silber, 1979).

Empirical studies substantiate the hypothesis that trading costs play a determining role in intermarket competition across cross-listed securities exchanges. Chou and Lee (2002) examine the dominant and satellite markets of the Taiwan stock index futures and assesses the impact that trading costs have on these exchanges' relative rates of price discovery. A 2.5 basis point reduction in transaction tax on the Taiwan Futures Exchange (TAIFEX) is found to significantly improve the speed at which information is impounded into prices compared to the Singapore Exchange (SGX). Furthermore, this microstructural change on the TAIFEX coincides with a substantial increase in trading volume and improvement in liquidity. Quoted and effective spreads on TAIFEX became significantly smaller than those on SGX. Hsieh (2004) examines a series of regulatory changes on the TAIFEX to determine its impact on the relative information efficiencies. Across dominant and satellite markets. Four types of policy changes are assessed in this study including a shortening of call frequencies, a change in position limits, a reduction in transaction tax and an extension in trading hours. Anomalous to the findings of Chou and Lee (2002), trading cost changes is identified as the only policy amendment to affect the relative price discovery efficiencies across the TAIFEX and SGX.

The degree of stringency in an exchange's regulatory regime also determines the relative trading that takes place across competing cross-listed securities markets (Subrahmanyam, 1994; Berkman and Steenbeek, 1998). Earlier studies examine the role of price limits in determining the flow of trading interest across satellite and dominant bourses (Subrahmanyam, 1994; Berkman and Steenbeek, 1998). According to Subrahmanyam (1994), liquidity traders have the discretion to choose when and where to execute their trades. If the price is close to the price limit and the discretionary trader has the possibility to switch to a satellite market, he will switch if the cost of not being able to trade is sufficiently high. As a result, trading volume and volatility migrate from the dominant market to the satellite market when the price of a security on a dominant market approaches its price limit. Berkman and Steenbeek (1998) provide empirical evidence to substantiate the model theorised by Subrahmanyam (1994). While stringent price limits apply for the Nikkei 225 index futures contract traded on the Osaka Stock

Exchange (OSE), a more lenient price limit is imposed for the same contract traded on the Singapore Mercantile Exchange (SIMEX). The study finds that when the likelihood of reaching the price limit on the increases, more trading migrates to SIMEX. The migration of order flow to the less stringent regulatory environment facilitates efficient price formation on the Osaka Stock Exchange (Berkman and Steenbeek, 1998).

If rivalry for order flow exists between cross-listed securities bourses, as theorised by the Order Flow Diversion Hypothesis (Domowitz, Glen and Madhavan, 1998), the cross-listing of a financial instrument may potentially impair the market quality of an incumbent exchange. Domowitz, Glen and Madhavan (1998) argue that two opposing factors determine the overall impact of listing a security on multiple bourses i.e. order flow migration and intermarket competition. In transparent exchanges, the cross-listing of a financial instrument leads to enhanced market quality. As the existence of an alternative trading venue promotes foreign participation by overseas investors who otherwise would not trade, there is an upward adjustment in the aggregate number of market participants. Consequently, the liquidity and precision of public information in both exchanges improve. When intermarket price information is difficult to obtain, the listing of an asset on multiple bourses causes an outflow of informative orders from the domestic trading venue. This leads to a deterioration in liquidity and exacerbates price volatility. In an intermediate case, two opposing changes take place on the domestic bourse. While bid-ask spreads improve due to greater cross-market competition, the outflow of informative orders impairs liquidity and exacerbates price volatility (Domowitz, Glen and Madhavan, 1998). They argue that the relative degree of these two opposing effects determines the overall impact of cross-listing a financial instrument.

Consistent with the idea that the cross-listing of a security causes competition across financial exchanges are empirical studies that document adverse changes to a market due to the establishment of competing bourses. Huang and Stoll (1996) find that the development of electronic trading systems in the early 1990s including ASX, Instinet, Medoff and Posit coincides with a significant widening of bid-ask spreads on the NYSE and NASDAQ. This empirical finding supports the Spread-sensitive-uninformed-order-flow hypothesis (Harris, McInish and Wood, 2002). It argues that the development of alternative trading venues with comparatively competitive trading costs causes a migration of uninformed order flow by spread sensitive traders. A consequence of lower uninformed order flow is that the market would then less likely attract information traders (Benveniste and Wilhelm, 1992). Recently, the establishment of alternative trading venues such as Chi-X and BATS has fragmented trading in the U.S. and Western Europe. According to a report published by the U.S. Securities and Exchange Commission, the New York Stock Exchange's market share of equity trading was significantly higher in January 2005. Approximately 79.1% of its listed shares' aggregate trading volume was transacted on the exchange. By October 2009, the bourse's market share declined to 25.1%.

While a line of studies describe the relationship between cross-listed securities markets to be competing in nature (Domowitz, Glen and Madhavan, 1998; Chou and Lee, 2002), an opposing view is that they are mutually beneficial and that the development of an alternative trading venue has a positive impact on incumbent markets (Ding, Harris, Lau and McInish, 1999; Covrig, Ding and Low, 2004; Xu and Fung, 2002). This is evident in the price formation process that takes place across cross-listed security markets. Information linkages exist across different market centres that trade the same or similar assets (Fleming, Ostdiek and Whaley, 1996; Hauser, Tanchuma and Yaari, 1998; Xu and Fung, 2002; Covrig, Ding and Low, 2004; Hsieh, 2004). As cross-listed futures markets are driven by the same fundamentals, they should be closely related to the common efficient price and co-integrated with a single stochastic trend (Booth, Lee and Tse, 1996; Hua and Chen, 2007; Chen and Gau, 2009). Studies that examine the informational linkages across satellite and dominant exchanges find that satellite markets play a significant role in the price formation process (Ding, Harris, Lau and McInish, 1999; Covrig, Ding and Low, 2004). The Singapore Exchange is found to contribute to 42% of the futures and 33% of the total price discovery that takes place across the Tokyo Stock Exchange, the Osaka Stock Exchange and the Singapore Exchange. This level of contribution to the overall price formation of the Nikkei 225 is greater than the proportion of their market share (Covrig, Ding and Low, 2004). Furthermore, an analysis of China-backed stocks dual-listed on financial exchanges located in Hong Kong and New York finds that there exists significant mutual feedback of information between these markets (Xu and Fung, 2002). Roope and Zurbruegg (2002) empirically demonstrate that price leadership for the Taiwan equity index futures market originates in the offshore market.

The existence of multiple trading venues may have a beneficial impact on the volumes of all competing markets due to the arbitrage trading that takes place across informationally-linked financial instruments. An analysis of cross-listed futures contracts finds evidence of a mutually beneficial relationship between the daily turnovers of the off-shore and domestic markets. That is, there exists a significantly positive relationship between the turnovers of cross-listed Japan, India and Taiwan index futures contracts (Frino, Harris, Lepone and Wong, 2014). As described in Board and Sutcliffe (1996), cross-listed equity-index futures contracts that are written on the same market index and have a common expiration date must have the same value at delivery. Discrepancies in their value at expiration give rise to spread arbitrage profit opportunities. As the cost of trading futures is substantially lower than the cost of a basket of shares in the index, prices of cross-listed futures contracts will more likely be kept in line through spread arbitrage, rather than by trading the underlying. Consequently, multiple listing of a futures contract could potentially lead to an increase in the volumes of all exchanges due to intermarket trading (Board and Sutcliffe, 1996). Furthermore, an improvement to the contract specification of a financial instrument traded on one financial exchange may not necessarily detriment the demand for the same asset on a competing market but rather promote trading on both bourses.

Microstructural improvements on a competing financial exchange may concurrently improve both markets due to increased competition (Foucault and Menkveld, 2008). Studies find that the intermarket competition that arises from the fragmentation of order flow may not necessarily be detrimental to incumbent markets (Foucault and Menkveld, 2008). Foucault and Menkveld (2008) examine the cross-listing of Dutch equities arising from the establishment of an alternative trading venue i.e. EuroSETS by the London Stock Exchange. Prior to the inception of EuroSETS, trading in Dutch equities was concentrated on the NSC, a limit order bourse operated by Euronext. They find that the market depth of the consolidated limit order book improves significantly subsequent to the establishment of the entrant trading venue. Interestingly, the liquidity of the incumbent bourse also increases following the cross-listing of Dutch equities. The observed improvement in market depth coincides with a reduction in limit order fees by the NSC following the entrant of the EuroSETS. It suggests that the greater demand of stocks arising from reduced fees on the incumbent market exceeds the migration of order flow to the alternative trading venue. Cross listing of securities is, therefore, not necessarily adverse to liquidity levels of the incumbent exchange, as it promotes intermarket competition and therefore prompts policymakers to respond accordingly. The findings of Foucault and Menkveld (2008) suggests that disparities in market microstructure across cross-listed securities bourses is material to intermarket competition and therefore the relative trading that takes place on these financial exchanges.

Overall, extant literature suggests that the listing of a security across multiple exchanges may be beneficial or detrimental to the market quality of incumbent bourses. The establishment of an alternative trading venue could potentially reduce the demand for an asset on an existing bourse (Domowitz, Glen and Madhavan, 1998). When cross-listed security markets compete for the same order flow and intermarket price information is difficult to obtain, the development of a trading venue may cause an outflow of orders on incumbent bourses. This would consequently lead to a deterioration of its market quality. Alternatively, greater intermarket competition may reduce bid-ask spreads or prompt incumbent markets to make policy changes to attract order flow (Foucault and Menkveld, 2008). Furthermore, as identical financial instruments listed on multiple exchanges are driven by the same fundamentals, they are informationally-linked (Booth, Lee and Tse, 1996; Hua and Chen, 2007; Chen and Gau, 2009). Arbitrage profit opportunities exist when prices deviate from their relative values (Board and Sutcliffe, 1996). Consequently, the multiple listing of an asset may positively impact the market quality of all exchanges due to cross-border trading activities (Board and Sutcliffe, 1996). This thesis examines the role of microstructural improvements, namely the introduction of co-location services, on the relationship between cross-listed equity-index futures markets.

2.4. Hypothesis Development

This section uses the literature reviewed in earlier sections of this chapter to develop several hypotheses that are tested in this dissertation. Policymakers introduce co-location facilities to attract HFT orders in the market by reducing the distance and therefore the time it takes for orders to reach financial bourses. Previous studies find that the implementation of co-location facilities have a positive impact on HFT levels on futures markets (Frino, Mollica and Webb, 2014) and equity markets (Boehmer, Fong and Wu, 2012). If the Singapore's equity-index futures market is conducive to low latency trading, an introduction of co-location services should lead to greater HFT demand. This leads to the first hypothesis:

$H_{1:}$ High frequency trading levels increase when co-location services are introduced.

The general agreement in empirical literature is that increased HFT participation in financial exchanges narrow bid-ask spreads (Brogaard, 2010; Hendershott, Jones and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hasbrouck and Saar, 2013). Hendershott, Jones and Menkveld (2011) hypothesis that liquidity-demanding and liquidity-supplying traders have a disparate impact on spreads. The greater competition among liquidity providers should lead to an improvement in spreads. When liquidity-demanding algorithmic traders, however, prevail in the market, their trading activities may narrow or widen spreads. If the implementation of co-location services on SGX gives rise to an inflow of HFT orders and the high frequency traders on this bourse are predominately liquidity-suppliers, bid-ask spreads should narrow significantly.

H_2: Bid-ask spreads narrow when co-location services are introduced.

Existing literature document improvements in market depth arising from changes in the availability of latency speed. Following the introduction of co-location services (Frino, Mollica and Webb, 2014; Boehmer, Fong and Wu, 2012) and structural upgrades to faster trading speeds (Brogaard, Hagströmer, Nordén and Riordan, 2013), market depth is found to improve. Considering existing literature, the following hypotheses are tested for Singapore's equity-index futures contracts:

H_3: Best depth improves when co-location services are introduced.

H_4: Total depth improves when co-location services are introduced.

A financial exchange with low trading costs and fragmented order flow should attract greater HFT activity subsequent to the implementation of co-location facilities. High frequency trading strategies are often characterised by frequent submission, amendments and cancellations of orders (Aldridge, 2009; Brogaard, 2010). If a large proportion of the order submissions are either amended or cancelled prior to transaction, heightened HFT activity attributable to the introduction of co-location services does not necessarily lead to greater trading activity. The following hypothesis is tested by assessing the variables: transactions, trading volume and open interest.

H_5: Trading activity remains unchanged when co-location services are introduced.

Singapore's equity-index futures markets are informationally-linked to other equity, futures and options exchanges if they are driven by the same source of information. This gives rise to arbitrage profits when prices deviate from fundamental values or statistical intermarket relationships. As Hasbrouck and Saar (2013) explains increased prevalence of arbitrage activities that trade away price deviations and therefore revert prices back to equilibrium has a mitigating impact on price volatility. If the availability of lower latency speeds on Singapore's stock index futures exchange promotes arbitrage trading, then the introduction of co-location services should reduce market volatility. This rationale gives rise to the following hypothesis:

H_6: Price volatility decreases when co-location services are introduced.

Whether cross-listed financial exchanges compete for order flow or are mutually beneficially is debated in extant literature (e.g. Board and Sutcliffe, 1996; Fleming, Ostdiek and Whaley, 1996; Domowitz, Glen and Madhavan, 1998). If Singapore's equity-index futures bourses and its respective home bourses are of a competing nature, a migration of HFT order flows from the dominant to the satellite market may take place following the infrastructural improvement on SGX. However, if significant cross-border HFT activity takes place, correlated changes in high frequency trading levels across financial markets may take place. To determine the nature of intermarket trading dynamics in the context of high frequency trading and cross-listed securities exchanges, the following hypothesis is tested:

H_7: HFT order flow migrates from the dominant market to the satellite market when co-location services are introduced on the satellite market.

3. INSTITUTIONAL DETAILS

On 18 April 2011, the Singapore Exchange introduced co-location facilities to its equities and derivatives markets.[13] This infrastructural development allows latency-sensitive market participants to situate their trading systems in the same data centre as the exchange's trading, market data and clearing engines. The central trading engine of SGX's derivatives market is the Quotation and Execution System for the Trading of the Derivatives Market (QUEST-DT). An order message submitted to the exchange travels from a trading participant's order management system (OMS) to a QUEST-DT network gateway and finally onto the central trading system, QUEST-DT. The physical proximity of OMS to both QUEST-DT and real-time market data, improves a trader's speed of access and therefore reduces the time it takes for co-located market participants to trade and execute trading decisions.

Prior to the introduction of co-location services, traders had the option of connecting to the exchange via an approved network service provider or directly through SGX's managed network service.[14] Network service providers are third parties who have existing connections to QUEST-DT and that sell their network access to traders. Proximity hosting, a type of network service, allows market participants to place their trading systems in facilities located near exchanges and operated by third parties. The proximity hosting facility for SGX is managed by Singapore's telecommunications conglomerate, Singtel. Alternatively, market participants have the option to connect directly via leased lines. For this method of access, subscribers purchase bandwidth ranging from 512 Kbps to 6 Mbps and their network connections are managed by the exchange.

The decrease in the distance between traders' servers and both the exchange's central matching engine and real-time data feeds improves the round-trip network latency of trades i.e. the time it takes for information to travel from OMS to QUEST-DT and back. As Frino, Mollica and Webb (2014) suggest

[13] The adoption of co-location facilities is part of a $250 million initiative that was put into effect by the Singapore exchange to improve the speed of market accessibility. The opening of a new data centre and the implementation of a new trading engine for its equities market which took place on 11 April 2011 and 15 August 2011, respectively, were the other two microstructure changes that made up this initiative.
[14] These services are still available for non-colocated market participants.

latency is a function of three factors: the distance between a broker's office and the exchange, the quality of the infrastructure in which a broker is located in and the quality of the infrastructure provided by the telecommunications supplier. Brokers who connect through leased lines and SGX's proximity hosting service incur a round-trip network latency of 6,000 to 13,000μs and 800 to 1,250μs, respectively.[15] The introduction of co-location services substantially improved this to less than 100μs.

The price of hiring rack space in the exchange's data centre, inclusive of power supply, ranges from S$ 4,500 per month. All co-located members are provided with 4KVA of power supply per rack. Furthermore, market participants that trade on Singapore's derivatives market are subjected to a clearing fee, a trading access fee and a GST tax. The clearing fee and the access trading fee amount to 0.04% and 0.0075% of the traded contract's value, respectively.[16] A GST of 7% is charged on clearing fees, trading access fees and any brokerage fees incurred.

The Singapore Exchange's derivatives market is an order driven market and operates under a continuous auction system during regular trading hours. It provides a trading platform for the exchange-listed products: equity index futures and options, interest rate futures and options, foreign-exchange futures, commodities futures and a dividend index futures contract. For Singapore's equity-index futures market, trading takes place during the day (T session) and during the evening (T+1 session). A pre-opening period and a pre-closing period are held prior to and following each trading session, respectively. During these periods, orders can be submitted, amended and cancelled but are not matched. A non-cancel phase concludes both periods during which orders are matched at a single price.[17]

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[15] Round-trip latency refers to the total time it takes for information to be transmitted from OMS to QUEST-DT and back.
[16] There is a cap of S$200 for clearing fees.
[17] For further institutional details of SGX's equity-index futures market, refer to Table 4-1.

4. DATA AND RESEARCH DESIGN

4.1. Data

To assess the impact that co-location services have on Singapore's futures market, intraday tick data time-stamped in milliseconds is analysed. This dataset is sourced from Thomson Reuters and provides trade and order book information for each of the contracts examined. Specifically, it contains the price and volume of every transaction and the bid price, bid volume, ask price and ask volume for the ten best price levels. These variables are used to compute trading activity, high frequency trading and liquidity metrics (refer to Section 6 for further information). Daily open interest data, which provides information on the quantity of futures contracts that remain unsettled from the previous trading session, is also retrieved from Thomson Reuters and used in the analysis.

A sample period extending from 18 October 2010 to 17 October 2011 is studied, which coincides with a six-month event window around the implementation of co-location services. As financial institutions may not have made the transition to the new facility immediately following its launch, a one-year sample period is also analysed. The sample is restricted to trades in the nearest to maturity contracts and that occur during the day session. This excludes trades that take place during the pre-opening and pre-closing periods. To preclude maturity effects from confounding the analysis, expiration day observations are omitted from the sample.[18]

This thesis compares the behaviour of HFT activity and market quality around the introduction of co-location services for the four most liquid equity-index futures traded on Singapore's derivatives market (SGX). The Singapore Exchange's Nikkei 225 Index Futures, MSCI Taiwan Index Futures, CNX Nifty Index Futures and the FTSE China A50 Index Futures are examined in this research. For the purpose of assessing how satellite markets respond to infrastructure improvements differently from home markets,

[18] Expiration day effects of Singapore's stock index futures contracts are documented in literature (Chung and Hseu, 2008; Hsieh and Ma, 2009).

the domestic stock index futures i.e. the MSCI Singapore Index Futures is also included in the study.[19] Table 4-1 documents the market structure and contract specifications of the five treatment contracts.

For robustness, data for the Nikkei 225 Index Futures listed on the Osaka Stock Exchange (OSE), the Taiwan Stock Index listed on the Taiwan Futures Exchange (TAIFEX), the CNX Nifty Index listed on the National Stock Exchange of India (NSE) and the China Shanghai Shenzhen 300 Stock Index listed on the China Financial Futures Exchange (CFFEX), are collected. These futures constitute the control sample as they are written on the same or similar assets as the treatment sample but co-location facilities were not introduced on 18 April 2011 in the financial markets of these contracts. They provide an indication of the market quality and HFT intensity in bourses with no infrastructure changes at the time Singapore introduced their co-location facilities.[20] While three of the four control contracts expire during both serial and quarterly months, the Nikkei 225 (OSE) trade only on a quarterly cycle. The contract months of the Nikkei 225 (SGX), however, are both serial and quarterly. Preliminary analysis of the Nikkei (SGX) shows that trading activity in contracts that expire during the non-quarterly months is very thin. Therefore, these contracts are omitted from the treatment sample. Table 4-2 documents the market structure and contract specifications of the four control contracts.

