The Impact of Market Conditions, Global Market Liquidity and High Frequency Trading on the Price Effects of Trades in Futures Markets

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Certification

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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Preface

Some of the work presented in this thesis has been published as joint work in refereed journals.

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Synopsis

This dissertation presents three sets of analysis on the price effects of trades in futures markets. Specifically, this dissertation examines the impact of market conditions, global market liquidity and high frequency trading (HFT) on the price effects of trades. The empirical evidence presented in this dissertation addresses a number of outstanding issues in the existing literature. The findings in this dissertation also provide valuable insights for regulators and market participants to understand the importance of market sentiment in the price formation process, systematic liquidity risk across international borders, and the role of HFT in influencing market quality on information sensitive days.

The first set of empirical tests examines the impact of market conditions on the price effects of block trades in the E-mini S&P 500 index futures and SPDR S&P 500 exchange traded fund (ETF) for the period extending February 2014 to January 2016. Three discrete explanations have been developed by Kraus and Stoll (1972) and Scholes (1972) to account for the price effects associated with block trades: (1) short-run liquidity costs, (2) information, and (3) imperfect substitution. This dissertation focuses on the information effects and extends previous literature by examining the price effects of block trades in bull and bear market conditions. Specifically, it develops a theoretical model that predicts block purchases as being relatively more informed than sales in bear markets; and block sales being relatively more informed than purchases in bull markets. This dissertation uses a sample of block orders, identified as the largest one percent of transactions, in index future contracts and ETF shares across bull and bear market conditions. Results are robust to multiple definitions of market conditions. In the first definition, a bull market is identified as the period that depicts the largest cumulative return, and a bear market is defined as the period that depicts the smallest cumulative return. In the second definition, which is not a continuous trading period, a bull market is defined as the collection of macro-economic releases that are categorized as good news days, and a bear market as the collection of macro-economic releases that are categorized as bad news days. Empirical results provide similar findings between the two market sentiment definitions and demonstrates that the information price effect of block purchases is greater than sales during bearish periods and the information price effect of block sales is greater than buys during bullish periods. These empirical results are consistent with theoretical propositions developed that propose contrarian signals are more valuable than confirming signals. Further the findings contribute to the toolbox models espoused in the literature that examine the impact of market sentiment on the price formation process.

The second set of empirical tests examines the impact of global market liquidity on the price effects of trades transacted in individual share price index futures markets. Global commonality in liquidity refers to the liquidity of an individual market co-moving with global-wide liquidity. Previous research has explained global commonality in liquidity in equity markets and not derivative markets. Considering the differences in market participants and speed of trading between share price index futures and equities, this dissertation extends previous literature by examining the global commonality in liquidity across nine share price index futures markets in five different MSCI regions over a 10-year period from October 2002 to September 2012. Further, the dissertation examines whether liquidity commonality varies over a 10-year period to identify if commonality in liquidity has become more pronounced in recent periods. Empirical results reveal strong evidence of global commonality in liquidity for index futures markets, i.e. the liquidity of the individual futures market co-moves with the global market liquidity, where liquidity is measured as the total price effect of trades. Furthermore, such liquidity commonality is higher in significance and more pervasive in recent years than that observed in early 2000. These results are robust to the inclusion of expiration effects, alternative weighting structures for global market liquidity and different measures of liquidity. As liquidity commonality is considered as a common risk factor shared by every country in the global markets, results reported in this analysis improve our understanding of systematic liquidity risk across international borders in index futures markets.

The final set of empirical tests investigates the impact of HFT on the price effects of trades for futures contracts listed on the Australian Securities Exchange around scheduled macroeconomic announcements. High frequency trading increased sharply following the introduction of co-location in 2012 by the ASX (Frino et al. 2014). The existing literature mainly focuses on the overall impact of HFT on market quality in normal times, i.e. non-announcement periods, and finds that HFT improves liquidity in general. However, the impact of HFT on market liquidity around public information arrivals remains unclear, especially for the futures market. Furthermore, the causality effect between HFT and market liquidity is also a puzzle for the futures market. The futures market has different participants, speed of trading and market structure relative to the equity market. Announcement periods represent a very different informational environment relative to the normal times. This dissertation employs an exogenous event, the introduction of co-location facilities at the beginning of 2012 by the Australian Securities Exchange, to document the first empirical evidence on the impact of a reduction in latency on HFT and how HFT affects market liquidity around scheduled information releases for the futures market. Results of this dissertation demonstrate that HFT increases dramatically for intervals surrounding news releases after the introduction of co-location in Australia. Moreover, the results suggest that the increased amount of HFT improves market liquidity around macroeconomic announcements for various liquidity measures, including effective spreads, relative spreads, quoted spreads and different levels of market depth.

CHAPTER 1. Introduction

1.1 Overview

Transaction costs in financial markets consist of at least three components. The primary component is the liquidity based bid-ask spread. To provide liquidity between buyers and sellers in a marketplace, a bid-ask spread emerges between the best buying price and the best selling price to compensate the middle-man (market makers) (O'Hara 2003). The second component is the commission fee charged by brokers, which is normally quoted on a per-share (or contract) basis. The last component is the price impacts associated with a trade. The extant empirical literature has developed a raft of measures to quantify such impacts and categorised them as temporary, permanent and total impacts. The trading cost hypothesis predicts that price discovery tends to occur first in the market with the least transaction costs (Fleming, Ostdiek and Whaley 1996). As liquidity is a major component of transaction costs, a variation in liquidity, across market conditions, international markets and algorithmic trading environments, will therefore influence the price discovery process in financial markets.

Futures markets are an integral part of the global financial system as they facilitate risk transfer and provide a venue for forward price discovery. They have different participants, speeds of trading, market structures and trading cycles relative to equity markets. Price discovery is the extent to which new information (public/private) is incorporated into asset prices. The inherent leverage of futures contracts provides larger profit margins for informed traders relative to equity markets, and therefore makes the futures market a preferred place to trade new information. In this dissertation, three examinations are conducted that seek to explore the impact of liquidity variations on the price formation process in futures markets, specifically in relation to: (1) an anomaly that has pervaded the literature in terms of an asymmetric information conveyed between buyer and seller initiated large trades, across different market conditions; (2) liquidity spill-over across international index futures markets; and (3) algorithmic trading around periods of heightened asymmetric information environments.

The behaviour of block trading has received considerable attention in the literature, especially in the context of measurements of the best execution and information asymmetry. Asymmetric information implies that for block orders the true cost of trading will exceed the quoted bid-ask spread. The existing literature has identified an asymmetric relationship between the price impacts of block purchases and sales whereby the price impact of block purchases is greater than that of block sales (Chan & Lakonishok, 1993, 1997; Keim & Madhavan, 1995, 1997; Saar, 2001; Bozcuk & Lasfer, 2005). Chiyachantana et al. (2004) was one of the first studies to examine the asymmetric relationship under varying market conditions. However, their study exclusively measured the total price impact of block trades, not the permanent price impact and was not underpinned by a theoretical model. The permanent price impact of trades is a more dominant source of transaction costs as it represents the informational content of block trades.

Chiyachantana et al. (2004) examines block trading in equity markets, not futures markets. The presence of short selling constraints in equity markets, which is not as evident in futures markets, may affect the trading strategies used by institutional investors. The removal of short selling constraints generates asymmetrical price patterns between purchases and sales, which results in different impacts of trading between equities and futures. In addition to market structure differences between equities and futures, Subrahmanyam (1991) suggests that index futures and ETFs provide weaker information asymmetry as compared to underlying securities as index products are not driven by stock-specific information, but by the aggregate beliefs of market participants. This may alter the permanent price changes associated with block trades between index products and individual securities.

Commonality in liquidity refers to the liquidity of individual securities co-moving with market-wide liquidity. The existence of liquidity commonality suggests that the global market liquidity affects the liquidity in individual markets and therefore alters the price impact of trades in that market (Chordia, Roll, & Subrahmanyam, 2000; Mancini, Ranaldo, & Wrampelmeyer, 2013; Brockman & Chung, 2002; Fabre & Frino, 2004). Furthermore, the existence of liquidity commonality necessitates a new price factor in asset pricing models that represents the systematic liquidity risk around the world (Acharya & Pederson, 2005; Lee, 2011; Pastor & Stambaugh, 2003; Sadka, 2006; Korajczyk & Sadka, 2008; Bekaert, Harvey & Lundblad, 2007; Moshirian, Qian, Wee & Zhang, 2017). To date, commonality in liquidity amongst international futures markets has not been extensively studied. The existing literature in this area is limited to stock markets and over short time horizons. An understanding of the liquidity-spillover effect in futures markets and the evolution of this effect through time is important given the size and systemic rick futures markets pose in the economy.