[19] The MSCI Singapore Index Futures (SiMSCI) is one of two domestic stock index futures traded on the Singapore Exchange. The other futures contract i.e. the Straits Times Index Futures is thinly traded.
[20] During the period of analysis, co-location facilities were available on the Osaka Stock Exchange and the National Stock Exchange of India. It was not available on the Taiwan Futures Exchange or the China Financial Futures Exchange.

Table 4-1 Market Structure and Contract Specifications of SGX Futures Contracts

This table reports the market structure and contract specifications of the Nikkei 225 Index Futures, MSCI Taiwan Index Futures, CNX Nifty Index Futures and the FTSE China A50 Index Futures traded on the Singapore Exchange. For each contract, the underlying stock index, multiplier, minimum price fluctuation, contract months, trading hours, price limits, settlement procedure, position limit and trading costs are provided.

Exchange	Singapore Exchange		Singapore Exchange		Singapore Exchange		Singapore Exchange		Singapore Exchange	
Underlying Stock Index	Nikkei 225 Index		MSCI Taiwan Index^{SM}		CNX Nifty Index		FTSE China A50 Index		MSCI Singapore Free Index^{SM}	
Multiplier	¥500		US$100		US$2		US$1		S$200	
Minimum Price Fluctuation	Outright: 5 index points (¥2500) Strategy Trades: 1 index point (¥500)		0.1 index points (US$10)		0.5 index point (US$1)		5 index point (US$5)		0.1 index point (S$20)	
Contract Months	6 nearest serial months 20 nearest quarterly months		2 nearest serial months 12 nearest quarterly months		2 nearest serial months 4 nearest quarterly months		2 nearest serial months 4 nearest quarterly months		2 nearest serial months 4 nearest quarterly months	
Trading Hours	T Session:		T Session:		T Session:		T Session:		T Session:	
	Pre -Opening	07.30-07.43	Pre -Opening	08.30-08.43	Pre –Opening	08:45-08:58	Pre -Opening	08:45-08:58	Pre –Opening	08:15-08:28
	Non -Cancel Period	07:43-07:45	Non -Cancel Period	08:43-08:45	Non -Cancel Period	08:58-09:00	Non -Cancel Period	08:58-09:00	Non -Cancel Period	08:28-08:30
	Opening	07:45-14:25	Opening	08:45-13:45	Opening	09:00-18:10	Opening	09:00-15:55	Opening	08:30-17:10
	Pre-Closing	14:25-14:29	Pre-Closing	13:45-13:49	Pre-Closing	18:10-18:14	Pre-Closing	15:55-15:59	Pre-Closing	17:10-17:14
	Non-Cancel Period	14: 29-14:30	Non -Cancel Period	13:49-13:50	Non -Cancel Period	18:14-18:15	Non -Cancel Period	15:59-16:00	Non -Cancel Period	17:14-17:15
	T+1 Session:		T+1 Session:		T+1 Session:		T+1 Session:		T+1 Session:	
	Pre –Opening	15:00-15:13	Pre -Opening	14:20-14:33	Pre –Opening	19:00-19:13	Pre -Opening	16:30-16:38	Pre -Opening	18:00–18:13
	Non -Cancel Period	15:13-15:15	Non -Cancel Period	14:33-14:35	Non -Cancel Period	19:13-19:15	Non -Cancel Period	16:38-16:40	Non -Cancel Period	18:13–18:15
	Opening	15:15-02:00	Opening	14:35-02:00	Opening	19:15-02:00	Opening	16:40-02:00	Opening	18:15-02:00
	Pre-Closing	N.A.	Pre-Closing	N.A.	Pre-Closing	NA	Pre-Closing	N.A.	Pre-Closing	N.A.
	Non-Cancel Period	N.A.	Non -Cancel Period	N.A.	Non -Cancel Period	NA	Non -Cancel Period	N.A.	Non -Cancel Period	N.A.
Price Limits	Below 7,000 pts:*		Initial	7%	Initial	10%	Initial	10%	Final	15%
	Initial	1,000 points	Intermediate	10%	Intermediate	15%	Final	15%		
	Intermediate	1,500 points	Final	15%	Final	20%				
	Final	2,000 points								
	7,000 pts to below 10,000 pts									
	Initial	N.A.								
	Intermediate	1,500 points								
	Final	2,000 points								
	10,000 pts and above:									
	Initial	N.A.								
	Intermediate	N.A.								
	Final	/-2,000 points								

Table 4-1 Market Structure and Contract Specifications of SGX Futures Contracts (Cont.)

Exchange	Singapore Exchange	Singapore Exchange	Singapore Exchange	Singapore Exchange	Singapore Exchange
Underlying Stock Index	Nikkei 225 Index	MSCI Taiwan IndexSM	CNX Nifty Index	FTSE China A50 Index	MSCI Singapore Free IndexSM
Settlement Procedure	Cash Settlement	Cash Settlement	Cash Settlement	Cash Settlement	Cash Settlement
Position Limit	10,000 futures or futures equivalent contracts net long or net short in all contract months combined.	10,000 futures or futures equivalent contracts net long or net short in all contract months combined.	25,000 futures or futures equivalent contracts net long or net short in all contract months combined.	15,000 futures or futures equivalent contracts net long or net short in all contract months combined.	10,000 futures or futures equivalent contracts net long or net short in all contract months combined.
Trading Costs	Clearing Fee: 0.04% Trading Access Fee: 0.0075%	Clearing Fee: 0.04% Trading Access Fee: 0.0075%	Clearing Fee: 0.04% Trading Access Fee: 0.0075%	Clearing Fee: 0.04% Trading Access Fee: 0.0075%	Clearing Fee: 0.04% Trading Access Fee: 0.0075%

Table 4-2 Market Structure and Contract Specifications of Control Futures Contracts

This table reports the market structure and contract specifications of the Nikkei 225 Index Futures listed on the Osaka Stock Exchange, Taiwan Stock Index listed on the Taiwan Futures Exchange, CNX Nifty listed on the National Stock Exchange of India and the China Shanghai Shenzhen 300 Stock Index listed on the China Financial Futures Exchange. For each contract, the underlying stock index, multiplier, minimum price fluctuation, contract months, trading hours, price limits, settlement procedure, position limit and trading costs are provided.

Exchange	Osaka Stock Exchange	Taiwan Futures Exchange	National Stock Exchange of India	China Financial Futures Exchange
Underlying Stock Index	Nikkei 225 Index	TAIEX Index	CNX Nifty Index	CSI 300 Index
Multiplier	¥1000	NT$200	Re. 1	CNY 300
Min Price Fluctuation	0.01 index points (¥10)	1 index point (NT$200)	0.5 index point (Rs.0.05)	0.2 index point (CNY 60)
Contract Months	Jun and Dec: 10 nearest contract months Mar and Sep: 3 nearest contract months	2 nearest serial months 3 nearest quarterly months	3 nearest serial months	2 nearest serial months 2 nearest quarterly months
Trading Hours	Day Session: Pre -Opening: 08:00-09:00 Opening Auction: 9:00 Regular Session: 09:00-15:10 Pre-Closing: 15:10-15:15 Closing Auction: 15:15 Night Session: Pre -Opening: 16:15-16:30 Opening Auction: 16:30 Regular Session: 16:30-02:55 Pre-Closing: 02:55-03:00 Closing Auction: 3:00	Regular Trading Days: Trading Hours: 08:45-13:45	Regular Trading Days: Normal Market: 09:15-15:30 Setup Cutoff Time: 16:15 Trade Modification: 16:15	Regular Trading Days: First Session: 09:15-11:30 Second Session: 13:00-15:15
Price Limits	Normal: 8% 1st Expansion: 12% 2nd Expansion: 16%	Daily Price limit: 7%	Daily Price limit: 10%	Daily Price limit: 10%
Settlement Procedure	Cash Settlement	Cash Settlement	Cash Settlement	Cash Settlement
Position Limit	N.A.	Individual: 5000 Institution: 10000 Proprietary Trader: 30000	Higher of Rs.500 crores or 15% of the total open interest	Unilater position limit: 100 Lots
Trading Costs	Clearing Fee (Proprietary): ¥20 Clearing Fee (Customer): ¥20 Trading Fee (Proprietary): ¥70 Trading Fee (Customer): ¥110	Transaction Fee: NT$12 Clearing Fee: NT$8 Settlement Fee: NT$8 Futures Transaction Tax: 0.002%	Transactions Tax: 0.01% (SELL only) Transaction Charges: 0.00185% SEBI Turnover Charges : 0.0001% Stamp Duty: 0.002%	Trading Fee: CNY 30

4.2. Variable Measurements

4.2.1. Measures of High Frequency Trading Activity

This dissertation compares the behaviour of high frequency trading activity and market quality around the commencement of co-location services on the Singapore Exchange. Firstly, three measures of high frequency trading are employed to examine changes in its prevalence around this structural improvement. Messages per minute, order to trade ratio and algo trade (Hendershott, Jones and Menkveld, 2011) are used to quantify the level of high frequency trading (HFT) intensity in the control and treatment samples. As the dataset does not contain proprietary information, it is not feasible to directly observe HFT transactions or differentiate them from non-HFT transactions. The above proxies are therefore used to infer HFT activity.

Messages per minute refers to the aggregate number of new order submissions, modifications and order cancellations taken place over a one-minute time interval. In the market depth data retrieved from Thomson Reuters, each line denotes a new order or the revision of an existing order and therefore represents message traffic. Messages per minutes for contract *i* is calculated as the total number of message traffic on day *t* divided by the number of one-minute intervals during that trading day.

$$Messages\ per\ Minute_{it} = \frac{Message\ Traffic_{it}}{No.\ of\ One\ Minute\ Intervals_{it}} \qquad (1)$$

Order to trade ratio measures the quoting intensity of a financial market and is computed as the aggregate number of messages for contract *i* on day *t* divided by the total number of trades executed over that trading day. High frequency trading strategies are often characterised by frequent submission, amendments and cancellations of limit orders (Aldridge, 2009; Brogaard; 2010). Therefore, an increase in order to trade ratios may be indicative of greater HFT activity.

$$Order\ to\ Trade_{it} = \frac{Message\ Traffic_{it}}{No.\ of\ Trades_{it}} \qquad (2)$$

Algo trade, which was first introduced by Hendershott, Jones and Menkveld (2011), quantifies market wide algorithmic trading activity (AT) by standardising electronic message traffic by trading volume. As it is standardised by the quantity of futures contracts traded during a given period, changes in algo trade reflect changes in the submission and cancellations of limit orders. This proxy for AT therefore largely captures algorithmic liquidity supply (Hendershott, Jones and Menkveld, 2011). In this dissertation, algo trade is calculated as the negative of the trading volume for contract *i* on day *t* divided by the aggregate number of messages transmitted over that trading day.

$$Algo\ Trade_{it} = -\left(\frac{Trading\ Volume_{it}}{Message\ Traffic_{it}}\right) \qquad (3)$$

4.2.2. Measures of Market Quality

Various measures of market quality are analysed to assess changes in the behaviour of liquidity, trading activity and price volatility around the implementation of co-location facilities. To assess changes in market liquidity, proportional spreads, tick spreads, time-weighted spreads, best depth and total depth of each treatment contract is benchmarked against its respective control contract. The proportional bid-ask spread is computed as the difference between the ask price and the bid price divided by the midpoint price.[21] The midpoint price is the average of the ask price and the bid price. Daily proportional spread for contract *i* on day *t* is calculated as the average of all proportional spreads *j* prevailing during that day session.

$$Proportional\ Spread_{it} = \left[\sum_{j,i,t=1}^{n} \frac{Ask\ Price_{j,i,t} - Bid\ Price_{j,i,t}}{0.5\left(Ask\ Price_{j,i,t} + Bid\ Price_{j,i,t}\right)}\right] / n \qquad (4)$$

Tick spread refers to the bid-ask spread of a security as a proportion of its minimum price increment. It is calculated as the difference between the ask price and the bid price divided by the minimum tick size of the contract examined. For details on the tick size and tick value of each stock index futures contract in the treatment sample and the control sample, refer to Table 4-1 and 4-2, respectively. Daily tick

[21] Bid price and ask price refer to the best prevailing bid price and the best prevailing ask price, respectively.

spread for contract i on trading day t is computed as the average of all tick spreads j prevailing during that day session.

$$Tick\ Spread_{it} = \left[\sum_{j,i,t=1}^{n} \frac{Ask\ Price_{j,i,t} - Bid\ Price_{j,i,t}}{Minimum\ Tick\ Size_i}\right] / \ n \qquad (5)$$

The final measure of quoted bid-ask spread employed in this study is the time-weighted spread (McInish and Wood, 1992). This measure weights each proportional bid-ask spread h of the contract analysed by the percentage of time it remains prevailing in the order book. It is calculated over one-minute intervals and the weighting of each quote revision is computed as the percentage of time it remains 'alive' during its respective interval. Daily time-weighted spread for contract i on day t is calculated as the average of all one-minute spreads prevailing j during that trading day.

$$Time\ Weighted\ Spread_{it} = \left[\sum_{j,i,t=1}^{n} One\ Min\ TW\ Spread_{j,i,t}\right] / \ n \qquad (6)$$

$$One\ Min\ TW\ Spread_{j,i,t} = \sum_{h,j,i,t}^{m} \left[Prop\ Spread_{h,j,i,t}\ x\ \frac{Time\ Alive_{h,j,i,t}}{One\ Minute}\right] \qquad (7)$$

The other dimension of liquidity that is assessed in this study is quoted depth. It reflects the ability of a financial market to sustain sizeable market orders without substantially impacting the security's price. In this study, best depth and total depth are used to quantify the degree of depth in the market. Best depth is measured as the aggregate number of contracts available at the best prevailing bid price and the best prevailing ask price. Using tick market data, daily best depth for contract i on day t is computed as the average of all observations j over that trading day.

$$Best\ Depth_{it} = \left[\sum_{j,i,t=1}^{n} Prevailing\ Ask\ Volume_{j,i,t} + \ Prevailing\ Bid\ Volume_{j,i,t}\right] / \ n \quad (8)$$

Total visible depth refers to the aggregate number of contracts available in the limit order book on both the bid and ask sides. The tick dataset utilised in this study contains market depth information for the ten best price levels. Therefore, the measure of total depth includes the volume at the ten best prevailing bid prices and the ten best prevailing ask prices. Daily total depth for contract *i* on day *t* is computed as the average of all observations *j* over the day session.

$$Total\ Depth_{it} = \left[\sum_{j=1}^{n} Total\ Ask\ Volume_{j,t} + Total\ Bid\ Volume_{j,t}\right] / n \qquad (9)$$

To examine changes in trading activity around the commencement of co-location services, the average daily number of trades, the average daily trading volume, the average daily trade size and open interest are compared before and after the event. While the daily number of trades for contract *i* on day *t* measures the average frequency of transactions, the daily trading volume for contract *i* on day *t* measures the average number of contracts transacted during that trading day.

Average trade size is the average dollar value of each transaction that takes place during a particular trading session.[22] It is calculated as the aggregate daily trading value for contract *i* on day *t* divided by the total number of trades transacted over that day session. The traded value of a transaction *j* is calculated as the price of the transaction *j* multiplied by both the quantity of the transaction *j* and the multiplier of the contract *i*. For details on the multiplier of each equity index futures contract in the treatment sample and the control sample, refer to Table 4-1 and 4-2, respectively.

$$Trade\ Size_{it} = \frac{Daily\ Traded\ Value_{it}}{No.\ of\ Daily\ Trades_{it}} \qquad (10)$$

$$Daily\ Traded\ Value_{it} = \sum_{j,i,t=1}^{n}\left[Price_{j,i,t}\ x\ Volume_{j,i,t}\ x\ Multiplier_{i}\right] \qquad (11)$$

Open interest refers to the quantity of outstanding futures contracts that were not executed or did not expire during the previous session of trading. It provides an indication of the level of trading intensity in the futures market. Daily open interest data for each of the contracts in the treatment and control samples is obtained from Thomson Reuters.

[22] The Nikkei 225 (SGX) and (OSE) are denominated in yen, the CNX Nifty is denominated reminbi in and the CSI 300 Index is denominated in yuan. Refer to Table 4-1 and Table 4-2 for further details.

Finally, to study the impact that the introduction of co-location services have on the volatility of satellite markets, the behaviour of price volatility around its implementation is assessed. Price volatility for contract *i* on day *t* is measured as the natural log of the highest traded price divided by the lowest traded price during that trading day (Parkinson, 1980).

$$Volatility_{it} = \ln \frac{Daily\ High_{it}}{Daily\ Low_{it}} \tag{12}$$

4.3. Univariate and Multivariate Analysis

4.3.1. Univariate Analysis

Changes in the pervasiveness of HFT activity and the level of market quality are statistically tested using the daily measures described in 4.2.1 and 4.2.2. Firstly, the data is partitioned into two sub-periods: the pre-event period and the post-event period. The pre-event period extends from 18 October 2010 to 17 April 2011 and the post-event period extends from 18 April 2011 to 17 October 2011. For every equity-index futures contract included in the analysis, each daily measure of HFT activity and market liquidity are averaged over their respective sub-periods. Subsequently, a two-sample t-test is conducted for each daily measure to assess whether the means are statistically different between the sub-periods. The futures contract in both the treatment group and the control group are examined.

Paired t tests are conducted to evaluate the relative market behaviour of the treatment sample relative to the control sample around the implementation of co-location services. The daily HFT and market quality variables for each treatment contract is normalised by that of its respective control contract.[23] An analysis of the daily ratios find that the normality assumption is not met for all metrics examined. Therefore, the natural logarithm of each daily ratio is calculated.[24]

$$Daily\ Log\ Ratio\ (HFT)_{it} = Ln\ (\frac{Daily\ HFT\ of\ Treatment\ Contract_{it}}{Daily\ HFT\ of\ Control\ Contract_{it}}) \tag{13}$$

[23] The paired t-test is not performed for the MSCI Singapore Free Index (SiMSCI) as it does not have a control contract.
[24] The absolute value of each daily algo trade ratio is computed before the natural logarithm is applied.

$$Daily\ Log\ Ratio\ (MQ)_{it} = Ln\ (\frac{Daily\ MQ\ of\ Treatment\ Contract_{it}}{Daily\ MQ\ of\ Control\ Contact_{it}}) \quad (14)$$

For every HFT and market quality measure, the daily log ratio is averaged across their respective sub-period. A two-sample t-test is then conducted to assess whether the difference in the two means are significantly different from zero. The purpose of the paired t-test is to identify changes in the relative market behaviour from the pre-event period to the post-event period. By doing so, market-wide factors that affect both sub-samples are controlled for.[25]

4.3.2. Multivariate Analysis of High Frequency Trading

Multivariate analysis of high frequency trading activity (HFT) is conducted to control for the variables additional to the introduction of co-location services that explain variations in the level of HFT activity in a financial market. A system of regression models is estimated to control for the explanatory variables that have been identified to have a material impact on HFT intensity. In doing so, the effect of the exchange's infrastructure improvement is isolated from extraneous influences. The first set of regression models control for the contract-specific factors price volatility and open interest (Frino, Webb and Mollica, 2014).

Studies find that a security's price volatility affects its level of high frequency trading activity (Brogaard, 2010; Zhang, 2010; Kirilenko, Kyle, Samadi and Tuzun, 2011). Zhang (2010) empirically demonstrates that high frequency trading is positively correlated with stock price volatility. Conversely, Brogaard (2010) finds that HFT levels on the US equities market moderately decline when volatility increases. To preclude variations in HFT activity due to changes in price volatility from confounding the analysis, this variable is controlled for.

Hagströmer and Nordén (2013) find that market makers, a type of HFT trader, are more prevalent in stocks that are characterised by high trading activity. Brogaard (2010), on the other hand, provide

[25] The market for a cross-listed equity-index futures contract includes both the home market and the satellite markets.

empirical evidence to support that HFTs prefer to enter the market during periods of low trading activity on the US equities market. Changes in trading activity, therefore, are shown to have a material impact on HFT levels (Brogaard, 2010). Consequently, analogous to Frino, Mollica and Webb (2014), open interest is employed in the analysis as a control. In the futures market, open interest is indicative of the market's trading activity and liquidity (Wang, Yau and Baptiste, 1997).