Over the last decade, forces of technology, speed, and computer-based trading have increasingly re-shaped the structure and behaviour of trading. Co-location is an important technology service upgrade for high frequency traders (at a fee) which permits HFTs to locate themselves with minimum latency between then and the exchange server. The introduction of co-location facilities significantly reduces latency for HFTs and allows them to response more rapidly to new information releases (see Jiang, Lo & Valente, 2015; Chaboud, Chiquoine, Hjalmarsson & Vega, 2014, Chordia, Green & Kottimukkalur, 2016; Brogaard, Hendershott & Riordan, 2014, Frino, Mollico & Romano, 2013). While it is not possible to identify computer-based traders explicitly in Australian exchange data (or most other exchanges), the introduction of co-location facilities provides the best laboratory to isolate the effect of latency on liquidity and price discovery around information releases.

This dissertation extends previous studies in equity markets and conducts analyses on the price impact of trading in futures markets. The issues examined in this dissertation include asymmetric information effects of block trades under different market sentiment conditions, commonality in liquidity across international borders and the impact of algorithmic trading on market quality on information sensitive days.

1.2 Asymmetry in the Permanent Price Impact of Block Purchases and Sales: Theoretical and Empirical Evidence

A large body of research has examined the impact of block trades in equities markets (Holthausen, Leftwich & Mayers, 1987, 1990; Chan & Lakonishok, 1993, 1995, 1997;

Chiyachantana et al., 2004), derivative markets (Frino & Oetomo, 2005; Berkman, Brailsford & Frino, 2005; Pan & Poteshman, 2006; Ahn, Kang & Ryu, 2010; Ryu, 2013), and fixed-income markets (Bessembinder, Maxwell & Venkataraman, 2006; Edwards, Harris & Piwowar, 2007). This dissertation builds a theoretical model of the price impact asymmetry of block trades in bull and bear markets and tests the empirical predictions of the model using trade and quote data in futures markets and exchange traded funds (ETF).

Asymmetric findings between the impact of purchases and sales are not unique to the block trade literature. Easley and O'Hara (1996), Neal (1992) and Vijh (1988, 1990) find that inventory considerations force market markers to quote different prices for buyer and seller initiated trades. Additionally, Bohl and Klein (2012) report that short-sale constraints limit the ability for bad news to be impounded into prices and increase the likelihood of tail events to occur vis-à-vis purchases. In addition, Ryu (2013) points out that the payoff structures between selling and buying certain financial instruments may give rise to differences between purchases and sales in order to exploit favourable information. In the case of stock options, if one were aware of bad news, one could write a call or buy a put. Traders would prefer buying a put as it limits their losses if their information or signal is wrong, whereas writing a call exposes them to unlimited losses.

Bull and bear market settings have isolated several asymmetric responses in the microstructure literature. Pradkhan (2015), for example, finds that the relation between trading activity and subsequent returns is asymmetric across market settings in the precious metals futures market. Furthermore, Chiang, Lin and Yu (2009) report an asymmetric relation between depth and transient volatility in bull and bear markets, in their examination of liquidity provision of limit order traders in futures markets.

Chapter 2 indicates that the extant literature identifies an asymmetric relationship between the price impacts of block purchases and sales using block transactions data. Chiyachantana et al. (2004) is among the first to test the asymmetric total price effect between block purchases and sales, and they suggest that liquidity available to purchasers is higher in bearish markets, whereas in bullish markets the available liquidity is higher for sellers. The authors use this insight to predict that block purchases will have a bigger total impact in bull markets while block sales will have a bigger impact in bear markets. They therefore conclude that the total price impact of block trades varies with market conditions. However, their study focuses purely on the total price impact of block trades and ignores the permanent price impact, which measures the information content of block trades.