The following regression models are estimated for each treatment contract:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (15)$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (16)$$

$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (17)$$

The dependent variables of the first set for the multivariate HFT analysis are *Messages per Minute*$_{it}$, *Ln(Order to Trade)*$_{it}$ and *Algo Trade*$_{it.}$[26] Analyses of order-to-trade ratios show that the data exhibits right skewness for selected contracts and therefore this variable is logarithmically transformed. These dependent variables are regressed on following three independent variables. *Colocation*$_{it}$ is a dummy variable which equals 1 if the observation takes place during the pre-event period, and 0 otherwise. *Open Interest*$_{it}$ refers to the quantity of futures contracts that have not been settled during the previous session of trading. *Price Volatility*$_{it}$ is the natural logarithm of the ratio highest traded price of the day session to the lowest traded price. The three equations are estimated individually for the Nikkei 225 Index, MSCI Taiwan Index, CNX Nifty Index, FTSE China A50 Index and the MSCI Singapore Index futures contracts listed on the Singapore Exchange.

Arbitrage, a type of high frequency trading strategy, attempts to capitalise on price discrepancies across financial instruments and markets. As the treatment contract and its respective control contract are written on the same or similar underlying stock index, arbitrage opportunities arise when there are prices differ across locations (Brennan and Schwartz, 1990). In this case, a market participant may

[26] Refer to Sections 4.2.1 and 4.2.2 for further details on these HFT proxies.

choose to enter both markets. Therefore, HFT activity on the home market may explain variations in the HFT activity on the satellite market. Furthermore, as both markets compete for order flow (Covrig, Ding and Low, 2004), changes in the HFT activity of one exchange may affect that of the other exchange. Consequently, the level of high frequency trading on the home market is controlled for in the analysis.

The following regression models are estimated for each treatment contract:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Messages\ per\ Minute_{i,t} + \varepsilon_{i,t} \quad (18)$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Order\ to\ Trade)_{i,t} + \varepsilon_{i,t} \quad (19)$$

$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Algo\ Trade_{i,t} + \varepsilon_{i,t} \quad (20)$$

The response variables for the second set of regression models are analogous to the first set and are detailed in section 4.2.1. Each dependent variable is regressed on the co-location dummy variable, which is explained above, and its respective control market variable. *Control Messages per Minute*$_{i,t}$ refers to the control market's daily average number of messages per minutes, *Ln (Control Order to Trade)*$_{i,t}$, measures the natural logarithm of the control market's daily average order-to-trade ratio and *Algo Trade*$_{i,t}$ quantifies the control market's daily average number of normalised messages. [27]

The Singapore Exchange's equity-index futures market are informationally-linked to other bourses that trade the same or similar stock index futures contracts, as they are driven by the same fundamentals (Covrig, Ding and Low, 2004; Hsieh, 2004). As international linkages exist across these markets, the volatility and the trading activity of home markets are related to that of its satellite market (Booth, Lee and Tse, 1996; Fung, Leung and Xu, 2001; Chng, 2004). Consequently, variations in the price volatility and trading activity of the control contract may explain that of the treatment contract which, in turn,

[27] The Nikkei 225 Index Futures traded on the Osaka Stock Exchange is the control contract for the Nikkei 225 Index Futures (SGX). The Taiwan Stock Index Futures traded on the Taiwan Futures Exchange is the control contract for the MSCI Taiwan Index Futures (SGX). The CNX Nifty Index Futures traded on the National Stock Exchange of India is the control contract for the CNX Nifty Index Futures (SGX). The China Shanghai Shenzhen 300 Stock Index Futures traded on the China Financial Futures Exchange is the control contract for the FTSE China A50 Index Futures (SGX).

explains the variations in its HFT level. Therefore, the home market's open interest and price volatility are controlled for in the following regression models of the multivariate analysis.

$$Message\ per\ Minute_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (21)$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (22)$$

$$Algo\ Trade_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (23)$$

The dependent variables of the final set for the multivariate HFT analysis are analogous to the previous sets. The explanatory variables for each multiple regression model in this set are the price volatility and open interest of both the treatment and its respective control contract and a colocation dummy variable. *Control Open Interest*$_{i,t}$ refers to the number of outstanding futures contracts on the control market and *Control Price Volatility*$_{i,t}$ measures the price volatility of the control contract. The remaining variables in this analysis are explained in the above sections.

For each multiple regression model that examines the Nikkei 225 Index Futures, a dummy variable *Earthquake*$_{i,t}$ is included in the analysis. This variable equals 1 if the observation takes place before the Tōhoku Earthquake on 11 March 2011, and 0 otherwise.[28] This natural disaster had a material impact on the high frequency trading activity of Singapore's Nikkei 225 market and therefore it is controlled for in the multivariate analysis.

4.3.3. Multivariate Analysis of Liquidity

According to Copeland and Galai (1983), liquidity providers set a bid-ask spread that trade-offs inflows expected to be gained from liquidity-motivated market participants and outflows expected to be lost to informed traders.[29] They theorise that the bid-ask spread of a security is positively related to its price volatility and negatively related to its trading volume. Price volatility quantifies the risk borne by market makers per unit of time. Consequently, during periods of greater volatility, they demand greater

[28] On 11 March 2011, an earthquake of magnitude 9.0 struck Tōhoku in Japan. Analysis of this event shows that it had a significant impact on the high frequency trading activity and market quality of both Singapore's Nikkei 225 and Japan's Nikkei 225 futures markets.

[29] Other theoretical models of bid-ask spreads are described in Demsetz (1968) and Stoll (1978).

compensation in the form of wider bid-ask spreads. As volatility and trading activity are determinants of liquidity, (Demsetz, 1968; Copeland and Galai, 19830) and to isolate the impact of co-location facilities on liquidity, these variables are controlled for. Analogous to Frino, Mollica and Webb (2014), open interest is employed to control for trading activity in this multivariate analysis of the futures market.

The following regression models are estimated for each treatment contract:

$$Ln(Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (24)$$

$$Ln(Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (25)$$

$$Ln(TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (26)$$

$$Best\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (27)$$

$$Total\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (28)$$

The dependent variables of the first set of regression models for the multivariate liquidity analysis include three measures of bid-ask spreads and two measures of market depth. $Ln\ (Prop\ Spread)_{it}$ denotes the natural logarithm of the daily average proportional spread, $Ln\ (Tick\ Spread)_{it}$ denotes the natural logarithm of the daily average tick spread and $Ln\ (TW\ Spread)_{it}$ denotes the natural logarithm of the daily average time-weighted spread. To correct for the right skewness present in the bid-ask spreads of selected contracts, all three measures are logarithmically transformed. $Best\ Depth_{it}$ refers to the daily average number of contracts available at the best bid and ask prices and $Total\ Depth_{it}$ the daily average number of contracts available in the visible limit order book. These response variables are regressed on the explanatory variables $Colocation_{it}$, $Open\ Interest_{it}$ and $Price\ Volatility_{it}$.[30] The above regression models are estimated individually for the Singapore Exchange's Nikkei 225 Index, MSCI Taiwan Index, CNX Nifty Index, MSCI Singapore Index and the FTSE China A50 Index futures contracts.

Previous studies find evidence of commonality in liquidity in financial markets and across exchanges (Chordia, Roll and Subrahmanyam, 2000; Karolyi, Lee and Dijk, 2002). If commonality in liquidity exists between SGX and the home markets, then changes in the bid-ask spread and depth of the home

[30] An explanation of these variables is provided in section 4.3.2.

market contracts would explain changes in the liquidity of the satellite market. To control for any commonality in liquidity across exchanges, the bid-ask spreads and the depth measures of the control contracts are included as explanatory variables in the regression analysis.

The following regressions are estimated:

$$Ln\ (Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t} \quad (29)$$
$$Ln\ (Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Tick\ Spread)_{i,t} + \varepsilon_{i,t} \quad (30)$$
$$Ln\ (TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ TW\ Spread)_{i,t} + \varepsilon_{i,t} \quad (31)$$
$$Best\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Best\ Depth_{i,t} + \varepsilon_{i,t} \quad (32)$$
$$Total\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Total\ Depth_{i,t} + \varepsilon_{i,t} \quad (33)$$

The second set of regression models employ the same dependent variables as the first set and are described in the previous section. Each dependent variable is regressed on a co-location dummy variable, which is explained in section 4.2.3, and its respective control market variable. *Ln (Control Prop Spread)$_{it}$* , *Ln (Control Tick Spread)$_{it}$* and *Ln (Control TW Spread)$_{it}$* refers to the natural logarithms of the daily average proportional spread, tick spread and time-weighted spread, respectively, for the control contract. *Control Best Depth$_{i,t}$*, measures the control market's daily average best depth and *Control Total Depth$_{i,t}$*, measures the control market's daily average total depth. [31]

As with the multivariate analysis of high frequency trading, the volatility and trading activity of the home markets are controlled for in the final set of regression models. The international linkage that exists across financial markets that trade the same or similar equity-index futures contracts is the reason for its inclusion in the regression analysis. Refer to section 4.3.2 for further details.

The following regressions are estimated:

$$Ln(Prop\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \quad (34)$$
$$Ln(Tick\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t}$$

[31] The Nikkei 225 Index Futures traded on the Osaka Stock Exchange is the control contract for the Nikkei 225 Index Futures (SGX). The Taiwan Stock Index Futures traded on the Taiwan Futures Exchange is the control contract for the MSCI Taiwan Index Futures (SGX). The CNX Nifty Index Futures traded on the National Stock Exchange of India is the control contract for the CNX Nifty Index Futures (SGX). The China Shanghai Shenzhen 300 Stock Index Futures traded on the China Financial Futures Exchange is the control contract for the FTSE China A50 Index Futures (SGX).

$$+ \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \qquad (35)$$

$$Ln(TW\ Spread)_{\mathrm{i,t}} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t}$$
$$+ \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \qquad (36)$$

$$Best\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t}$$
$$+\alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \qquad (37)$$

$$Total\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t}$$
$$+\alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t} \qquad (38)$$

The dependent variables for the final set of the multivariate liquidity analysis are analogous to the two previous sets. The explanatory variables are the price volatility and open interest of both the treatment and its respective control contract and a colocation dummy variable. These variables are detailed in the preceding sections.

5. RESULTS [32]

5.1. Univariate Results

Table 5-1 presents the annual trading volumes of the stock index futures traded on both the satellite and home exchanges. A comparison of volume levels of the Nikkei 225 index futures shows that the Singapore Exchange (SGX) captures the majority of market activity in this contract. Furthermore, it demonstrates that SGX's market share of this contract has increased steadily over the past five years. The majority of trading in Taiwan's equity-index futures contracts, however, takes place on the home market. SGX accounts for approximately a third of this market's trading volume and this proportion has remained steady over the past five years. Trading in the CNX Nifty Index Futures, on the other hand, is concentrated on the National Stock Exchange of India and less than 1% of this contract's total annual volume is transacted on the satellite market. Finally, since its inception in 2010, the China Financial Futures Exchange has captured the majority of the market for stock index futures contracts of China.[33] Volume levels of China-SGX, however, have increased substantially over the past five years. There was an abrupt drop in demand for this contract in 2009 with only one contract traded during the entire year. An increase in its demand saw its proportion increase from 1% in 2010 to over 7% in 2012. From the above results, it is evident that while SGX accounts for a significant proportion of the market share for Japan and Taiwan's equity-index futures. Trading in India and China's equity-index futures, however, are dominated on their home exchanges.

[32] For clarity and comparability, each equity index futures contract discussed in the results section will be referred to by the origin of their underlying index. Japan-SGX, Taiwan-SGX, India-SGX and China-SGX denotes the Singapore Exchange's Nikkei 225 Index Futures, MSCI Taiwan Index Futures, CNX Nifty Index Futures and CSI 300 Index Futures contracts, respectively. Japan-OSE, Taiwan-TAIFEX, India-NSE and China-CCFEX refers to the Nikkei 225 Index Futures denotes the Osaka Stock Exchange, the Taiwan Stock Exchange Index Futures traded on the Taiwan Futures Exchange, the CNX Nifty Index Futures traded on the National Stock Exchange of India and the China Shanghai Shenzhen 300 Index Futures traded on the China Financial Futures Exchange, respectively.

[33] The China Shanghai Shenzhen 300 stock index futures was introduced on 16 April 2010.

Table 5-1 Annual Trading Volume

This table reports the annual trading volumes for Singapore Exchange's Nikkei 225 futures index, MSCI Taiwan futures index, CNX Nifty futures index and China A50 futures index. It also reports the annual trading volumes for the Nikkei 225 index futures traded on the Osaka Stock Exchange, the Taiwan Stock Exchange index futures traded on the Taiwan Futures Exchange, the CNX Nifty index futures traded on the National Stock Exchange of India and the China Shanghai Shenzhen 300 index futures traded on the China Financial Futures Exchange. The period of analysis extends from 2008 to 2009. The proportion of the total trading volume that the satellite market accounts for is provided.[34]

Year	Japan			Taiwan			India			China		
	SGX	OSE	Percent	SGX	TAIFEX	Percent	SGX	NSE	Percent	SGX	CFFEX	Percent
2008	24,042,341	31,521,576	43.27%	11,680,971	20,295,484	36.53%	4,279,900	9,207,490,500	0.05%	21,214		
2009	23,863,146	19,926,216	54.50%	11,922,906	25,388,243	31.96%	3,999,830	8,532,876,650	0.05%	1		
2010	27,983,249	17,813,909	61.10%	14,414,688	26,411,482	35.31%	9,443,424	6,703,637,450	0.14%	508,319	45,945,151	1.09%
2011	28,254,637	14,707,842	65.77%	16,139,858	31,905,250	33.59%	12,614,413	6,429,529,250	0.20%	2,657,774	50,684,480	4.98%
2012	26,878,858	14,355,666	65.19%	15,112,942	25,417,975	37.29%	12,075,282	4,133,695,900	0.29%	8,499,337	105,174,949	7.48%

[34] The trading volumes reported in this table are not adjusted for contract size.

5.1.1. Two-Sample T-Test

Table 5-2 presents the descriptive statistics of the treatment sample. During the six months following the introduction of co-location facilities, liquidity improvements are observed for the India-SGX and China-SGX contracts. The liquidity of the Japan-SGX and Taiwan-SGX contracts decline over this period, as evident by the significantly wider bid-ask spreads and lower market depth. Results for the Singapore-SGX generally indicate that there is greater liquidity in this contract. Total depth, however, declines significantly at a 5% level. These observed changes in liquidity may be driven by factors other than the introduction of co-location services. Therefore, further analysis is required where other determinants of liquidity are controlled for.

Changes in the trading activities of most contracts are largely in line with its liquidity levels. During the post-event period, trading activity is greater for the India-SGX and the Singapore-SGX contracts but lower for the Japan-SGX contract. There is some evidence of greater trading activity for the China-SGX contract, as shown by a significant increase in open interest levels. Increases in the number of trades or trading volume, however, are not observed for this contract. Despite a marked decline in the liquidity of the Taiwan-SGX contract, its trading activity is significantly higher in the post-event period.

Order to trade and algo trade ratios suggest a greater level of HFT activity in the Japan-SGX contract but lower levels in the Taiwan-SGX and China-SGX contracts. The results suggest that high frequency trading in the India-SGX remains unchanged across sub-periods. Brogaard (2010) finds that on the U.S. equities market, moderate declines in high frequency trading levels arise when volatility increases. That is, volatility and other exogenous factors may have a material impact on low latency activity and therefore drive these observed changes. Further analyses that address these issues are conducted and presented in Sections 5.1.2, 5.2.1 and 5.4.1.

Table 5-2 Descriptive Statistics for SGX Futures Contracts

This table reports the descriptive statistics of proportional spreads, tick spreads, time-weighted spreads, best depth, total depth, messages per minutes, order to trade ratio, algo trade, the number of trades, trading volume, trade size, open interest and price volatility. The analysis is based on daily observations over a 6 months event window around the implementation of co-location facilities. For information on the market quality and high frequency trading measures refer to sections 4.2.1 and 4.2.2. The results for Nikkei 225 Index (SGX) are reported in Panel A, MSCI Taiwan Index (SGX) in Panel B, CNX Nifty Index (SGX) in Panel C, FTSE China A50 Index (SGX) in Panel D and MSCI Singapore Free Index (SGX) in Panel E. The pre-event period extends from 18 October 2010 to 17 April 2011 and the post-event period extends from 18 April 2011 to 17 October 2011. Reported are t-statistics and p-values comparing the means of the pre and post periods.

	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
	Panel A: Nikkei 225 Index (SGX)												
Pre	0.000502	0.002015	0.000501	344	5,386	50.52	1.35	-3.98	16,816	84,556	25,914,030	223,372	0.0192289
Post	0.000549	0.002044	0.000548	300	5,176	48.67	1.47	-3.37	14,659	68,617	21,400,304	205,685	0.0183484
Difference	0.000047	0.000029	0.000047	-44	-210	-1.85	0.12	0.62	-2,158	-15,939	-4,513,726	-17,686	-0.0008805
T-statistics	8.77	2.23	8.92	-3.40	-1.02	-1.23	2.33	4.45	-1.90	-3.06	-7.70	-5.26	-0.43
P-value	<.0001	0.026	<.0001	0.001	0.310	0.219	0.021	<.0001	0.059	0.003	<.0001	<.0001	0.670
	Panel B: MSCI Taiwan Index (SGX)												
Pre	0.000340	0.010443	0.000339	125	2,483	86.36	2.05	-1.66	13,778	43,920	99,548	149,567	0.0148165
Post	0.000367	0.010552	0.000366	104	2,021	91.44	1.88	-1.85	15,641	51,635	96,362	166,972	0.0232743
Difference	0.000026	0.000109	0.000027	-21	-462	5.08	-0.16	-0.19	1,863	7,715	-3,186	17,404	0.0084578
T-statistics	6.88	2.92	6.96	-6.30	-8.23	4.07	-2.74	-2.18	2.80	2.86	-0.72	4.11	5.84
P-value	<.0001	0.004	<.0001	<.0001	<.0001	<.0001	0.007	0.030	0.006	0.005	0.473	<.0001	<.0001
	Panel C: CNX Nifty Index (SGX)												
Pre	0.000278	1.603061	0.000440	20	280	66.24	3.93	-0.98	10,052	35,094	40,179	195,332	0.0208684
Post	0.000269	1.423481	0.000390	21	256	71.28	3.68	-1.01	11,637	39,741	35,712	247,514	0.0221573
Difference	-0.000009	-0.179579	-0.000050	0	-24	5.04	-0.24	-0.03	1,585	4,647	-4,467	52,182	0.0012889
T-statistics	-0.86	-3.60	-3.86	1.09	-5.35	4.19	-1.58	-0.47	2.96	1.54	-2.19	10.04	0.99
P-value	0.393	0.000	0.000	0.278	<.0001	<.0001	0.115	0.635	0.003	0.126	0.030	<.0001	0.322
	Panel D: FTSE China A50 Index (SGX)												
Pre	0.001024	9.872810	0.001414	51	618	39.39	16.77	-0.43	1,062	6,354	295,589	26,912	0.0220157
Post	0.000843	7.418469	0.001175	56	811	35.48	12.81	-0.54	1,196	7,110	255,924	45,923	0.0195383
Difference	-0.000182	-2.454341	-0.000239	5	193	-3.91	-3.96	-0.11	134	757	-39,665	19,011	-0.0024774
T-statistics	-8.20	-12.54	-6.63	3.55	10.37	-5.72	-4.11	-3.25	1.90	1.45	-3.39	13.06	-1.59
P-value	<.0001	<.0001	<.0001	0.001	<.0001	<.0001	<.0001	0.001	0.059	0.148	0.001	<.0001	0.114

Table 5-2 Descriptive Statistics for SGX Futures Contracts (Cont.)