Chapter 3 extends the analysis of Chiyachantana et al (2004) by examining the permanent price impact of block trades in bull and bear market settings. More importantly, Chapter 3 develops and tests a theoretical model grounded in Easley and O'Hara (1987) and Saar (2001), which produces the somewhat counter-intuitive prediction that the information effect of block purchases relative to block sales is greater in bear markets relative to bull markets. By incorporating market sentiment and its interaction with contrarian information, this dissertation builds on the workhorse models of the permanent price impact. The sequential trading model in Chapter 3 allows traders to transact in block (large) or small quantities with no short-selling constraints, unlike the model developed in Saar (2001), where short-selling is restricted. The model assumes risk neutral informed traders prefer to trade in blocks at any given price. Consequently, the market maker sets a wider spread for block trades. However, if sufficient market width is available, informed traders place only large orders, and therefore small orders are uninformative in equilibrium. In bull markets, traders who receive an adverse signal of the assets true value have a larger informational advantage than traders who receive a favourable signal. Sell orders convey more information than buy orders, and prices adjust more for sales than for purchases. Similarly, in bear markets, traders who receive a favourable signal have a larger informational advantage than traders who receive an adverse signal. Buy orders convey more information than sell orders, and prices adjust more for buys than for sells. This yields the empirical prediction that the information or permanent price effect of block sales is greater than block purchases in bull markets, and the information effect of block purchases is greater than block sales in bear markets.

1.3 Commonality in Liquidity across International Borders: Evidence from Futures Markets

Commonality in liquidity refers to the liquidity of individual securities co-moving with market-wide or global-wide liquidity. Cross-listing is considered as one of the primary channels through which liquidity spills across international borders. Dang et al. (2015) provide empirical evidence that international cross-listing of securities influences the co-movements in liquidity between securities and their primary home markets, and between securities and their host markets. The liquidity-spill-over effect is an important source of liquidity risk in the global market, and it is essential to understand the impact of such a risk component on the price effect of trades. Previous studies examine commonality in liquidity across international borders using data drawn from various equity markets. Chapter 4 extends previous work by identifying commonality in liquidity across index futures markets for a 10-year sample period.

Index derivatives have substantially higher trading value compared to their underlying cash markets (Schoenfeld, 2004). As index futures contracts adopt margin trading, informed traders are more inclined to trade in the futures market to benefit the lower capital requirements, compared with investing in the underlying index. With the presence of more informed trading, the price of index futures is more sensitive to new information and therefore tends to lead the underlying indexes (Frino & West, 2003), which highlights the importance of stock index futures as a useful price discovery vehicle. Stock index futures have several unique characteristics that may lead to differences in liquidity commonality across international borders and exchanges relative to equity markets. First, the maturity cycle in futures markets and the associated seasonality in liquidity (Xu, 2014; Frino & McKenzie, 2002) may cause additional commonality in liquidity. Since the typical share price futures contract expiration cycle is quarterly, with expirations in March, June, September, and December, it is likely that global commonality is stronger for futures markets relative to equities markets. Second, the participants in futures markets are also likely to differ significantly from those in equities markets. Hedge funds, such as global macros, prefer to trade in the futures market to efficiently obtain exposure to different international markets (Chen, 2011). Hence, when such market participants obtain investment cash inflows, their co-ordinated global activities in obtaining exposures may also likely manifest in greater commonality in liquidity across international borders.

Chapter 4 also tests whether the liquidity commonality across international borders varies through time. Since the Brockman, Chung and Perignon (2009) study, a number of significant changes in global markets have transpired, which may have an impact on commonality in liquidity across exchanges in equity and derivative markets. First, the most significant transformation in international markets has been the introduction and growth of algorithmic and high frequency trading (HFT). Algorithmic trading in markets has significantly increased since 2002 (Hendershott, Jones & Mankveld, 2011; Frino, Mollica & Webb, 2014). Since large HFT firms, for example KCG Holdings and Virtu, are registered market participants in various financial markets and are likely to have transported trading strategies across international markets, it is expected that commonality in liquidity across borders has increased in recent times. Second, the connectivity between markets has also increased through time. For example, BT Radianz has introduced dedicated telecommunication lines to facilitate cross-market activity since 2008[1]. In 2013, BT, for example, introduced services in the Interxion data centre in London, which houses more than 200 financial services institutions and access points to more than 15 markets including NYSE Euronext, NYSE Liffe, Nasdaq OMX, Bats Chi-X Europe, the London Metal Exchange, Toronto Exchange, Singapore Exchange, Australian Securities Exchange, Spanish Exchange, ITG Posit and Equiduct. These initiatives are likely to have increased the commonality in liquidity across international borders. Third, market conditions vary through time and the associated liquidity commonality may also change accordingly.

1.4 The Impact of High Frequency Trading on Market Liquidity around Macroeconomic Announcements

A number of studies have investigated asset price dynamics on announcement days across various asset market structures. Typically, they find that the intraday patterns appear to be largely driven by macro announcements across major financial markets, such as interest rate futures markets, index futures markets, treasury markets, commodity futures markets and

[1] See BT Group Annual Report 2008 and http://www.globalservices.bt.com/us/en/products/radianz

foreign exchange markets (Ederington & Lee, 1993, 1995: Frino & Hill, 2001; Cai, Cheung & Wong, 2001; Andersen & Bollerslev, 1998).

Most previous empirical studies were conducted over a relatively short time frame, and ignore the developments in trading environment and market structure over time. Over the last decade, financial markets have been transformed due to the introduction and growth of algorithmic trading (AT). AT is commonly defined as "the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission" (Hendershott, Jones & Menkveld, 2011, Page 1). Co-location is an important technology upgrade for algorithmic traders due to the fact that it significantly reduces latency and allows traders to respond more rapidly to information releases (Jiang, Lo & Valente, 2015; Chaboud et al., 2014, Chordia, Green & Kottimukkalur, 2016; Brogaard, Hendershott & Riordan, 2014; Frino et al., 2016). The characteristics of trading are expected to change following the introduction of co-location facilities through various channels. First, the improvement in latency enables algorithmic traders to adjust their prices more rapidly when new information arrives and therefore improves price discovery efficiency. Second, the popularity and usage of algorithmic trading has brought significant changes to the way traders execute their trades. It is commonly recognized that algorithmic traders are inclined to break down a large order into smaller orders in order to minimise market impacts (Keim & Madhavan, 1995). Third, as market makers are able to trade faster following the introduction of co-location, on one hand, the market liquidity might be improved (Brogaard, 2010; Brogaard, Hendershott & Riordan, 2014; Riordan & Storkenmaier, 2012; Frino, Mollica & Webb, 2014; Brogaard, Hagströmer, Nordén, & Riordan, 2015; Hendershott, Jones & Menkveld, 2011). On the other hand, the adverse selection costs may be higher for non-HFT participants (Boehmer, Fong, & Wu, 2014; Kirilenko, Kyle, Samadi & Tuzun, 2014; Chaboud et al., 2014; Rosu, 2016; Cartea & Panelva, 2012). Therefore, it is crucial for researchers and policy makers to understand the behaviour of algorithmic traders, especially how they impact market quality around macro news releases.

Chapter 2 indicates that the extant literature documents announcement periods represent a very different informational environment relative to normal trading conditions, and therefore understanding the consequences of these releases is important to ensure market integrity. Chapter 2 also identifies a gap in the literature on the impact of co-location on algorithmic trading around macroeconomic announcements in the futures market.

Chapter 5 extends previous literature by examining whether intraday patterns, in relation to announcements, vary under different levels of HFT. While it is not possible to identify high frequency traders explicitly in the Australian exchange data, the introduction of co-location facilities provides a natural experiment to isolate the effect of latency on liquidity and price discovery, and also to identify the causal effect of a change in the level of HFT on liquidity. Chapter 5 compares futures market responses to macro release between pre- and post- co-location periods and demonstrates that the introduction of co-location leads to an increase in HFT activity around news releases. Chapter 5 provides evidence that the increased HFT, resulting from co-location facilities, improves market liquidity around news releases.

1.5 Summary

The three research topics investigated in this dissertation shed light on the price effect of trades in futures markets and provide empirical evidence on the impact of market sentiments, global market liquidity and HFT on the trade price effects.

The remainder of this dissertation is organised as follows. Chapter 2 provides a literature review relating to block transactions, global commonality in liquidity, the development and the impact of HFTs, and presents the hypothesis development. Chapter 3 examines the relationship between the market sentiments and the permanent price impact of block trades. Chapter 4 investigates the impact of global liquidity commonality on the price effect of trades in index futures markets. Chapter 5 reports the impact of co-location on HFT activity and, more importantly, identifies a causal effect of a change in the level of HFT on market liquidity during information sensitive days. Finally, Chapter 6 provides a concluding review and brings together the results of the three studies.