	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
	Panel E: MSCI Singapore Index (SGX)												
Pre	0.000324	0.006016	0.000331	17	302	38.76	3.59	-0.50	5,729	9,799	131,029	45,629	0.0132600
Post	0.000346	0.005923	0.000347	19	281	50.92	3.20	-0.50	8,675	13,330	109,117	44,521	0.0197047
Difference	0.000022	-0.000094	0.000016	2	-21	12.16	-0.39	0.00	2,945	3,530	-21,911	-1,109	0.0064447
T-statistics	6.54	-2.95	4.30	3.16	-2.33	10.60	-5.74	0.02	9.10	4.44	-2.42	-0.89	5.96
P-value	<.0001	0.004	<.0001	0.002	0.021	<.0001	<.0001	0.985	<.0001	<.0001	0.016	0.376	<.0001

5.1.2 Paired T-Test

Table 5-3 presents the descriptive statistics of the daily log ratios.[35] A significant increase indicates that the log difference between the treatment contract and its respective control contract has increased across sub-periods. This analysis, therefore, controls for broad market movements that affect both dual-listed futures contracts. Improvements in bid-ask spreads are most evident for the India-SGX and China-SGX contracts with all three measures reporting a significant decline at the 1% and 5% levels, respectively. The market depth of India-SGX correspondingly increases in the post-event period while the market depth of China-SGX reports a decline. There is some evidence to suggest that bid-ask spreads are narrower for the Japan-SGX and Taiwan-SGX contracts. Furthermore, both the best and total depth measures suggest greater market depth levels for the Taiwan-SGX contract. Although market-wide factors are accounted for in this analysis, other contract specific determinants of liquidity have not been controlled for. Therefore, further analysis using a multivariate regression framework is conducted and presented in Sections 5.2.2 and 5.4.2.

As the log ratios of algo trade are calculated from absolute values, a negative change across sub-periods suggests greater HFT activity. The results for the two normalised measures of message traffic show that high frequency trading increase in the Japan-SGX and Taiwan-SGX contracts but decrease in the India-SGX and China-SGX contracts. Interestingly, while HFTs have a presence in the Japan-OSE and Taiwan-TAIFEX home markets, the India-NSE and China-CFFEX home markets are largely inaccessible to HFT foreigners due to regulatory and tax reasons. This suggests that a structural improvement aimed at promoting low latency trading is most effective on dual-listed futures markets where there are profit opportunities from cross-border trading. The robustness of these results are tested and presented in Sections 5.2.1, 5.3 and 5.4.1.

[35] For the discussion of log ratios, the ratios will be referred to by their satellite market.

Table 5-3 Descriptive Statistics of Daily Log Ratios

This table reports the descriptive statistics of the daily log ratios for the variables: proportional spreads, tick spreads, time-weighted spreads, best depth, total depth, messages per minutes, order to trade ratio, algo trade, the number of trades, trading volume, trade size, open interest and price volatility. For further information on the market quality and high frequency measures assessed see sections 4.2.1 and 4.2.2. Daily log ratios are calculated as the natural log of daily measures for each treatment contract divided by the daily measures of its respective control contract. Panel A provides the results for the Nikkei 225 Index (SGX) and its control contract, the Nikkei 225 Index (OSE). Panel B provides the results for the MSCI Taiwan Index (SGX) and its control contract, the Taiwan Stock Index (TAIFEX). Panel C provides the results for the CNX Nifty Index (SGX) and its control contract, the CNX Nifty Index (NSE). Panel D provides the results for the FTSE China A50 Index (SGX) and its control contract, the China Shanghai Shenzhen 300 Stock Index (CFFEX). The event window extends 6 months around the implementation of co-location facilities with the pre-event period extending from 18 October 2010 to 17 April 2011 and the post-event period extending from 18 April 2011 to 17 October 2011. Reported are t-statistics and p-values for comparing the means of the pre-event and post-event periods.

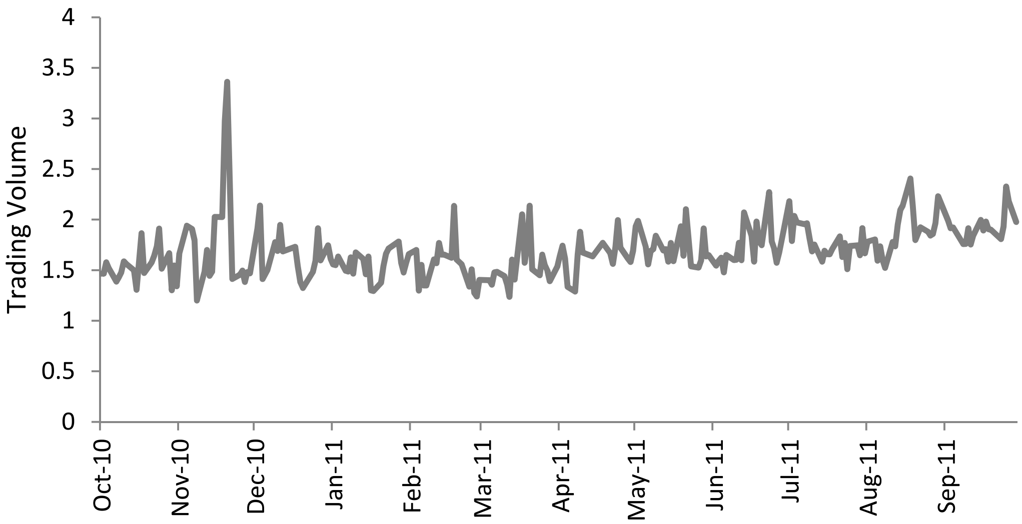
	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
	Panel A: Japan [Nikkei 225 Index (SGX) / Nikkei 225 Index (OSE)]												
Pre	-0.68545	0.70084	-0.68257	-1.08867	-0.87952	-1.12026	-2.18321	1.32412	1.31529	0.45620	-1.55229	-0.37137	1.11356
Post	-0.68747	0.69880	-0.68669	-0.95642	-0.91845	-0.50771	-1.93328	1.00179	1.50317	0.57168	-1.62465	-0.30457	1.01750
Difference	-0.00202	-0.00204	-0.00412	0.13225	-0.03893	0.61255	0.24993	-0.32233	0.18788	0.11548	-0.07236	0.06679	-0.09606
T-statistics	-1.76	-1.75	-2.70	8.32	-2.34	15.82	8.50	-10.16	10.44	6.76	-4.05	8.10	-3.78
P-Value	0.080	0.081	0.007	<.0001	0.020	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.000
	Panel B: Taiwan [MSCI Taiwan Index (SGX) / Taiwan Stock Index (TAIFEX)]												
Pre	0.91007	0.56924	0.91342	1.11306	1.63339	-0.71452	0.35314	-0.15036	-1.06766	-0.86489	-3.82698	0.93507	1.39104
Post	0.89816	0.54983	0.89856	1.25169	1.75434	-0.65925	0.54826	-0.26225	-1.20751	-0.92150	-3.75116	1.02332	1.56270
Difference	-0.01191	-0.01941	-0.01486	0.13863	0.12095	0.05527	0.19512	-0.11189	-0.13984	-0.05661	0.07582	0.08825	0.17165
T-statistics	-1.48	-2.39	-1.77	5.69	4.06	5.68	9.21	-2.85	-6.07	-1.47	2.18	1.87	2.54
P-Value	0.141	0.018	0.078	<.0001	<.0001	<.0001	<.0001	0.005	<.0001	0.144	0.031	0.063	0.012
	Panel C: India [CNX Nifty Index (SGX) / CNX Nifty Index (NSE)]												
Pre	0.99987	1.91577	1.44600	-4.73587	-3.57093	0.12910	1.19347	-7.06815	-0.71094	-6.58562	-9.09388	-4.77235	1.28951
Post	0.89299	1.80875	1.25320	-4.54892	-3.42686	0.20506	1.10142	-6.86966	-0.53489	-6.30313	-8.98751	-4.52686	1.28376
Difference	-0.10688	-0.10702	-0.19279	0.18695	0.14407	0.07596	-0.09205	0.19848	0.17605	0.28249	0.10638	0.24549	-0.00575
T-statistics	-5.64	-5.65	-6.31	8.31	8.02	6.30	-2.61	3.64	4.15	5.27	2.15	11.89	-0.06
0P-Value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.010	0.000	<.0001	<.0001	0.032	<.0001	0.955
	Panel D: China [FTSE China A50 Index (SGX) / China Shanghai Shenzhen 300 Stock Index (CFFEX)]												
Pre	2.13579	8.92984	2.45197	1.18507	1.82973	-1.04663	2.53171	-2.58212	-3.27026	-3.32067	-1.44506	0.24738	1.11246
Post	2.06593	8.86703	2.37667	1.06584	1.80574	-1.14960	2.26502	-2.36648	-3.13003	-3.23149	-1.48909	0.54558	1.26032
Difference	-0.06986	-0.06280	-0.07530	-0.11923	-0.02399	-0.10296	-0.26669	0.21564	0.14022	0.08917	-0.04403	0.29820	0.14786
T-statistics	-2.39	-2.17	-2.14	-2.89	-0.50	-5.27	-4.46	2.36	2.01	0.89	-0.77	3.05	1.41
P-Value	0.018	0.031	0.033	0.004	0.619	<.0001	<.0001	0.019	0.046	0.373	0.440	0.003	0.161

Figure 5-1 presents the daily relative trading volumes. Results show greater trading activity in the Japan-SGX, India-SGX and China-SGX contracts as evident by the significant increases in the number of trades, trading volumes and open interest levels.[36] The number of trades and the trading volume of the Taiwan-SGX contract, however, report significant declines. On the contrary, high frequency trading in the Taiwan-SGX contract increases over the same period. This suggests that a more pervasive high frequency trading presence does not necessarily lead to greater trading activity. That is, the large number of order submissions, amendments and cancellations carried out by high frequency trading systems do not necessarily lead to more transactions. A robustness tests where the last five trading days prior to expiration is deleted from the sample is conducted and presented in Section 5.3.

Figure 5-1 Relative Trading Volumes

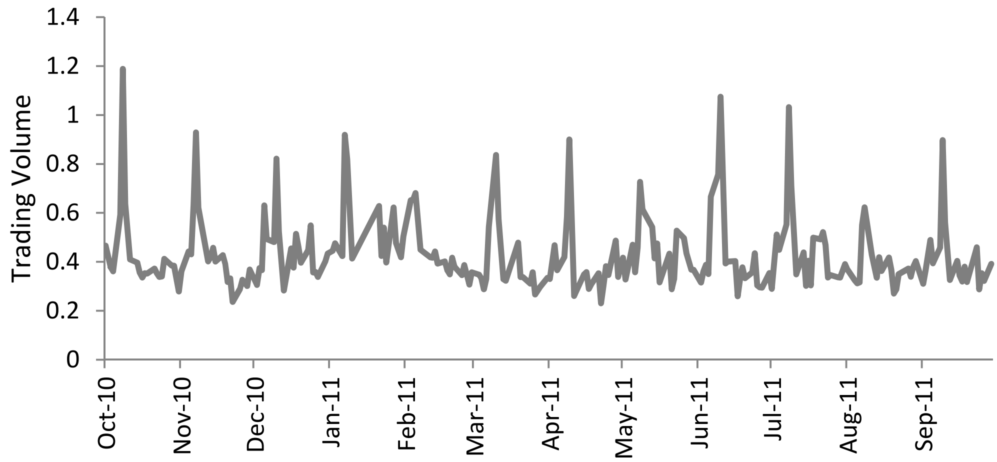
This figure presents the daily relative trading volumes. It is calculated as the daily trading volume of the satellite market contract divided by the daily trading volume of the home market contract. Panel A presents the results for the Nikkei 225(SGX) and the Nikkei 225 (OSE) contracts. Panel B presents the results for the MSCI Taiwan Index (SGX) and the Taiwan Stock Index (TAIFEX). Panel C presents the results for the CNX Nifty Index (SGX) and the CNX Nifty Index (NSE). Panel D presents the results for the FTSE China A50 Index (SGX) and the China Shanghai Shenzhen 300 Stock Index (CFFEX). The event window extends from 18 October 2010 to 17 October 2011.

Panel A: Japan

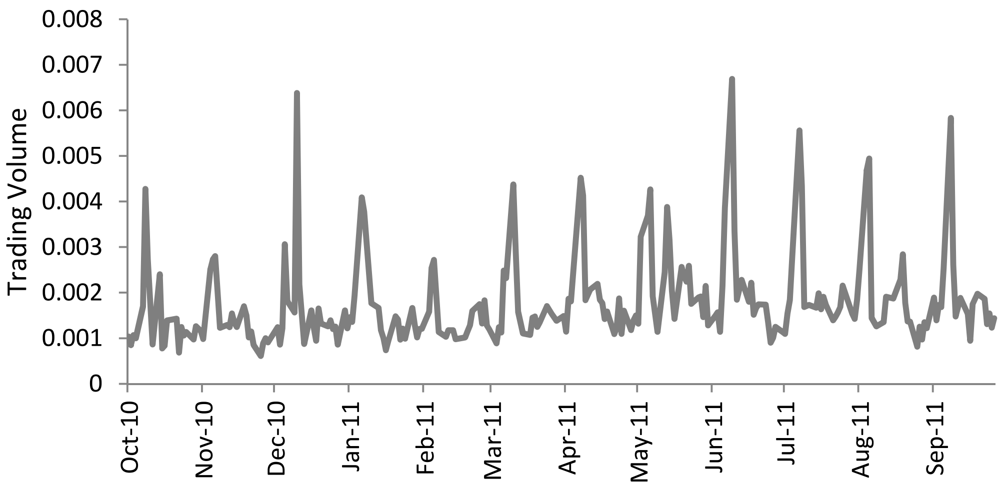


[36] This excludes the trading volumes of the China-SGX contract, which reports no significant change.

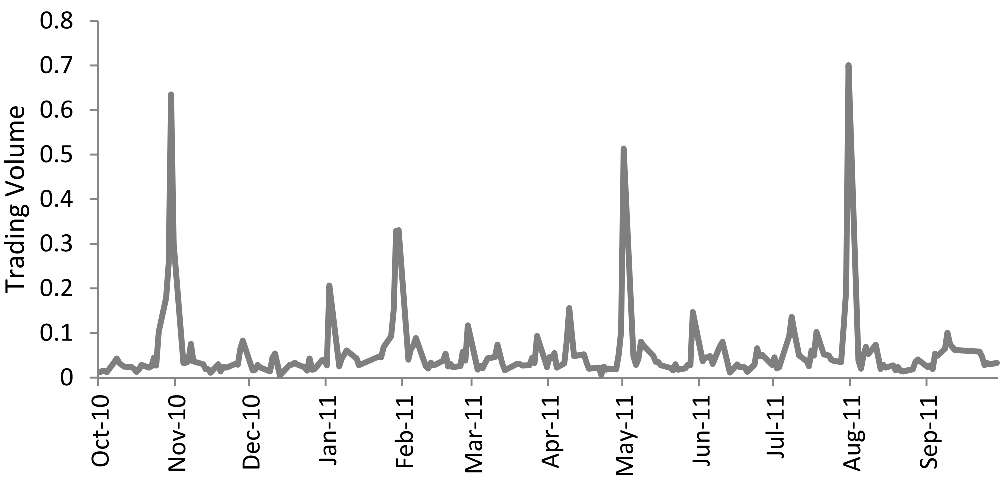
Panel B: Taiwan



Panel C: India



Panel D: China



Panel E: Singapore

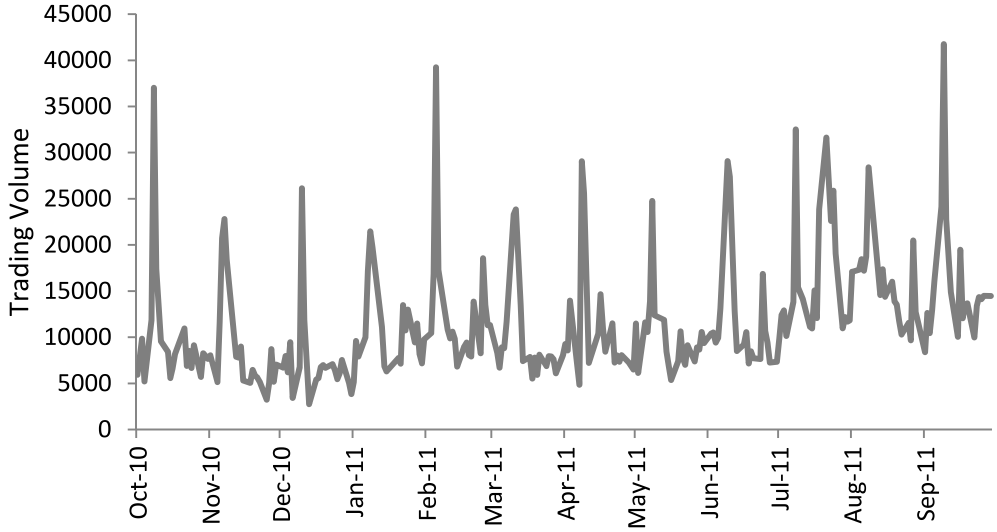
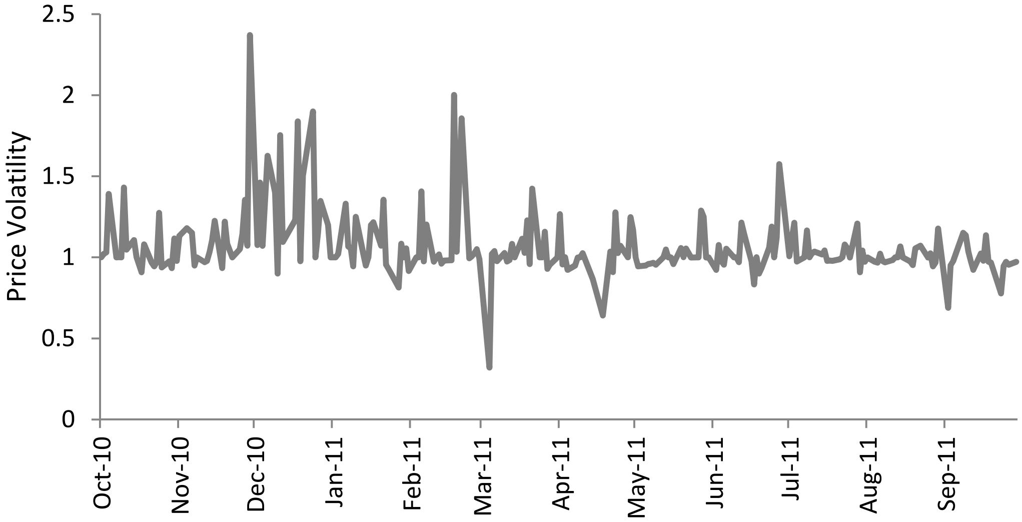


Figure 5-2 presents the daily relative trading volumes. Consistent with the findings of Hagströmer and Nordén (2013) and Hasbrouck and Saar (2013), the price volatility of the Japan-SGX contract declines significantly. The price volatility of the Taiwan-SGX contract, on the contrary, increases significantly over the same period. As reported earlier, both contracts exhibit greater high frequency trading levels following the introduction of co- location services. The directionally different impact that this microstructural change has on volatility levels may reflect the different types of trading strategies employed in these two contracts. Hagströmer and Nordén (2013) find that market making HFTs ease volatility while the causality of opportunistic HFT on volatility cannot be established. Results suggest that there is greater market making presence in the Japan-SGX contract than in the Taiwan-SGX contrac. Therefore greater HFT activity mitigates price volatility in the Japan-SGX contract. A multivariate analysis of liquidity in Sections 5.2.2 and 5.4.2 examines this issue further. No significant changes are observed for the price volatility of India-SGX and China-SGX.