CHAPTER 2. Literature Review

2.1 Introduction

Chapter 1 identified that the main objective of this dissertation is to provide empirical evidence to demonstrate the impact of market conditions, global market liquidity and HFT on price effects in futures markets. This chapter provides an overview of the literature related to the three examinations presented in this dissertation in order to provide further motivations for the empirical analyses of block transactions, liquidity commonality and HFT.

2.2 Asymmetry in the Permanent Price Impact of Block Purchases and Sales: Theoretical and Empirical Evidence

2.2.1 Definition of the Price Impact of Trades

A large body of research has examined the impact of block trades in equities markets, derivative markets and fixed-income markets. Three hypotheses have been developed in the literature that predict the price effects associated with block trades: (1) short-run liquidity costs, (2) information asymmetry, and (3) imperfect substitution (Kraus and Stoll 1972, and Scholes 1972).

Short-run liquidity costs refer to the costs faced by trade initiators with the aim of compensating trade counterparties for inventory and search costs (Demsetz, 1968; Glosten & Milgrom, 1985; Amihud & Mendelson, 1980). The greater the trade is, the larger the price concession is to cover the liquidity costs. The liquidity costs come in the form of deviations from equilibrium market prices, i.e. a lower price for large sells and a higher price for large buys, relative to the existing market prices. Given that the price impact is solely associated with a specific transaction, a temporary price change is expected whereby the price eventually reverts back to the pre-block equilibrium price level.

The information hypothesis states that rational informed traders utilise their private information to exploit market mispricing and subsequently establish a new equilibrium price level. The private information creates a permanent price impact in the market, in the form of a decrease in prices following informed sales and an increase in prices following informed purchases. Easley and O'Hara (1987) link the information hypothesis with block transactions and argue that block trades induce adverse selection costs in markets, as informed traders exhibit a preference to trade in large quantities to maximise profits gained from their private information. Scholes (1972) emphasizes the urgency in informed trading and argues that informed traders tend to execute in large quantities, as private information is often short lived. Kyle (1985), Barclay and Warner (1993), however, state that traders, who are informed, act with stealth and tend to break up a large trade into medium-sized trades. Chakravarty (2001) re-examines the proposed hypothesis on stealth trading and provides new evidence that medium-sized trades executed by institutional investors are the main force that drives a large proportion of cumulative price changes. O'Hara (1995) addresses that many block trades are not directly transacted in the downstairs market (primary trading market), but rather are executed in the upstairs market. As documented in Burdett and O'Hara (1987), block trades are transacted in the upstairs market through search-brokerage mechanisms. Under such mechanisms, block traders reveal part of their private information to the upstairs market through the search and negotiation process, which occurs before a transaction being completed.

In a perfect capital market, demand curves are perfectly elastic for securities that are perfect substitutes for one another. In a market where securities are imperfect substitutes for one another, each security becomes a unique asset. In relation to block trades, imperfect substitution implies that a change in price levels occurs around block trades as a response to supply and demand disturbances. For example, block buyers face an upward sloping excess supply curve while block sellers face a downward sloping excess demand curve. Empirical evidence provided by Shleifer (1986), Biais, Hillion and Spatt (1995), and Levin and Wright (2002) for U.S., French and UK stock markets, respectively, support the views that the supply and demand curves of securities are not infinitely elastic. The empirical tests demonstrate that block purchases pay premiums to sellers, and block sellers offer discounts to purchasers, due to the inelasticity of excess demand and supply curves. Furthermore, this price impact could either be temporary or permanent, determined by how resilient the market is and what price benchmarks are involved.

As suggested by Holthausen, Leftwich and Mayers (1987), and Kraus and Stoll (1972), three hypotheses related to block trades are examined through a breakdown of price changes surrounding large transactions into temporary impact, permanent impact and total price impact. The temporary impact is generally defined as the deviation between the price of the block transaction and the post-equilibrium price. The permanent price impact measures the difference between the pre- and the post-equilibrium prices. The total impact is normally calculated as the deviation between the pre-equilibrium price and the price of the block transaction.