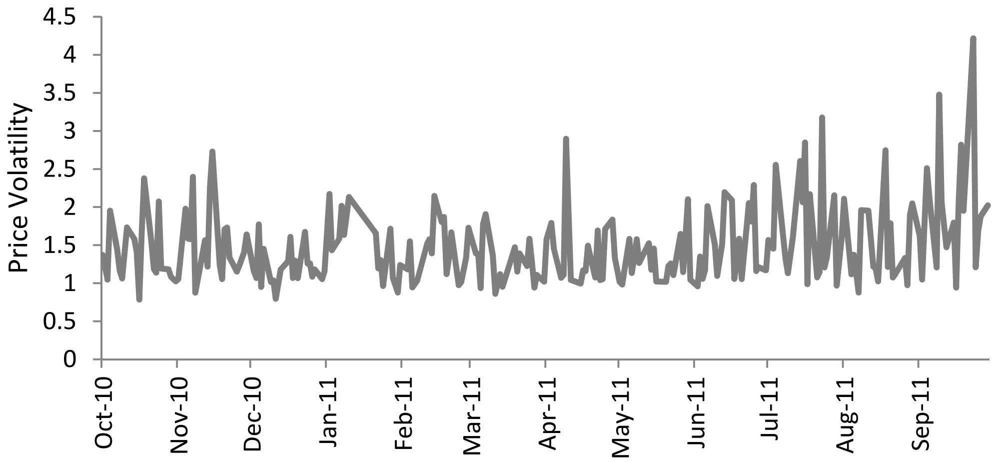
Figure 5-2 Relative Volatility

This figure presents the daily relative volatility. It is calculated as the daily volatility of the satellite market contract divided by the daily volatility of the home market contract. Panel A presents the results for the Nikkei 225(SGX) and the Nikkei 225 (OSE) contracts. Panel B presents the results for the MSCI Taiwan Index (SGX) and the Taiwan Stock Index (TAIFEX). Panel C presents the results for the CNX Nifty Index (SGX) and the CNX Nifty Index (NSE). Panel D presents the results for the FTSE China A50 Index (SGX) and the China Shanghai Shenzhen 300 Stock Index (CFFEX). The event window extends from 18 October 2010 to 17 October 2011.

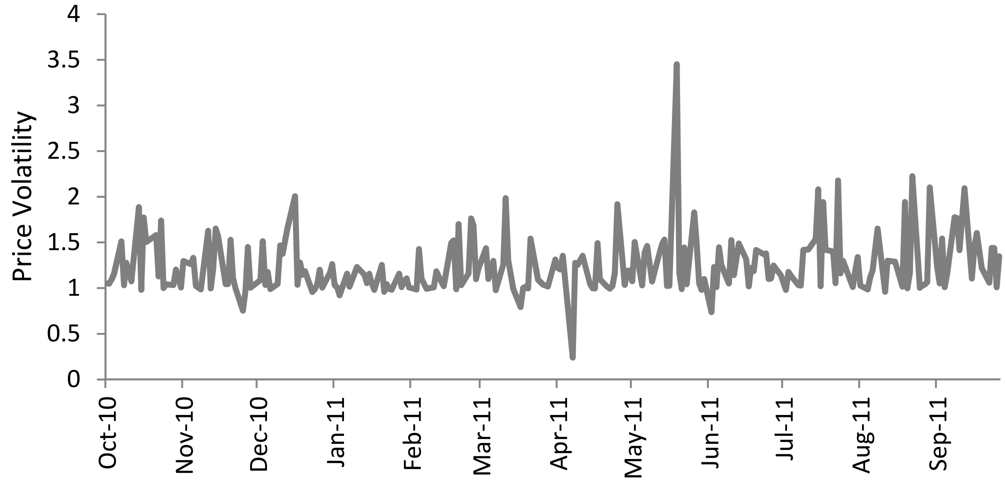
Panel A: Japan



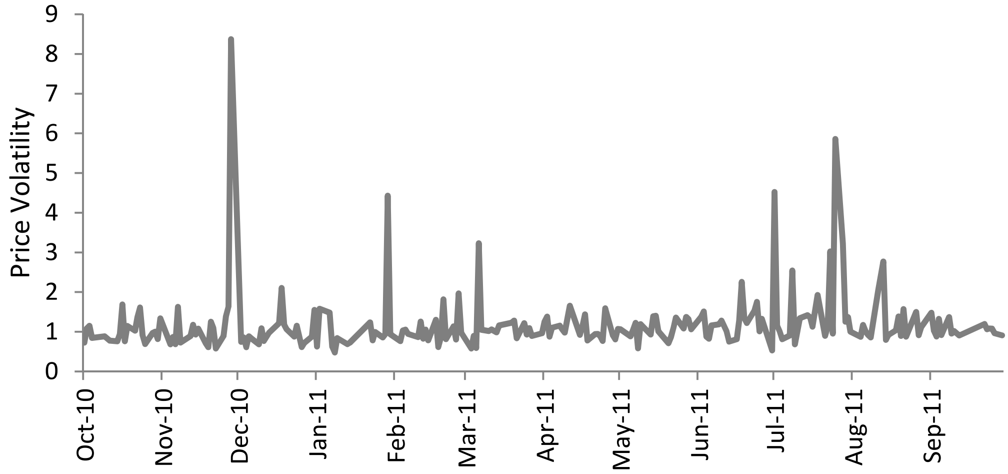
Panel B: Taiwan



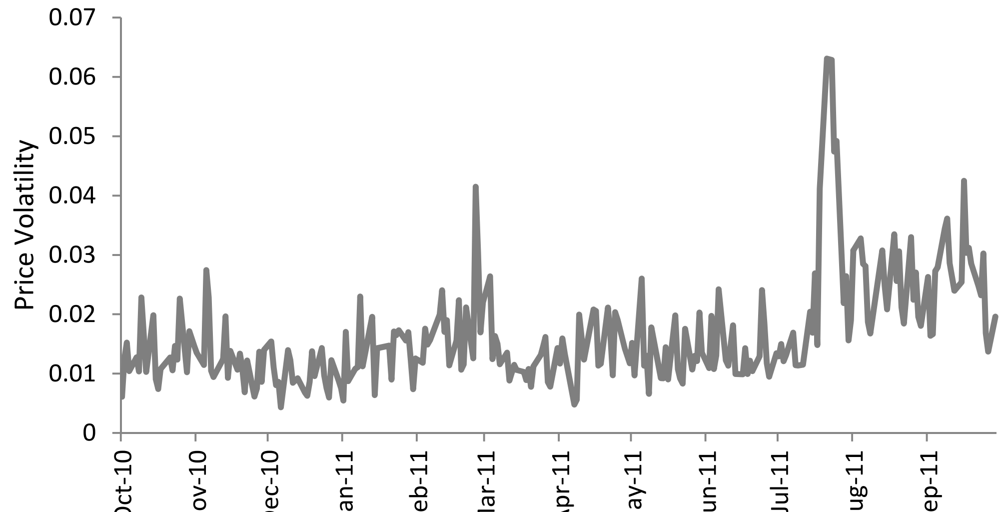
Panel C: India



Panel D: China



Panel E: Singapore



5.2. Multivariate Results

5.2.1 High Frequency Trading

Table 5-4 presents the coefficients for the contract-specific regressions examining high frequency trading. After controlling for open interest and price volatility, the results suggest that HFT activity on the India-SGX and the China-SGX contracts decline significantly. This is consistent with the conjecture put forward earlier that stock index futures markets with limited cross-market profit opportunities do not attract greater high frequency trading activity after co-location facilities are introduced. The increase in the number of messages per minute and algo trade ratio for the Singapore-SGX contract suggests that there may have been an increase in high frequency trading. However, the negative coefficient of the ln(order to trade) ratio provides evidence to support otherwise. The results for the Singapore-SGX contract are, therefore, inconclusive. Similarly, the results for the Japan-SGX and Taiwan-SGX contracts do not lead to meaningful conclusions. Further analysis is therefore conducted for a more detailed insight into the impact that co-location services have on low latency activity. Interestingly, the coefficients for the variable price volatility are negative and significant at the 1% level.[37] It suggests that high frequency trading is contingent upon market conditions and that on equity index futures exchanges HFTs reduce their presence in the market when price volatility increases. This finding is consistent with Brogaard (2010).

[37] The coefficients for the variable price volatility are significant at the 1% level for all futures contracts except for the China-SGX contract where it is significant at the 5% level.

Table 5-4 Contract-Specific High Frequency Trading Regression

This table reports the coefficients for the following regressions:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading and *Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. Results for the Singapore Exchange's SiMSCI, Nikkei 225, MSCI Taiwan, CNX Nifty and FTSE ChinaA50 are reported. The period of analysis extends from 18 October 2010 to 17 October 2011.

	SiMSCI (SGX)			Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages Per Minute														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	20.582	10.60	<.0001	30.081	8.21	<.0001	73.129	30.28	<.0001	59.054	28.05	<.0001	37.358	34.11	<.0001
Colocation	7.949	9.37	<.0001	-4.003	-2.54	0.012	-0.182	-0.17	0.867	6.036	6.31	<.0001	-3.266	-3.62	0.000
Open Interest	198.660	4.72	<.0001	50.560	3.07	0.002	34.010	2.29	0.023	3.030	0.30	0.766	-12.450	-0.41	0.685
Price Volatility	687.616	14.12	<.0001	402.974	13.98	<.0001	553.396	12.53	<.0001	315.767	7.78	<.0001	109.240	3.83	0.000
Earthquake				6.657	4.12	<.0001									
Adj. R Squared			0.683			0.584			0.458			0.351			0.161
	Panel B: Ln (Order to Trade)														
Intercept	1.393	36.20	<.0001	0.453	6.21	<.0001	1.026	19.44	<.0001	1.358	15.30	<.0001	2.891	32.84	<.0001
Colocation	-0.036	-2.11	0.036	0.081	2.59	0.010	0.068	2.86	0.005	-0.121	-3.00	0.003	-0.257	-3.55	0.001
Open Interest	0.824	0.99	0.325	0.029	0.09	0.929	-0.702	-2.16	0.032	1.410	3.30	0.001	-0.691	-0.28	0.779
Price Volatility	-12.375	-12.81	<.0001	-8.723	-15.19	<.0001	-15.801	-16.36	<.0001	-14.952	-8.74	<.0001	-6.629	-2.89	0.004
Earthquake				-0.071	-2.22	0.028									
Adj. R Squared			0.484			0.568			0.561			0.256			0.111
	Panel C: Algo Trade														
Intercept	-1.313	-18.99	<.0001	-2.579	-6.30	<.0001	-2.889	-18.75	<.0001	-2.558	-18.43	<.0001	-0.590	-11.30	<.0001
Colocation	0.082	2.73	0.007	-0.048	-0.27	0.786	-0.130	-1.88	0.062	-0.518	-8.21	<.0001	-0.285	-6.62	<.0001
Open Interest	20.390	13.59	<.0001	-3.000	-1.63	0.104	11.150	11.75	<.0001	9.550	14.25	<.0001	8.740	5.98	<.0001
Price Volatility	-9.165	-5.28	<.0001	-44.178	-13.73	<.0001	-30.173	-10.71	<.0001	-13.542	-5.06	<.0001	-3.228	-2.37	0.018
Earthquake				0.556	3.09	0.002									
Adj. R Squared			0.437			0.491			0.541			0.470			0.178

Table 5-5 presents the coefficients for the market-wide regressions examining high frequency trading. After controlling for high frequency trading activity on the alternative trading venues, the results are more consistent across the normalised message traffic measures. The coefficients for the co-location dummy variable suggests that the infrastructural change has a positive impact on HFT levels in the Japan-SGX and Taiwan-SGX contracts but a negative impact in the India-SGX and China-SGX contracts. These results are consistent with the findings of Table 5-3. They support the conjecture that co-location services increase low latency trading activity in markets where there are cross-border profit opportunities i.e. markets with alternative venues that have HFT presence. While there is active HFT participation on the Osaka Stock Exchange and the Taiwan Futures Exchange, the China Financial Futures Exchange and the National Stock Exchange of India are largely inaccessible to HFT foreigners due to regulatory and tax reasons. Therefore, co-location facilities do not generate more trading interest among HFTs in the India-SGX or the China-SGX contracts but significantly increases high frequency trading in the Japan-SGX and the Taiwan-SGX contracts. Evidence of cross-border trading is provided by the variables: control messages per minute, ln(control order to trade) and control algo trade. The coefficients of all three measures are positive and statistically significant at the 1% level.[38] This result is consistent across all futures contracts examined. It suggests that an increase in high frequency trading on the alternative trading venue leads to an increase in high frequency trading on Singapore's stock index futures market. The findings suggest that low latency traders on dual-listed futures markets do not compete for HFT order flow but engage in cross-border trading on both markets.

[38] Except for the coefficient of the variable control algo trade for the China-SGX contract which is significant at the 5% level.

Table 5-5 Market-Wide High Frequency Trading Regression

This table reports the coefficients for the following regressions:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Messages\ per\ Minute_{i,t} + \varepsilon_{i,t}$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Order\ to\ Trade)_{i,t} + \varepsilon_{i,t}$$

$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Algo\ Trade_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Control Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval for the control contract, *Ln (Control Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade for the control contract and *Control Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages per Minute											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	28.580	11.78	<.0001	-42.560	-6.77	<.0001	-192.558	-11.40	<.0001	21.112	4.81	<.0001
Colocation	-7.513	-3.98	<.0001	4.507	5.96	<.0001	1.627	2.27	0.024	-3.718	-5.53	<.0001
Control Messages per Minute	0.111	8.16	<.0001	0.735	20.56	<.0001	4.468	15.33	<.0001	0.164	4.20	<.0001
Earthquake	20.194	10.63	<.0001									
Adj. R Squared			0.370			0.679			0.591			0.176
	Panel B: Ln (Order to Trade)											
Intercept	-0.730	-8.35	<.0001	0.435	22.31	<.0001	0.962	23.70	<.0001	2.721	53.93	<.0001
Colocation	0.168	5.20	<.0001	0.128	5.68	<.0001	-0.135	-4.13	<.0001	-0.255	-4.60	<.0001
Ln (Control Order to Trade)	0.415	12.34	<.0001	0.759	19.13	<.0001	2.794	10.76	<.0001	0.018	0.11	0.911
Earthquake	-0.059	-1.63	0.105									
Adj. R Squared			0.475			0.632			0.335			0.080
	Panel C: Algo Trade											
Intercept	-1.947	-14.30	<.0001	-0.477	-3.16	0.002	-0.307	-2.29	0.023	-0.323	-5.66	<.0001
Colocation	0.349	2.29	0.023	0.100	1.15	0.252	-0.152	-2.12	0.035	-0.117	-3.37	0.001
Control Algo Trade	1.963	16.64	<.0001	0.636	8.53	<.0001	0.001	5.37	<.0001	0.018	2.06	0.041
Earthquake	0.642	3.86	0.000									
Adj. R Squared			0.566			0.257			0.104			0.053

Table 5-6 presents the coefficients for the combined regressions examining high frequency trading. After controlling for open interest, price volatility, open interest of the control market and the price volatility of the control market, the results for the Japan-SGX and China-SGX contracts are consistent with earlier set of regression models. The coefficients of the co-location dummy variable for the Taiwan-SGX and India-SGX contracts are, however, not consistent across HFT measures. The results for this set of regression models demonstrates that high frequency trading activity on alternative markets are an important factor in explaining changes in HFT levels on Singapore's equity-index futures market. Its material impact on the treatment contracts' HFT activity necessitates its inclusion in the regression analysis.

Finally, previous studies find evidence of abnormal trading activity on Singapore's derivatives market close to a contract's expiration due to investors' rollover activities (Chung and Hseu, 2008). A robustness test is conducted where five trading days prior to a contract's maturity is deleted from the sample and the regression models are refitted. The results from the robustness test are presented in Table A-1 to Table A-8. Specifically, the results for the contract-specific, market-wide and combined regressions examining high frequency trading are reported in Table A-3, Table A-4 and Table A-5. After controlling for high frequency trading activity on the alternative trading venues, the results of the robustness test confirm the findings of Table 5-5. That is, the introduction of co-location services on Singapore's equity-index futures market leads to an increase in high frequency trading in the Japan-SGX and Taiwan-SGX contracts but a decrease in the India-SGX and China-SGX contracts.

Table 5-6 Combined High Frequency Trading Regression

This table reports the coefficients for the following regressions:

$$Message\ per\ Minute_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Algo\ Trade_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading and *Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. *Control Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading for the control contract and *Control Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages per Minute											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	27.365	6.56	<.0001	89.550	21.20	<.0001	64.467	21.89	<.0001	31.727	20.60	<.0001
Colocation	-2.972	-1.83	0.069	1.101	1.12	0.265	3.835	3.54	0.001	-3.287	-3.70	0.000
Open Interest	0.094	0.00	0.998	27.190	2.05	0.042	43.050	2.91	0.004	11.200	0.40	0.693
Price Volatility	70.619	0.59	0.557	192.238	2.73	0.007	132.267	2.82	0.005	1.704	0.05	0.959
Control Open Interest	44.190	1.84	0.067	-281.180	-4.55	<.0001	-0.643	-3.44	0.001	103.880	2.43	0.016
Control Price Volatility	337.609	2.80	0.006	518.418	5.95	<.0001	299.659	5.74	<.0001	232.675	6.13	<.0001
Earthquake	6.339	3.97	<.0001									
Adj. R Squared			0.602			0.570			0.453			0.312
	Panel B: Ln (Order to Trade)											
Intercept	0.410	4.85	<.0001	0.958	9.73	<.0001	1.187	9.21	<.0001	3.075	23.12	<.0001
Colocation	0.087	2.65	0.009	0.052	2.28	0.024	-0.050	-1.06	0.292	-0.284	-3.70	0.000
Open Interest	-0.279	-0.46	0.646	-0.609	-1.97	0.050	0.126	0.19	0.846	-1.400	-0.57	0.568
Price Volatility	-4.528	-1.86	0.064	-8.964	-5.46	<.0001	-8.876	-4.33	<.0001	-0.762	-0.27	0.788
Control Open Interest	0.338	0.69	0.488	1.200	0.83	0.407	0.021	2.53	0.012	-1.490	-0.40	0.688
Control Price Volatility	-4.359	-1.78	0.076	-10.108	-4.98	<.0001	-9.971	-4.37	<.0001	-11.936	-3.65	0.000
Earthquake	-0.063	-1.95	0.053									
Adj. R Squared			0.570			0.605			0.324			0.159

Table 5-6 Combined High Frequency Trading Regression (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel C: Algo Trade											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-4.167	-9.68	<.0001	-2.625	-8.88	<.0001	-2.735	-13.72	<.0001	-0.502	-6.24	<.0001
Colocation	0.340	2.03	0.044	-0.148	-2.15	0.032	-0.428	-5.84	<.0001	-0.288	-6.20	<.0001
Open Interest	-22.190	-7.18	<.0001	11.280	12.14	<.0001	7.910	7.91	<.0001	8.380	5.66	<.0001
Price Volatility	-39.165	-3.16	0.002	-16.239	-3.30	0.001	-2.929	-0.92	0.357	-1.281	-0.75	0.454
Control Open Interest	18.240	7.38	<.0001	-4.420	-1.02	0.308	0.026	2.06	0.040	-1.400	-0.63	0.531
Control Price Volatility	-7.163	-0.58	0.565	-21.089	-3.46	0.001	-18.202	-5.15	<.0001	-4.127	-2.08	0.038
Earthquake	0.649	3.95	0.000									
Adj. R Squared			0.584			0.562			0.528			0.190

5.2.2. *Liquidity*

Table 5-7 presents the coefficients for the contract-specific regressions examining market liquidity. Evidently, liquidity improvements are observed for the India-SGX and the China-SGX contracts, despite declines in high frequency trading activity. Bid-ask spreads narrow for the India-SGX and China-SGX contracts and the market depth measures of the China -SGX contract increase significantly. Total depth levels of the India-SGX contract, however, report a significant decline. Frino, Mollica and Webb (2013) find similar anomalous results for the SPI futures contract on the Australian Securities Exchange. They suggest that co-location services may improve the efficiency with which market participants are able to make markets, thereby increasing market liquidity, without additional high frequency trading activity.