2.2.2 Asymmetry between the Price Impact of Block Purchases and Sales: Empirical Evidence

Previous literature has identified an asymmetry in the temporary, total and permanent price impacts between purchases and sales. Kraus and Stoll (1972) is the seminal work that identifies an asymmetric relationship between the price impacts of block sales and purchases using data from NYSE. By using close prices surrounding block trades as the pre- and post-benchmark prices, the study shows that the total and the temporary impacts of large sells are significantly greater than the impacts of large buys. Conversely, large buys exhibit a higher permanent impact relative to large sells. The authors attribute the asymmetry in price impacts following block trades to the unwillingness of traders to go short and to facilitate block sales. Therefore, short-term liquidity costs are less likely to arise for block purchases, relative to block sales.

Unlike the seminal work that uses trade prices, Koski and Michaely (2000) demonstrate that the quoted price is a better measure of information/permanent impacts compared to the actual transaction price and also identify an asymmetric relationship between the information/permanent impact of block sales and purchases using quoted prices. The study reports that bid-ask spreads tend to increase following block trades and are more pronounced during periods of greater information asymmetry, i.e. days with dividend announcements. While block sales and purchases are both associated with significant changes in prices and market liquidity, quote prices vary significantly across information environments for block purchases, but not for block sales.

Following previous studies on the asymmetry between the price impact of block purchases and sales, Holthausen, Leftwich and Mayers (1990) conduct intraday analysis on the 50 largest block trades for 109 NYSE firms, and discover different price discovery patterns between block purchases and sales. Specifically, Holthausen, Leftwich and Mayers (1990) show that the price discovery associated with block sales is correlated with trade size, i.e. larger block trades take longer to adjust prices relative to smaller block trades. However, the price discovery associated with block purchases does not exhibit such a relationship between trade size and recovery times.

The asymmetric relationship between block purchases and sales, as identified previously in the U.S. market, also exists in other international markets. A study by Aitken, Frino and

Sayers (1994) provides evidence on the impact of large stock transactions in the Australian market and demonstrates that the permanent and temporary price impacts are asymmetric between large buys and large sells using quoted prices. Gemmill (1996) extends previous work to the U.K. market and discovers asymmetric results on the price impacts of large buys and large sells. Gemmill (1996) reports that the price impacts, including permanent, temporary and total impacts, of large transactions are significantly larger for buys than for sells. The discovered asymmetry does not appear to be explained by the constraints faced by traders to go short, calling for future research to find out the causes of the asymmetry.

Subsequent studies, that re-examine the asymmetry between purchases and sales, aim to explain the asymmetry using institutional transaction data. As the first comprehensive work on the impact of institutional transactions, Chan and Lakonishok (1993) examine all trades (rather than exclusively block trades) executed by 37 major institutional firms on both NYSE and AMEX, and identify asymmetric price impacts between purchases and sales. Specifically, the authors report that both total and permanent price impact are larger for institutional purchases, while temporary impacts are greater for institutional sales. More importantly, they suggest that trader and investment styles are important sources affecting the size of the price impact. In summary, the authors confirm an asymmetric relationship between the impacts of large buys and large sells, and argue that the asymmetric relationship may be caused by different information contents associated with large buys and large sells.

Keim and Madhavan (1995) provide a similar explanation on the asymmetric relationship between the impact of large buys and large sells. The authors state that institutional traders "…can choose among many potential assets to buy, but when they sell, they usually limit themselves to those assets they already own because of limitations or restrictions on short-sales. Thus, there are very few liquidity motivations for a large-block purchase in a particular stock, but there may be many such reasons for a large sale." (p. 389). Therefore, institutional purchases are believed to convey more information than institutional sales.