Conversely, the market liquidity of the Taiwan-SGX contract decline significantly despite greater HFT levels. Bid-ask spreads widened significantly and both the best depth and total depth report lower levels. A possible explanation for this result may be found in Hendershott, Jones and Menkveld (2011) and Hagströmer and Nordén (2013). Hagströmer and Nordén (2013) put forward the argument that high frequency market participants are a heterogeneous group of traders. Consequently, the impact that they have on the market quality of financial bourses is contingent upon the trading strategies they utilise. While HFT traders that employ market-making strategies primarily supply liquidity, those that employ opportunistic strategies predominately demand liquidity (Hagströmer and Nordén, 2013). The evident decline in liquidity, despite increased high frequency trading activity may reflect the type of traders prevailing in the Taiwan-SGX market. HFTs in this contract may be primarily liquidity-demand, opportunistic traders. Therefore a greater presence of HFTs causes a decline in market liquidity. Furthermore, earlier results suggest that there is an overall decline in market quality. Price volatility is significantly higher (Table 5-3 and Figure 5-2) and trading volumes are significantly lower (Table 5-3 and Figure 5-1) in the Taiwan-SGX contract. This is consistent with high frequency traders implementing more opportunistic trading strategies than beneficial strategies such as market making.

Table 5-7 Contract-Specific Liquidity Regression

This table reports the coefficients for the following regressions:

$$Ln(Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Ln(Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Ln(TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Best\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Total\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Ln (Prop Spread)$_{it}$* represents the natural logarithm of the daily average proportional spread, *Ln(Tick Spread)$_{it}$* represents the natural logarithm of the daily average tick spread and *Ln(TW Spread)$_{it}$* represents the natural logarithm of the daily average time-weighted spread. *Best Depth$_{it}$* refers to the daily average number of contracts available at the best bid and ask prices and *Total Depth$_{it}$* refers to the daily average number of contracts available in the visible limit order book. *Colocation$_{it}$* takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest$_{it}$* refers to the number of outstanding contracts from the previous session of trading and *Price Volatility$_{it}$* is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. Results for the Singapore Exchange's SiMSCI, Nikkei 225, MSCI Taiwan, CNX Nifty and FTSE ChinaA50 contracts are reported. The period of analysis extends from 18 October 2010 to 17 October 2011

	SiMSCI			Nikkei 225			MSCI Taiwan			CNX Nifty			FTSE China A50		
	Panel A: Ln (Proportional Spread)														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-8.137	-402.41	<.0001	-7.532	-295.09	<.0001	-7.993	-372.63	<.0001	-8.206	-152.63	<.0001	-6.956	-191.55	<.0001
Colocation	0.035	3.95	0.000	0.018	1.62	0.106	0.043	4.41	<.0001	-0.073	-2.97	0.003	-0.169	-5.65	<.0001
Open Interest	0.884	2.01	0.045	-0.498	-4.34	<.0001	-0.357	-2.70	0.007	-0.510	-1.97	0.051	-0.686	-0.67	0.500
Price Volatility	4.561	8.99	<.0001	1.700	8.47	<.0001	4.111	10.48	<.0001	4.954	4.78	<.0001	3.301	3.49	0.001
Earthquake				0.061	5.39	<.0001									
Adj. R Squared			0.400			0.564			0.453			0.150			0.268
	Panel B: Ln (Tick Spread)														
Intercept	-5.126	-401.99	<.0001	-6.222	-2472.70	<.0001	-4.542	-553.66	<.0001	0.527	10.63	<.0001	2.288	68.50	<.0001
Colocation	-0.022	-3.96	0.000	-0.007	-6.16	<.0001	0.007	1.90	0.058	-0.144	-6.40	<.0001	-0.221	-8.02	<.0001
Open Interest	-0.046	-0.17	0.867	0.017	1.52	0.131	-0.208	-4.11	<.0001	-0.660	-2.76	0.006	-2.690	-2.88	0.004
Price Volatility	1.027	3.21	0.002	0.510	25.77	<.0001	0.778	5.19	<.0001	3.027	3.17	0.002	2.631	3.02	0.003
Earthquake				0.007	6.76	<.0001									
Adj. R Squared			0.066			0.813			0.185			0.291			0.468
	Panel C: Ln (Time-weighted Spread)														
Intercept	-8.119	-354.47	<.0001	-7.535	-294.17	<.0001	-7.996	-373.02	<.0001	-7.728	-110.68	<.0001	-6.695	-147.49	<.0001
Colocation	0.020	1.98	0.049	0.019	1.73	0.085	0.044	4.51	<.0001	-0.143	-4.50	<.0001	-0.213	-5.69	<.0001
Open Interest	1.030	2.07	0.039	-0.496	-4.31	<.0001	-0.366	-2.77	0.006	-0.371	-1.10	0.272	1.370	1.08	0.282
Price Volatility	4.175	7.26	<.0001	1.664	8.26	<.0001	4.106	10.47	<.0001	2.476	1.84	0.067	3.436	2.91	0.004
Earthquake				0.060	5.29	<.0001									
Adj. R Squared			0.277			0.560			0.455			0.134			0.201

Table 5-7 Contract-Specific Liquidity Regression (Cont.)

	SiMSCI			Nikkei 225			MSCI Taiwan			CNX Nifty			FTSE China A50		
	Panel D: Best Depth														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	3.039	43.18	<.0001	5.845	50.31	<.0001	4.839	74.13	<.0001	2.840	54.58	<.0001	3.905	97.39	<.0001
Colocation	0.137	4.47	<.0001	0.480	9.61	<.0001	-0.136	-4.64	<.0001	-0.008	-0.36	0.723	0.068	2.06	0.041
Open Interest	-3.550	-2.33	0.021	0.657	1.26	0.210	0.588	1.46	0.145	0.735	2.93	0.004	1.620	1.45	0.150
Price Volatility	-6.220	-3.52	0.001	-4.651	-5.09	<.0001	-8.175	-6.85	<.0001	0.010	0.01	0.992	-1.842	-1.76	0.079
Earthquake				-0.634	-12.39	<.0001									
Adj. R Squared			0.123			0.523			0.314			0.033			0.080
	Panel E: Total Depth														
Intercept	6.140	98.07	<.0001	8.450	74.95	<.0001	7.982	148.15	<.0001	5.755	147.84	<.0001	6.347	146.72	<.0001
Colocation	-0.028	-1.03	0.303	0.572	11.79	<.0001	-0.127	-5.24	<.0001	-0.054	-3.06	0.002	0.189	5.31	<.0001
Open Interest	-7.620	-5.61	<.0001	1.370	2.71	0.007	-0.215	-0.65	0.519	-0.597	-3.18	0.002	4.720	3.90	0.000
Price Volatility	-8.060	-5.13	<.0001	-5.550	-6.26	<.0001	-9.885	-10.03	<.0001	-0.438	-0.58	0.560	-3.560	-3.16	0.002
Earthquake				-0.609	-12.28	<.0001									
Adj. R Squared			0.259			0.549			0.470			0.149			0.380

Table 5-8 presents the coefficients for the market-wide regressions examining market liquidity. After controlling for the liquidity of alternative trading venues, the results for the Taiwan-SGX, India-SGX and the China-SGX contracts are largely in line with the results presented in Table 5-7. The liquidity of the Japan-SGX contract shows significant improvements as evident by the narrowing of bid-ask spreads and greater market depth levels. Earlier, it is shown that high frequency trading activity in this contract increases following the introduction of co-location facilities. The improvement in liquidity, therefore, suggests that the HFTs in the Japan-SGX contract are primarily liquidity-supplying market makers.

Finally, coefficients for the variables Ln(Control Prop Spread), Ln(Control Tick Spread), Ln(Control Time-Weighted Spread), Control Best Depth and Control Total Depth variables are positive and statistically significant. These results are observed for all treatment contracts. This suggests that liquidity levels on Singapore's futures market exhibit positive relationships with liquidity levels on alternative trading venues. Correlated changes in liquidity are consistent with prior literature that document commonality in liquidity across financial markets (Chordia, Roll and Subrahmanyam, 2000; Domowitz, Hansch and Wang, 2005; Karolyi, Lee and Dijk, 2012) and for the stock index futures markets (Frino, Mollica and Zhou, 2014).

Table 5-8 Market-Wide Liquidity Regression

This table reports the coefficients for the following regressions:

$$Ln\ (Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Ln\ (Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Ln\ (TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Best\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Market\ Depth_{i,t} + \varepsilon_{i,t}$$
$$Total\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Market\ Depth_{i,t} + \varepsilon_{i,t}$$

where $Ln\ (Prop\ Spread)_{it}$ represents the natural logarithm of the daily average proportional spread, $Ln(Tick\ Spread)_{it}$ represents the natural logarithm of the daily average tick spread and $Ln(TW\ Spread)_{it}$ represents the natural logarithm of the daily average time-weighted spread. $Best\ Depth_{it}$ refers to the daily average number of contracts available at the best bid and ask prices and $Total\ Depth_{it}$ refers to the daily average number of contracts available in the visible limit order book. $Colocation_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. $Ln\ (Control\ Prop\ Spread)_{it}$ represents the natural logarithm of the daily average proportional spread for the control contract, $Ln(Control\ Tick\ Spread)_{it}$ represents the natural logarithm of the daily average tick spread for the control contract and $Ln(Control\ TW\ Spread)_{it}$ represents the natural logarithm of the daily average time-weighted spread for the control contract. $Best\ Depth_{it}$ refers to the daily average number of contracts available at the best bid and ask prices and $Total\ Depth_{it}$ refers to the daily average number of contracts available in the visible limit order book. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Ln (Proportional Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-0.348	-5.34	<.0001	-2.561	-11.88	<.0001	-1.815	-2.72	0.007	-4.370	-8.88	<.0001
Colocation	-0.015	-9.53	<.0001	0.021	3.59	0.000	-0.102	-5.59	<.0001	-0.156	-6.86	<.0001
Ln (Control Prop Spread)	1.049	111.56	<.0001	0.610	25.18	<.0001	0.694	9.56	<.0001	0.280	5.15	<.0001
Earthquake	0.012	6.76	<.0001									
Adj. R Squared			0.989			0.784			0.328			0.313
	Panel B: Ln (Tick Spread)											
Intercept	18.455	12.14	<.0001	-3.677	-28.90	<.0001	1.272	10.07	<.0001	3.751	10.62	<.0001
Colocation	-0.010	-7.44	<.0001	0.005	1.51	0.134	-0.137	-7.23	<.0001	-0.230	-9.79	<.0001
Ln (Control Tick Spread)	3.570	16.22	<.0001	0.172	6.96	<.0001	0.557	6.46	<.0001	0.222	4.18	<.0001
Earthquake	0.008	5.53	<.0001									
Adj. R Squared			0.651			0.201			0.362			0.474
	Panel C: Ln (Time-weighted Spread)											
Intercept	-0.305	-3.09	0.002	-2.711	-12.82	<.0001	-5.662	-6.98	<.0001	-4.760	-7.29	<.0001
Colocation	-0.017	-6.96	<.0001	0.021	3.56	0.000	-0.166	-6.23	<.0001	-0.171	-5.78	<.0001
Ln (Control T-weighted Spread)	1.055	74.21	<.0001	0.593	24.98	<.0001	0.227	2.57	0.011	0.202	2.79	0.006
Earthquake	0.010	3.89	0.000									
Adj. R Squared			0.976			0.783			0.147			0.195

Table 5-8 Market-Wide Liquidity Regression (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel D: Best Depth											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-0.111	-0.45	0.655	2.557	17.38	<.0001	1.382	1.76	0.079	3.612	29.10	<.0001
Colocation	0.134	4.34	<.0001	0.007	0.29	0.769	0.062	2.42	0.016	0.079	2.96	0.003
Control Best Depth	0.858	24.42	<.0001	0.609	15.37	<.0001	0.208	2.05	0.042	0.109	2.40	0.017
Earthquake	-0.031	-0.79	0.430									
Adj. R Squared			0.850			0.597			0.018			0.088
	Panel E: Total Depth											
Intercept	0.807	2.42	0.016	5.139	22.48	<.0001	4.186	5.31	<.0001	5.711	31.65	<.0001
Colocation	0.141	4.18	<.0001	-0.071	-2.95	0.004	-0.049	-1.99	0.048	0.241	8.07	<.0001
Control Total Depth	0.825	23.62	<.0001	0.432	11.69	<.0001	0.157	1.83	0.068	0.150	3.81	0.000
Earthquake	-0.203	-5.86	<.0001									
Adj. R Squared			0.843			0.525			0.124			0.361

Table 5-9 presents the coefficients for the combined regressions examining market liquidity. After controlling for open interest, price volatility, open interest of the control market and the price volatility of the control market, the results are largely in line with the findings of the previous regression models. Significantly narrower bid-ask spreads are observed for the Japan-SGX, India-SGX and China-SGX contracts. The bid-ask spreads of the Taiwan-SGX contract, however, widen following the introduction of co-location services. The best depth and total depth correspondingly increase in the Japan-SGX and China-SGX contracts but decrease in the Taiwan-SGX contract. Significant changes in market depth are not observed for the India-SGX contract. Finally, a robustness test is conducted where five trading days prior to a contract's maturity is deleted from the sample and the regression models are refitted. For the results of the contract-specific, market-wide and combined regression analyses of market liquidity, refer to Table A-6, Table A-7 and Table A-8.

Table 5-9 Combined Liquidity Regression

This table reports the coefficients for the following regressions:

$$Ln(Prop\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln(Tick\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln(TW\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Best\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Total\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where $Ln\ (Prop\ Spread)_{it}$ represents the natural logarithm of the daily average proportional spread, $Ln(Tick\ Spread)_{it}$ represents the natural logarithm of the daily average tick spread and $Ln(TW\ Spread)_{it}$ represents the natural logarithm of the daily average time-weighted spread. $Best\ Depth_{it}$ refers to the daily average number of contracts available at the best bid and ask prices and $Total\ Depth_{it}$ refers to the daily average number of contracts available in the visible limit order book. $Colocation_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. $Open\ Interest_{it}$ refers to the number of outstanding from the previous session of trading and $Price\ Volatility_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. $Control\ Open\ Interest_{it}$ refers to the number of outstanding contracts from the previous session of trading for the control contract and $Control\ Price\ Volatility_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Ln (Proportional Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-7.591	-268.91	<.0001	-7.901	-190.10	<.0001	-8.238	-100.24	<.0001	-6.955	-126.00	<.0001
Colocation	0.034	3.11	0.002	0.045	4.60	<.0001	-0.064	-2.10	0.037	-0.140	-4.40	<.0001
Open Interest	-1.300	-6.44	<.0001	-0.363	-2.78	0.006	-0.673	-1.63	0.104	-0.759	-0.75	0.455
Price Volatility	0.106	0.13	0.897	4.802	6.94	<.0001	5.011	3.83	0.000	0.862	0.74	0.463
Control Open Interest	0.747	4.60	<.0001	-1.560	-2.57	0.011	0.003	0.51	0.611	-2.010	-1.31	0.191
Control Price Volatility	1.561	1.92	0.057	-1.142	-1.33	0.184	0.101	0.07	0.945	4.488	3.30	0.001
Earthquake	0.062	5.70	<.0001									
Adj. R Squared			0.606			0.467			0.143			0.298
	Panel B: Ln (Tick Spread)											
Intercept	-6.225	-2171.40	<.0001	-4.547	-282.20	<.0001	0.439	5.82	<.0001	2.304	45.31	<.0001
Colocation	-0.006	-5.15	<.0001	0.007	1.99	0.047	-0.118	-4.26	<.0001	-0.192	-6.53	<.0001
Open Interest	-0.027	-1.34	0.183	-0.211	-4.16	<.0001	-1.130	-2.98	0.003	-2.830	-3.03	0.003
Price Volatility	0.331	4.01	<.0001	0.469	1.75	0.082	3.430	2.86	0.005	0.465	0.43	0.667
Control Open Interest	0.040	2.45	0.015	0.077	0.33	0.743	0.008	1.59	0.113	-2.300	-1.63	0.104
Control Price Volatility	0.180	2.18	0.031	0.467	1.41	0.161	-0.171	-0.13	0.898	3.891	3.11	0.002
Earthquake	0.007	6.74	<.0001									
Adj. R Squared			0.820			0.185			0.292			0.489

Table 5-9 Combined Liquidity Regression (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel C: Ln (Time-weighted Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-7.595	-268.49	<.0001	-7.904	-190.43	<.0001	-7.802	-73.36	<.0001	-6.735	-96.54	<.0001
Colocation	0.036	3.25	0.001	0.045	4.69	<.0001	-0.126	-3.21	0.002	-0.195	-4.85	<.0001
Open Interest	-1.320	-6.49	<.0001	-0.371	-2.84	0.005	-0.678	-1.27	0.205	1.500	1.17	0.245
Price Volatility	0.080	0.10	0.922	4.858	7.03	<.0001	1.573	0.93	0.354	1.172	0.79	0.430
Control Open Interest	0.762	4.69	<.0001	-1.570	-2.58	0.011	0.005	0.75	0.451	-0.489	-0.25	0.801
Control Price Volatility	1.549	1.90	0.059	-1.232	-1.44	0.151	2.123	1.13	0.261	4.415	2.57	0.011
Earthquake	0.061	5.62	<.0001									
Adj. R Squared			0.603			0.470			0.133			0.218
	Panel D: Best Depth											
Intercept	6.242	50.49	<.0001	4.789	38.41	<.0001	2.775	34.97	<.0001	3.872	62.54	<.0001
Colocation	0.377	7.83	<.0001	-0.151	-5.20	<.0001	0.010	0.35	0.729	0.042	1.17	0.243
Open Interest	5.730	6.45	<.0001	0.675	1.72	0.087	0.401	1.01	0.315	1.820	1.60	0.111
Price Volatility	-0.647	-0.18	0.856	-1.649	-0.79	0.428	0.195	0.15	0.877	-0.247	-0.19	0.851
Control Open Interest	-4.760	-6.70	<.0001	0.884	0.48	0.628	0.005	1.08	0.280	2.410	1.41	0.161
Control Price Volatility	-3.604	-1.01	0.314	-9.666	-3.76	0.000	0.076	0.05	0.957	-2.737	-1.80	0.074
Earthquake	-0.650	-13.74	<.0001									
Adj. R Squared			0.601			0.352			0.029			0.090
	Panel E: Total Depth											
Intercept	8.826	74.13	<.0001	8.041	77.12	<.0001	5.671	96.42	<.0001	6.293	94.79	<.0001
Colocation	0.471	10.16	<.0001	-0.133	-5.49	<.0001	-0.027	-1.27	0.207	0.152	3.97	<.0001
Open Interest	6.320	7.40	<.0001	-0.174	-0.53	0.597	-1.080	-3.66	0.000	5.040	4.13	<.0001
Price Volatility	1.172	0.34	0.733	-5.764	-3.32	0.001	0.494	0.53	0.598	-1.454	-1.03	0.304
Control Open Interest	-4.620	-6.75	<.0001	-0.980	-0.64	0.521	0.008	2.10	0.036	3.570	1.94	0.054
Control Price Volatility	-6.420	-1.87	0.063	-6.213	-2.89	0.004	-1.160	-1.11	0.267	-3.543	-2.17	0.031
Earthquake	-0.620	-13.63	<.0001									
Adj. R Squared			0.628			0.486			0.162			0.395

6. CONCLUSION

On 18 April 2011, the Singapore Exchange introduced co-location facilities to its derivatives and equities market to promote high frequency trading and enhance market accessibility. This infrastructural development allows latency-sensitive market participants to situate their trading systems in the same data centre as the exchange's trading, market data and clearing engines. The physical proximity of a trader's order management system to the exchange's engines increases the speed of access and therefore reduces the time it takes for traders to execute their trading decisions. High frequency trading is a controversial issue as there is a lack of agreement in empirical literature regarding its impact on market quality. While a line of research document its beneficial impact on market quality (e.g. Brogaard, 2010; Hendershott, Jones and Menkveld, 2011; Riordan and Storkenmaier, 2012; Hagströmer and Nordén, 2013), other studies find that it degrades the quality of financial exchanges (Kirilenko, Kyle, Samadi and Tuzun, 2011; Jarrow and Protter, 2012; Boehmer, Fong and Wu, 2012; Lee, 2013).

This thesis examines how the introduction of co-location services impacts high frequency trading and market quality on the Singapore's stock-index futures market. Increases in the pervasiveness of HFT trading are observed for the Nikkei 225 and MSCI Taiwan index futures contracts. HFT presence in the CNX Nifty and the CSI 300 index futures contracts, however, decline following the infrastructural change. The results suggest that co-location services attract more trading interest from high frequency traders on dual-listed stock index futures markets if there are cross-border profit opportunities i.e. markets with alternative trading venues that have HFT presence. Furthermore, analogous to Menkveld (2013), this thesis presents evidence of cross-border HFT trading. An increase in high frequency trading activity on the alternative venue is found to increase high frequency trading on Singapore's stock index futures market. This result is consistent across all futures contracts and proxies examined. It suggests that dual-listed futures contracts do not compete for HFT order flow but market participants on stock index futures bourses engage in cross-border arbitrage trading strategies.

The impacts that co-location services have on the market quality of the two futures contracts that exhibit significant increases in HFT activity, differ. Co-location services generate more trading activity, improve the liquidity and ease the volatility of the Nikkei 224 index futures market. The market quality of the MSCI Taiwan index futures market, however, deteriorates as evident by the decrease in trading activity, decline in liquidity and increase in price volatility. The different response to co-location services may reflect the different types of trading prevailing in the futures contracts. Hagströmer and Nordén (2013) put forward the argument that HFT market participants are a heterogeneous group of traders. Therefore, the impact that they have on the market quality of financial bourses is contingent upon the trading strategies they utilise. The results suggest that HFTs in the Nikkei 225 index futures contract are primarily liquidity-supplying market makers while HFTs in the MSIC Taiwan index futures contract are primarily liquidity-demanding opportunistic traders.

This thesis also finds that changes in the liquidity of the alternative trading venue explain changes in the liquidity of Singapore's stock-index futures market. A decrease (increase) in the bid-ask spread (depth) of the home market contract leads to a decrease (increase) in the bid-ask spread (depth) of the satellite market contract. This finding is consistent with prior literature that document commonality in liquidity across financial markets (Chordia, Roll and Subrahmanyam, 2000; Domowitz, Hansch and Wang, 2005; Karolyi, Lee and Dijk, 2012) and for the stock index futures markets (Frino, Mollica and Zhou, 2014). Finally, results suggest that high frequency trading on Singapore's derivatives market is contingent upon prevailing market conditions. That is, HFTs reduce their presence in the market when price volatility increases. This finding, which is consistent with Brogaard (2010), has important policy implications as it suggests that low latency market participants are less active during unfavourable conditions. The collective withdrawal of traders is found to have contributed to the liquidity shortage in the equities market during the Flash Crash (SEC and CFTC, 2010). It may a factor to consider when exchanges implement new policies pertaining to HFT.

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APPENDICES

Table A-1 Descriptive Statistics for SGX Futures Contracts (Exclusion of Five Trading Days)

This table reports the descriptive statistics of proportional spreads, tick spreads, time-weighted spreads, best depth, total depth, messages per minutes, order to trade ratio, algo trade, the number of trades, trading volume, trade size, open interest and price volatility. The analysis is based on daily observations over a 6 months event window around the implementation of co-location facilities. For information on the market quality and high frequency trading measures refer to sections 4.2.1 and 4.2.2. The results for Nikkei 225 Index (SGX) are reported in Panel A, MSCI Taiwan Index (SGX) in Panel B, CNX Nifty Index (SGX) in Panel C, FTSE China A50 Index (SGX) in Panel D and MSCI Singapore Free Index (SGX) in Panel E. The pre-event period extends from 18 October 2010 to 17 April 2011 and the post-event period extends from 18 April 2011 to 17 October 2011. Reported are t-statistics and p-values comparing the means of the pre and post periods.

	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
						Panel A: Nikkei 225 Index (SGX)							
Pre	0.0005041	0.0020159	0.0005028	338	5288	50.71	1.35	-3.87	16994	83021	25085040	223347	0.0195069
Post	0.000549	0.0020472	0.0005475	296	5131	48.65	1.49	-3.26	14533	66822	21035451	202995	0.0184107
Difference	0.0000449	0.0000313	0.0000447	-41	-157	-2.06	0.13	0.61	-2461	-16199	-4049589	-20352	-0.0010962
T-statistics	-7.84	-2.31	-8.09	2.94	0.71	1.27	-2.58	-4.46	1.95	2.87	7.65	6.1	0.48
P-value	<.0001	0.0226	<.0001	0.0037	0.4774	0.204	0.0107	<.0001	0.0524	0.0046	<.0001	<.0001	0.6344
						Panel B: MSCI Taiwan Index (SGX)							
Pre	0.0003401	0.0104485	0.0003385	121	2348	87	2	-1.49	14167	39989	85597	161923	0.0153413
Post	0.0003667	0.0105356	0.0003653	104	1985	91.48	1.89	-1.68	15719	47140	86019	178483	0.0235252
Difference	0.0000265	0.0000872	0.0000268	-17	-362	4.48	-0.12	-0.19	1552	7151	422	16560	0.0081839
T-statistics	-6.44	-2.11	-6.51	4.81	6.54	-3.13	1.7	2.43	-1.9	-2.53	-0.26	-9.63	-4.81
P-value	<.0001	0.0366	<.0001	<.0001	<.0001	0.002	0.0901	0.0159	0.0589	0.0123	0.7934	<.0001	<.0001
						Panel C: CNX Nifty Index (SGX)							
Pre	0.0002762	1.5910774	0.0004386	20	279	66.31	4.03	-0.8	9626	28820	34452	207982	0.0207328
Post	0.0002706	1.4284742	0.0003872	21	250	70.39	3.74	-0.81	11078	31172	30141	260889	0.0223503
Difference	-0.0000056	-0.1626032	-0.0000514	1	-29	4.08	-0.28	-0.01	1452	2352	-4311	52907	0.0016175
T-statistics	0.46	2.67	3.28	-1.47	6.3	-2.8	1.74	0.41	-2.62	-1.42	6.68	-23.38	-1.24
P-value	0.6486	0.0087	0.0013	0.1432	<.0001	<.0001	0.0837	0.6839	0.0097	0.1585	<.0001	<.0001	0.2184
						Panel D: FTSE China A50 Index (SGX)							
Pre	0.0010208	9.8682884	0.0013962	51	607	38.55	17.61	-0.37	997	5384	269053	29128	0.022379
Post	0.0008439	7.4182196	0.0011823	54	792	34.91	13.66	-0.44	1091	5635	228204	50513	0.0195995
Difference	-0.0001769	-2.4500687	-0.0002138	4	185	-3.64	-3.95	-0.07	94	251	-40849	21385	-0.0027795
T-statistics	6.46	10.14	4.91	-2.33	-9.17	4.62	3.26	2.61	-1.25	-0.61	5.38	-18.2	1.45
P-value	<.0001	<.0001	<.0001	0.0212	<.0001	<.0001	0.0014	0.01	0.214	0.5421	<.0001	<.0001	0.1503

Table A-1 Descriptive Statistics for SGX Futures Contracts (Exclusion of Five Trading Days) (Cont.)

	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
Panel E: MSCI Singapore Index (SGX)													
Pre	0.0003236	0.0060184	0.0003296	17	282	39.62	3.61	-0.38	5816	7888	100443	48682	0.0131952
Post	0.0003477	0.0059371	0.0003484	18	272	51.51	3.19	-0.43	8826	11698	90823	47393	0.0201596
Difference	0.000024	-0.0000813	0.0000188	2	-10	11.88	-0.41	-0.04	3010	3810	-9621	-1289	0.0069644
T-statistics	-6.25	2.23	-4.72	-2.51	1.14	-9.58	5.27	3.47	-7.86	-6.98	7.79	1.59	-5.37
P-value	<.0001	0.0274	<.0001	0.0129	0.2542	<.0001	<.0001	0.0006	<.0001	<.0001	<.0001	0.114	<.0001

Table A-2 Descriptive Statistics of Daily Log Ratios (Exclusion of Five Trading Days)

This table reports the descriptive statistics of the daily log ratios for the variables: proportional spreads, tick spreads, time-weighted spreads, best depth, total depth, messages per minutes, order to trade ratio, algo trade, the number of trades, trading volume, trade size, open interest and price volatility. For further information on the market quality and high frequency measures assessed see sections 4.2.1 and 4.2.2. Daily log ratios are calculated as the natural log of daily measures for each treatment contract divided by the daily measures of its respective control contract. Panel A provides the results for the Nikkei 225 Index (SGX) and its control contract, the Nikkei 225 Index (OSE). Panel B provides the results for the MSCI Taiwan Index (SGX) and its control contract, the Taiwan Stock Index (TAIFEX). Panel C provides the results for the CNX Nifty Index (SGX) and its control contract, the CNX Nifty Index (NSE). Panel D provides the results for the FTSE China A50 Index (SGX) and its control contract, the China Shanghai Shenzhen 300 Stock Index (CFFEX). The event window extends 6 months around the implementation of co-location facilities with the pre-event period extending from 18 October 2010 to 17 April 2011 and the post-event period extending from 18 April 2011 to 17 October 2011. Reported are t-statistics and p-values for comparing the means of the pre-event and post-event periods.

	Prop Spread	Tick Spread	TW Spread	Best Depth	Total Depth	Messages per Minute	OTT Ratio	Algo Trade	Trades	Volume	Trade Size	Open Interest	Volatility
Panel A: Japan [Nikkei 225 Index (SGX) / Nikkei 225 Index (OSE)]													
Pre	-0.68521	0.70108	-0.68207	-1.10336	-0.88468	-1.13183	-2.1829	1.31142	1.30684	0.43536	-1.56468	-0.37681	1.10996
Post	-0.68733	0.69894	-0.68656	-0.96345	-0.92517	-0.51348	-1.92587	0.99912	1.48997	0.56322	-1.61991	-0.31033	1.018
Difference	-0.00212	-0.00214	-0.0045	0.13991	-0.0405	0.61835	0.25703	-0.3123	0.18313	0.12786	-0.05522	0.06648	-0.09196
T-statistics	1.69	1.69	2.7	-8.91	2.32	-15.2	-8.41	9.66	-9.83	-8.57	3.07	-8.54	3.48
P-value	0.0935	0.0941	0.0078	<.0001	0.0216	<.0001	<.0001	<.0001	<.0001	<.0001	0.0024	<.0001	0.0007
Panel B: Taiwan [MSCI Taiwan Index (SGX) / Taiwan Stock Index (TAIFEX)]													
Pre	0.92353	0.58286	0.92649	1.06061	1.54611	-0.72522	0.32432	-0.23503	-1.04954	-0.96025	-3.94032	0.98752	1.46471
Post	0.90166	0.55287	0.9011	1.22868	1.69317	-0.66838	0.54915	-0.35088	-1.21753	-1.01926	-3.83933	1.09612	1.57021
Difference	-0.02186	-0.02999	-0.02539	0.16807	0.14706	0.05684	0.22483	-0.11585	-0.16799	-0.05901	0.10099	0.1086	0.10551
T-statistics	1.97	2.69	2.2	-4.75	-3.62	-4.15	-7.52	3.84	5.04	1.78	-4.97	-6.03	-1.06
P-value	0.052	0.0085	0.0304	<.0001	0.0004	<.0001	<.0001	0.0002	<.0001	0.0788	<.0001	<.0001	0.2914
Panel C: India [CNX Nifty Index (SGX) / CNX Nifty Index (NSE)]													
Pre	0.99212	1.90807	1.43796	-4.72286	-3.57033	0.12688	1.23477	-7.21475	-0.75519	-6.73517	-9.19918	-4.73784	1.19889
Post	0.88403	1.79959	1.23325	-4.53362	-3.44566	0.19947	1.12619	-6.98571	-0.5671	-6.42662	-9.07887	-4.49889	1.31119
Difference	-0.10809	-0.10847	-0.2047	0.18923	0.12466	0.07258	-0.10858	0.22905	0.18809	0.30855	0.12031	0.23895	0.1123
T-statistics	5.25	5.27	5.57	-7.29	-6.25	-5.04	2.98	-5.33	-4.23	-7.81	-2.92	-16.99	-2.25
P-value	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0033	<.0001	<.0001	<.0001	0.004	<.0001	0.0257
Panel D: China [FTSE China A50 Index (SGX) / China Shanghai Shenzhen 300 Stock Index (CFFEX)]													
Pre	2.23532	9.02879	2.53769	1.05951	1.64921	-1.10784	2.69672	-2.92859	-3.49656	-3.72843	-1.62677	0.10229	1.01485
Post	2.07864	8.88079	2.37479	0.99166	1.68954	-1.16502	2.34034	-2.59978	-3.2198	-3.47924	-1.64576	0.56929	1.24616
Difference	-0.15668	-0.148	-0.1629	-0.06785	0.04033	-0.05718	-0.35638	0.32881	0.27676	0.24919	-0.01899	0.46701	0.23131
T-statistics	5.39	5.11	3.84	1.8	-1.11	2.14	4.59	-3.98	-3.2	-2.88	0.35	-9.62	-2.44
P-value	<.0001	<.0001	0.0002	0.075	0.2713	0.0346	<.0001	0.0001	0.0018	0.0048	0.7282	<.0001	0.0166

Table A-3 Contract-Specific High Frequency Trading Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading and *Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. Results for the Singapore Exchange's SiMSCI, Nikkei 225, MSCI Taiwan, CNX Nifty and FTSE ChinaA50 are reported. The period of analysis extends from 18 October 2010 to 17 October 2011.

	SiMSCI (SGX)			Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages Per Minute														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	21.007	5.33	<.0001	25.512	6.24	<.0001	99.080	9.66	<.0001	31.599	5.39	<.0001	33.017	16.50	<.0001
Colocation	7.649	8.11	<.0001	-3.292	-2.02	0.0445	3.064	1.55	0.1241	-1.181	-0.69	0.4915	-2.847	-1.62	0.1079
Open Interest	207.180	2.47	0.0143	71.500	3.88	0.0001	-128.980	-2.05	0.0429	126.900	4.42	<.0001	36.510	0.58	0.5627
Price Volatility	646.519	12.38	<.0001	394.511	13.39	<.0001	477.702	7.77	<.0001	401.126	8.19	<.0001	197.172	4.00	0.0001
Earthquake				6.675	4.03	<.0001									
Adj. R Squared			0.6915			0.6001			0.4287			0.4732			0.1496
	Panel B: Ln (Order to Trade)														
Intercept	1.416	17.06	<.0001	0.406	5.05	<.0001	1.152	5.27	<.0001	1.934	8.20	<.0001	3.574	24.42	<.0001
Colocation	-0.038	-1.91	0.0576	0.097	3.03	0.0028	0.101	2.41	0.0178	0.008	0.12	0.9075	0.078	0.60	0.5466
Open Interest	0.388	0.22	0.8265	0.267	0.74	0.4624	-1.490	-1.11	0.2682	-1.110	-0.96	0.3381	-17.360	-3.78	0.0003
Price Volatility	-12.319	-11.19	<.0001	-8.806	-15.19	<.0001	-15.910	-12.15	<.0001	-16.759	-8.50	<.0001	-13.058	-3.62	0.0005
Earthquake				-0.076	-2.34	0.0202									
Adj. R Squared			0.5110			0.5905			0.5894			0.3219			0.3194
	Panel C: Algo Trade														
Intercept	-0.363	-8.67	<.0001	-2.929	-8.06	<.0001	-0.296	-0.68	0.4974	-0.480	-2.17	0.0311	-0.051	-0.90	0.3727
Colocation	0.005	0.53	0.5956	0.094	0.65	0.5177	0.216	2.58	0.0113	0.011	0.18	0.8588	0.056	1.12	0.2667
Open Interest	1.350	1.51	0.1320	-0.714	-0.44	0.6638	-3.960	-1.49	0.1404	-0.217	-0.20	0.8417	-7.070	-3.95	0.0001
Price Volatility	-6.595	-11.90	<.0001	-45.130	-17.22	<.0001	-37.589	-14.45	<.0001	-13.179	-7.14	<.0001	-4.910	-3.49	0.0007
Earthquake				0.412	2.80	0.0057									
Adj. R Squared			0.4863			0.6202			0.6751			0.2285			0.2947

Table A-4 Market-Wide High Frequency Trading Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Messages\ per\ Minute_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Messages\ per\ Minute_{i,t} + \varepsilon_{i,t}$$
$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Order\ to\ Trade)_{i,t} + \varepsilon_{i,t}$$
$$Algo\ Trade_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Algo\ Trade_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Control Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval for the control contract, *Ln (Control Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade for the control contract and *Control Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages Per Minute											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	26.027	9.97	<.0001	-37.041	-4.55	<.0001	-265.790	-12.05	<.0001	-133.450	-5.08	<.0001
Colocation	-6.925	-3.60	0.0004	4.602	4.46	<.0001	1.263	1.62	0.1068	-1.193	-1.37	0.1727
Control Messages per Minute	0.122	8.55	<.0001	0.698	15.08	<.0001	5.713	15.06	<.0001	1.498	6.53	<.0001
Earthquake	21.236	10.83	<.0001									
Adj. R Squared			0.3984			0.7047			0.6312			0.3021
	Panel B: Ln (Order to Trade)											
Intercept	-0.774	-8.34	<.0001	0.398	13.18	<.0001	1.037	25.24	<.0001	2.660	20.22	<.0001
Colocation	0.174	5.27	<.0001	0.163	4.82	<.0001	-0.159	-4.62	<.0001	-0.365	-4.43	<.0001
Ln (Control Order to Trade)	0.432	12.16	<.0001	0.800	13.53	<.0001	2.635	9.55	<.0001	1.266	1.45	0.1488
Earthquake	-0.052	-1.38	0.1704									
Adj. R Squared			0.4938			0.6415			0.3511			0.1412
	Panel C: Algo Trade											
Intercept	-1.875	-13.90	<.0001	0.134	1.37	0.1726	-0.328	-5.49	<.0001	-0.275	-3.80	0.0002
Colocation	0.387	2.71	0.0072	0.227	3.89	0.0002	-0.107	-3.30	0.0012	-0.114	-3.67	0.0004
Control Algo Trade	1.953	16.03	<.0001	0.873	17.74	<.0001	0.000	8.45	<.0001	0.011	1.01	0.3145
Earthquake	0.555	3.47	0.0006									
Adj. R Squared			0.5790			0.7580			0.2854			0.0980

Table A-5 Combined High Frequency Trading Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Message\ per\ Minute_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln\ (Order\ to\ Trade)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Algo\ Trade_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Messages per Minute*$_{it}$ represents the daily average number of messages submitted over a one-minute interval, *Ln (Order to Trade)*$_{it}$ represents the log of the daily average number of messages per trade and *Algo Trade*$_{it}$ represents the daily average number of messages that has been standardised by trading volume. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading and *Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. *Control Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading for the control contract and *Control Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Messages per Minute											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	23.791	5.31	<.0001	107.662	9.86	<.0001	42.312	6.92	<.0001	30.448	9.19	<.0001
Colocation	-2.406	-1.43	0.1529	2.390	1.29	0.1996	-2.408	-1.38	0.1684	-2.625	-1.49	0.1392
Open Interest	14.760	0.39	0.6962	-74.090	0.39	0.6962	157.980	5.44	<.0001	43.060	0.69	0.4911
Price Volatility	45.295	0.37	0.7125	90.336	0.84	0.4025	108.269	1.28	0.2027	62.578	0.83	0.4111
Control Open Interest	45.050	1.56	0.1196	-295.500	-2.08	0.0402	-0.755	-3.73	0.0003	56.970	0.50	0.6174
Control Price Volatility	357.327	2.90	0.0041	559.185	4.23	<.0001	378.872	3.86	0.0002	177.019	2.37	0.0199
Earthquake	6.437	3.91	0.0001									
Adj. R Squared			0.6173			0.5120			0.5393			0.1810
	Panel B: Ln (Order to Trade)											
Intercept	0.410	4.57	<.0001	0.958	9.73	<.0001	1.896	7.19	<.0001	3.874	15.71	<.0001
Colocation	0.091	2.70	0.0074	0.052	2.28	0.0240	0.004	0.06	0.9545	0.116	0.88	0.3788
Open Interest	0.672	0.89	0.3749	-0.609	-1.97	0.0500	-1.140	-0.91	0.3626	-16.480	-3.55	0.0006
Price Volatility	-4.416	-1.80	0.0739	-8.964	-5.46	<.0001	-14.064	-3.85	0.0002	-14.037	-2.49	0.0144
Control Open Interest	-0.299	-0.52	0.6055	1.200	0.83	0.4070	0.002	0.27	0.7889	-13.060	-1.54	0.1257
Control Price Volatility	-4.510	-1.83	0.0691	-10.108	-4.98	<.0001	-3.657	-0.86	0.3889	0.564	0.10	0.9195
Earthquake	-0.071	-2.17	0.0313									
Adj. R Squared			0.5939			0.6050			0.3171			0.3219

Table A-5 Combined High Frequency Trading Regression (Exclusion of Five Trading Days) (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel C: Algo Trade											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-3.645	-9.24	<.0001	0.035	0.08	0.9358	-0.308	-1.26	0.2104	-0.119	-1.23	0.2210
Colocation	0.280	1.89	0.0596	0.209	2.84	0.0055	-0.038	-0.55	0.5843	0.050	0.98	0.3305
Open Interest	-12.460	-3.75	0.0002	-4.180	-1.71	0.0908	0.570	0.49	0.6254	-7.190	-3.95	0.0001
Price Volatility	-38.724	-3.58	0.0004	-17.295	-4.04	0.0001	-11.781	-3.47	0.0007	-5.495	-2.48	0.0147
Control Open Interest	10.260	4.04	<.0001	-4.690	-0.83	0.4096	-0.013	-1.65	0.0999	2.650	0.80	0.4257
Control Price Volatility	-7.304	-0.67	0.5016	-29.558	-5.61	<.0001	-2.445	-0.62	0.5353	0.898	0.41	0.6818
Earthquake	0.493	3.41	0.0008									
Adj. R Squared			0.6441			0.7544			0.2343			0.2868

Table A-6 Contract-Specific Liquidity Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Ln(Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Ln(Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Ln(TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Best\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$
$$Total\ Depth_{it} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest + \alpha_3 Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Ln (Prop Spread)*$_{it}$ represents the natural logarithm of the daily average proportional spread, *Ln(Tick Spread)*$_{it}$ represents the natural logarithm of the daily average tick spread and *Ln(TW Spread)*$_{it}$ represents the natural logarithm of the daily average time-weighted spread. *Best Depth*$_{it}$ refers to the daily average number of contracts available at the best bid and ask prices and *Total Depth*$_{it}$ refers to the daily average number of contracts available in the visible limit order book. *Colocation*$_{it}$ takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest*$_{it}$ refers to the number of outstanding contracts from the previous session of trading and *Price Volatility*$_{it}$ is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. Results for the Singapore Exchange's SiMSCI, Nikkei 225, MSCI Taiwan, CNX Nifty and FTSE ChinaA50 contracts are reported. The period of analysis extends from 18 October 2010 to 17 October 2011

	SiMSCI			Nikkei 225			MSCI Taiwan			CNX Nifty			FTSE China A50		
	Panel A: Ln (Proportional Spread)														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-8.238	-193.15	<.0001	-7.509	-264.62	<.0001	-7.572	-84.40	<.0001	-8.354	-50.81	<.0001	-6.972	-108.50	<.0001
Colocation	0.047	4.60	<.0001	0.013	1.12	0.2634	0.101	5.82	<.0001	-0.122	-2.54	0.0118	-0.206	-3.66	0.0004
Open Interest	3.080	3.39	0.0009	-0.597	-4.66	<.0001	-2.860	-5.20	<.0001	0.195	0.24	0.8085	-0.414	-0.21	0.8378
Price Volatility	3.841	6.79	<.0001	1.747	8.54	<.0001	3.201	5.96	<.0001	5.168	3.76	0.0002	4.716	2.98	0.0036
Earthquake				0.058	5.08	<.0001									
Adj. R Squared			0.4378			0.5531			0.5003			0.1518			0.3472
	Panel B: Ln (Tick Spread)														
Intercept	-5.117	-187.51	<.0001	-6.224	-2224.10	<.0001	-4.392	-132.02	<.0001	0.497	3.29	0.0012	2.383	41.97	<.0001
Colocation	-0.021	-3.21	0.0016	-0.006	-5.59	<.0001	0.022	3.40	0.0010	-0.163	-3.69	0.0003	-0.174	-3.50	0.0007
Open Interest	-0.228	-0.39	0.6953	0.025	1.95	0.0526	-1.090	-5.35	<.0001	-0.502	-0.68	0.4990	-6.020	-3.37	0.0010
Price Volatility	1.069	2.95	0.0036	0.513	25.41	<.0001	0.521	2.61	0.0103	3.016	2.39	0.0180	3.756	2.68	0.0085
Earthquake				0.007	6.44	<.0001									
Adj. R Squared			0.0595			0.8231			0.2617			0.2965			0.5868
	Panel C: Ln (Time-weighted Spread)														
Intercept	-8.249	-184.55	<.0001	-7.511	-263.86	<.0001	-7.578	-84.00	<.0001	-7.589	-34.82	<.0001	-6.781	-77.64	<.0001
Colocation	0.035	3.23	0.0015	0.014	1.22	0.2228	0.101	5.80	<.0001	-0.119	-1.86	0.0642	-0.278	-3.63	0.0004
Open Interest	3.760	3.96	0.0001	-0.597	-4.64	<.0001	-2.850	-5.16	<.0001	-1.180	-1.10	0.2709	2.340	0.85	0.3960
Price Volatility	3.489	5.89	<.0001	1.711	8.33	<.0001	3.202	5.93	<.0001	3.955	2.17	0.0312	6.768	3.14	0.0022
Earthquake				0.057	4.98	<.0001									
Adj. R Squared			0.3692			0.5477			0.4983			0.1569			0.2623

	SiMSCI			Nikkei 225			MSCI Taiwan			CNX Nifty			FTSE China A50		
	Panel D: Best Depth														
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	2.866	18.65	<.0001	5.869	45.22	<.0001	3.276	14.32	<.0001	2.729	18.02	<.0001	3.690	50.64	<.0001
Colocation	0.144	3.90	0.0001	0.470	9.09	<.0001	-0.327	-7.42	<.0001	-0.027	-0.60	0.5489	-0.129	-2.02	0.0457
Open Interest	-0.183	-0.06	0.9553	0.513	0.88	0.3823	9.900	7.06	<.0001	1.310	1.77	0.0791	9.550	4.17	<.0001
Price Volatility	-6.183	-3.03	0.0028	-4.729	-5.05	<.0001	-4.762	-3.48	0.0007	-0.623	-0.49	0.6229	-2.245	-1.25	0.2140
Earthquake				-0.620	-11.80	<.0001									
Adj. R Squared			0.0868			0.5255			0.4854			0.0204			0.1745
	Panel E: Total Depth														
Intercept	5.728	45.43	<.0001	8.442	67.11	<.0001	6.873	36.38	<.0001	5.554	51.49	<.0001	5.980	96.46	<.0001
Colocation	0.027	0.89	0.3763	0.569	11.34	<.0001	-0.247	-6.79	<.0001	-0.122	-3.88	0.0001	-0.120	-2.20	0.0299
Open Interest	0.600	0.22	0.8233	1.370	2.42	0.0165	6.200	5.35	<.0001	0.441	0.84	0.4049	17.150	8.81	<.0001
Price Volatility	-9.997	-5.98	<.0001	-5.682	-6.26	<.0001	-7.634	-6.75	<.0001	-1.109	-1.23	0.2199	-3.852	-2.52	0.0132
Earthquake				-0.596	-11.69	<.0001									
Adj. R Squared			0.1807			0.5551			0.5710			0.1888			0.6139

Table A-7 Market-Wide Liquidity Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Ln\ (Prop\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Ln\ (Tick\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Ln\ (TW\ Spread)_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Ln\ (Control\ Prop\ Spread)_{i,t} + \varepsilon_{i,t}$$
$$Best\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Market\ Depth_{i,t} + \varepsilon_{i,t}$$
$$Total\ Depth_{i,t} = \alpha_o + \alpha_1 Colocation_{i,t} + \alpha_2 Control\ Market\ Depth_{i,t} + \varepsilon_{i,t}$$

where *Ln (Prop Spread)$_{it}$* represents the natural logarithm of the daily average proportional spread, *Ln(Tick Spread)$_{it}$* represents the natural logarithm of the daily average tick spread and *Ln(TW Spread)$_{it}$* represents the natural logarithm of the daily average time-weighted spread. *Best Depth$_{it}$* refers to the daily average number of contracts available at the best bid and ask prices and *Total Depth$_{it}$* refers to the daily average number of contracts available in the visible limit order book. *Colocation$_{it}$* takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Ln (Control Prop Spread)$_{it}$* represents the natural logarithm of the daily average proportional spread for the control contract, *Ln(Control Tick Spread)$_{it}$* represents the natural logarithm of the daily average tick spread for the control contract and *Ln(Control TW Spread)$_{it}$* represents the natural logarithm of the daily average time-weighted spread for the control contract. *Best Depth$_{it}$* refers to the daily average number of contracts available at the best bid and ask prices and *Total Depth$_{it}$* refers to the daily average number of contracts available in the visible limit order book. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Ln (Proportional Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-0.332	-4.82	<.0001	-2.435	-7.76	<.0001	-1.293	-1.76	0.0799	0.392	0.27	0.7898
Colocation	-0.015	-9.03	<.0001	0.016	1.85	0.0668	-0.107	-5.32	<.0001	-0.169	-5.62	<.0001
Ln (Control Prop Spread)	1.052	105.82	<.0001	0.623	17.68	<.0001	0.752	9.42	<.0001	0.798	4.97	<.0001
Earthquake	0.012	6.48	<.0001									
Adj. R Squared			0.9883			0.7938			0.3926			0.4317
	Panel B: Ln (Tick Spread)											
Intercept	20.317	12.97	<.0001	-3.543	-19.82	<.0001	1.369	9.86	<.0001	5.896	5.30	<.0001
Colocation	-0.010	-7.06	<.0001	-0.001	-0.10	0.9170	-0.137	-6.49	<.0001	-0.226	-5.79	<.0001
Ln (Control Tick Spread)	3.840	16.94	<.0001	0.198	5.69	<.0001	0.629	6.62	<.0001	0.535	3.24	0.0016
Earthquake	0.008	5.07	<.0001									
Adj. R Squared			0.6821			0.2341			0.4233			0.5685
	Panel C: Ln (Time-weighted Spread)											
Intercept	-0.297	-2.84	0.0050	-2.577	-8.32	<.0001	-5.928	-6.42	<.0001	-0.990	-0.47	0.6383
Colocation	-0.016	-6.57	<.0001	0.016	1.79	0.0769	-0.180	-5.68	<.0001	-0.187	-4.21	<.0001
Ln (Control T-weighted Spread)	1.056	70.02	<.0001	0.607	17.48	<.0001	0.199	1.98	0.0498	0.613	2.66	0.0090
Earthquake	0.010	3.61	0.0004									
Adj. R Squared			0.9740			0.7904			0.1558			0.2403

Table A-7 Market-Wide Liquidity Regression (Exclusion of Five Trading Days) (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel D: Best Depth											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-0.305	-1.29	0.1977	2.561	11.75	<.0001	2.821	3.11	0.0022	2.749	4.51	<.0001
Colocation	0.115	3.95	0.0001	0.024	0.67	0.5037	0.044	1.57	0.1174	0.029	0.58	0.5648
Control Best Depth	0.883	26.38	<.0001	0.598	10.31	<.0001	0.022	0.18	0.8540	0.406	1.90	0.0606
Earthquake	0.009	0.25	0.8052									
Adj. R Squared			0.8748			0.5837			0.0085			0.0729
	Panel E: Total Depth											
Intercept	0.650	1.84	0.0667	5.122	16.60	<.0001	5.072	6.07	<.0001	3.502	6.08	<.0001
Colocation	0.125	3.56	0.0004	-0.057	-1.78	0.0773	-0.087	-3.39	0.0009	0.136	2.96	0.0038
Control Total Depth	0.841	22.73	<.0001	0.425	8.57	<.0001	0.060	0.66	0.5103	0.607	4.98	<.0001
Earthquake	-0.188	-5.24	<.0001									
Adj. R Squared			0.8445			0.5534			0.1869			0.4535

Table A-8 Combined Liquidity Regression (Exclusion of Five Trading Days)

This table reports the coefficients for the following regressions:

$$Ln(Prop\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln(Tick\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Ln(TW\ Spread)_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Best\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

$$Total\ Depth_{i,t} = \alpha_{ot} + \alpha_1 Colocation_{i,t} + \alpha_2 Open\ Interest_{i,t} + \alpha_3 Price\ Volatility_{i,t} + \alpha_4 Control\ Open\ Interest_{i,t} + \alpha_5 Control\ Price\ Volatility_{i,t} + \varepsilon_{i,t}$$

where *Ln (Prop Spread)$_{it}$* represents the natural logarithm of the daily average proportional spread, *Ln(Tick Spread)$_{it}$* represents the natural logarithm of the daily average tick spread and *Ln(TW Spread)$_{it}$* represents the natural logarithm of the daily average time-weighted spread. *Best Depth$_{it}$* refers to the daily average number of contracts available at the best bid and ask prices and *Total Depth$_{it}$* refers to the daily average number of contracts available in the visible limit order book. *Colocation$_{it}$* takes the value of 1 after the introduction of co-location services and, 0 otherwise. *Open Interest$_{it}$* refers to the number of outstanding from the previous session of trading and *Price Volatility$_{it}$* is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price. *Control Open Interest$_{it}$* refers to the number of outstanding contracts from the previous session of trading for the control contract and *Control Price Volatility$_{it}$* is calculated as the natural logarithm of the day's highest traded price proportional to its lowest traded price for the control contract. Nikkei 225 (OSE) is the control contract of Nikkei 225 (SGX). Taiwan Stock Index (TAIFEX) is the control contract of MSCI Taiwan (SGX). CNX Nifty (NSE) is the control contract of CNX Nifty (SGX). CSI 300 (CFFEX) is the control contract of FTSE China A50 (SGX). The period of analysis extends from 18 October 2010 to 17 October 2011.

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel A: Ln (Proportional Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-7.582	-262.06	<.0001	-7.435	-74.30	<.0001	-8.316	-45.58	<.0001	-6.808	-67.58	<.0001
Colocation	0.034	3.18	0.0017	0.093	5.51	<.0001	-0.113	-2.17	0.0316	-0.163	-3.04	0.0030
Open Interest	-1.980	-8.12	<.0001	-2.430	-4.32	<.0001	0.174	0.20	0.8408	0.663	0.35	0.7272
Price Volatility	0.107	0.13	0.8931	3.837	3.90	0.0002	1.309	0.52	0.6054	-1.779	-0.77	0.4419
Control Open Interest	1.180	6.34	<.0001	-3.440	-2.64	0.0096	-0.002	-0.35	0.7295	-9.440	-2.73	0.0074
Control Price Volatility	1.612	2.03	0.0441	-0.969	-0.80	0.4260	5.286	1.81	0.0728	7.887	3.47	0.0008
Earthquake	0.064	6.03	<.0001									
Adj. R Squared			0.6301			0.5309			0.1581			0.4367
	Panel B: Ln (Tick Spread)											
Intercept	-6.227	-2037.60	<.0001	-4.406	-114.61	<.0001	0.446	2.66	0.0085	2.506	27.56	<.0001
Colocation	-0.005	-4.58	<.0001	0.022	3.44	0.0009	-0.134	-2.82	0.0054	-0.141	-2.91	0.0044
Open Interest	-0.039	-1.51	0.1335	-1.120	-5.20	<.0001	-0.865	-1.09	0.2787	-5.190	-3.04	0.0030
Price Volatility	0.324	3.87	0.0001	0.289	0.76	0.4468	-0.164	-0.07	0.9437	-1.323	-0.64	0.5262
Control Open Interest	0.053	2.68	0.0079	0.325	0.65	0.5178	0.005	0.83	0.4103	-7.120	-2.28	0.0244
Control Price Volatility	0.191	2.27	0.0239	0.341	0.73	0.4656	4.591	1.71	0.0896	6.181	3.01	0.0033
Earthquake	0.007	6.57	<.0001									
Adj. R Squared			0.8321			0.2557			0.3040			0.6282

Table A-8 Combined Liquidity Regression (Exclusion of Five Trading Days) (Cont.)

	Nikkei 225 (SGX)			MSCI Taiwan (SGX)			CNX Nifty (SGX)			FTSE China A50 (SGX)		
	Panel C: Ln (Time-weighted Spread)											
	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value	Coefficient	T-Stat	P-Value
Intercept	-7.585	-261.71	<.0001	-7.435	-74.12	<.0001	-7.621	-31.33	<.0001	-6.753	-46.44	<.0001
Colocation	0.036	3.31	0.0011	0.094	5.50	<.0001	-0.096	-1.39	0.1667	-0.253	-3.28	0.0014
Open Interest	-2.000	-8.17	<.0001	-2.410	-4.27	<.0001	-1.450	-1.25	0.2116	2.970	1.08	0.2807
Price Volatility	0.075	0.09	0.9250	3.861	3.91	0.0002	1.015	0.30	0.7636	1.197	0.36	0.7196
Control Open Interest	1.190	6.40	<.0001	-3.580	-2.74	0.0073	0.003	0.38	0.7070	-3.340	-0.67	0.5051
Control Price Volatility	1.607	2.02	0.0451	-1.005	-0.83	0.4102	4.199	1.08	0.2837	7.021	2.14	0.0349
Earthquake	0.063	5.93	<.0001									
Adj. R Squared			0.6268			0.5318			0.1538			0.2822
	Panel D: Best Depth											
Intercept	6.277	48.66	<.0001	3.445	13.22	<.0001	2.589	15.44	<.0001	3.777	30.56	<.0001
Colocation	0.355	7.34	<.0001	-0.335	-7.57	<.0001	-0.002	-0.04	0.9642	-0.122	-1.86	0.0654
Open Interest	7.820	7.19	<.0001	10.270	7.00	<.0001	0.825	1.04	0.3019	9.700	4.17	<.0001
Price Volatility	-0.694	-0.20	0.8447	-1.667	-0.65	0.5174	1.479	0.64	0.5253	-1.416	-0.50	0.6176
Control Open Interest	-6.290	-7.58	<.0001	-3.790	-1.11	0.2677	0.010	1.83	0.0683	-3.390	-0.80	0.4253
Control Price Volatility	-3.739	-1.05	0.2935	-4.548	-1.44	0.1530	-2.541	-0.94	0.3465	-1.254	-0.45	0.6542
Earthquake	-0.658	-13.89	<.0001									
Adj. R Squared			0.6267			0.4956			0.0317			0.1656
	Panel E: Total Depth											
Intercept	8.860	73.17	<.0001	6.984	32.43	<.0001	5.432	46.10	<.0001	5.990	57.03	<.0001
Colocation	0.447	9.87	<.0001	-0.252	-6.89	<.0001	-0.107	-3.20	0.0016	-0.126	-2.26	0.0258
Open Interest	9.060	8.88	<.0001	6.390	5.27	<.0001	0.080	0.14	0.8862	16.980	8.60	<.0001
Price Volatility	1.031	0.31	0.7563	-4.697	-2.22	0.0290	2.058	1.26	0.2092	-1.838	-0.76	0.4461
Control Open Interest	-6.590	-8.45	<.0001	-2.310	-0.82	0.4121	0.009	2.21	0.0287	0.343	0.10	0.9243
Control Price Volatility	-6.483	-1.95	0.0530	-4.299	-1.65	0.1025	-4.081	-2.16	0.0324	-2.585	-1.09	0.2783
Earthquake	-0.631	-14.20	<.0001									
Adj. R Squared			0.6719			0.5793			0.2197			0.6108