Chan and Lakonishok (1997) compare execution costs for institutional trades across U.S. exchanges, and demonstrate that NASDAQ is cost efficient for small institutional trades, and on the other hand, NYSE has a cost advantage for more complex trades. As investment styles and order placement strategies adopted by institutional traders can result in different transaction costs, Keim and Madhavan (1997) further compare transaction costs associated with orders submitted by technical traders, value traders and index traders on NYSE and NASDAQ. Their study reports that value traders who trade patiently face the least transaction costs, relative to index and technical traders. Block trades by technical traders and index traders, who prefer market orders due to demand for immediacy, experience higher execution costs than value traders, with the technical traders having the highest transaction costs. Comparing transaction costs associated with institutional purchases and sales, Keim and Madhavan (1997) document that purchases are associated with larger execution costs than those with sales, even after controlling for trade complexity and firm size. The possible explanation for the asymmetry is that purchases are believed to deliver more information content than sales. In addition, Keim and Madhavan (1997) point out two other important determinants of transaction costs – trade size and liquidity of the stock. The authors also uncover the fact that institutional sales are in general larger and occur in more liquid stocks, compared to institutional purchases.

Bozcuk and Lasfer (2005) provide evidence on price impacts of institutional orders executed on the London Stock Exchange. The authors first discover that the permanent price impacts associated with institutional purchases are twice of those associated with institutional sales. Then they explain the asymmetry in institutional trades with the information associated with institutional ownership. Bozcuk and Lasfer (2005) provide evidence that a trader's identity contributes to the observed asymmetry. Specifically, block purchases transacted by fund managers with concentrated levels of ownership lead to positive abnormal returns reflecting private information and monitoring costs, and similarly, block sales transacted by fund managers with diminutive levels of ownership lead to negative abnormal returns reflecting private information and monitoring costs, which is consistent with the hypothesis developed by Keim and Madhavan (1995).

Chiyachantana et al. (2004) conduct a comprehensive study across 37 countries. The study uncovers three significant sources of execution costs across countries, which are order submission strategies, country specific and firm specific. Moreover, the study reveals a positive relationship between total price impact and order complexity, which is consistent with Keim and Madhavan (1997) and Chan and Lakonishok (1993). By comparing execution costs across countries, the study demonstrates that markets with poor shareholder rights, non-liberalised capital markets and emerging markets, exhibit the most expensive transactions. More importantly, Chiyachantana et al. (2004) observe an asymmetric relationship in the total price impacts of large buys and large sells and compare such asymmetric relationship across different market sentiments. Specifically, the study finds that the total price impact of large buys is greater in bull periods, whereas the total price impact of large sells is larger in bear periods. The study argues that large sells have relatively little impact on prices in bull periods due to the large quantity of buy orders available. Similarly, investors are relatively more motivated to sell in bear markets and hence it is easier to buy stocks. Chiyachantana et al. (2004) provide solid evidence on the total price impacts for international stock markets;

however, the study does not examine the permanent price impacts across different market sentiments where the permanent impact is also critical for market participants as it measures the informational content of block trades.

Hu (2009) further examines the role of market conditions in transaction costs of institutional trades. The study reviews measures of implicit trading costs incurred by institutional investors and split these measures into pre-trade, during-trade and post-trade measures based on the selection of the benchmark price. Hu (2009) confirms findings observed by Chiyachantana et al. (2004) that the total price impact, a pre-trade measure, of institutional sells is larger in bear market conditions and the total price impact of institutional buys is larger in bull market conditions. Furthermore, Hu (2009) demonstrates that the reverse is true when post-trade measures are used. Meanwhile, the during-trade measure, with a benchmark price setting at the volume-weighted-average-price, is not affected by market conditions.

The dramatic development of high frequency trading in the last decade has fostered substantial interest from researchers into its consequences in transaction costs incurred by institutional investors. Brogaard et al. (2014) examine the impact of HFTs on execution costs opposed to institutional investors, using data from the London Stock Exchange. The authors adopt an exogenous event that reduces exchange latency. The event allows them to quantify variations in the amount of HFTs in the marketplace. They show that the amount of HFTs rises following the event; however, institutional transaction costs remain unchanged after the event.

A recent study by Kervel and Menkveld (2016) provides new evidence on the relationship between HFTs and institutional transaction costs. The authors compute HFTs' net trading flow (i.e. the amount of buy volumes minus the amount of sell volumes) over the duration of each institutional order. They find that the net flow is correlated with institutional transaction costs. Specifically, the transaction cost decreases as high frequency traders sit on the opposite side of the order-book to institutional investors. However, the transaction cost increases as high frequency traders sit on the same side of the order-book with institutional investors, i.e. high frequency traders compete on order flows with institutional investors. The authors also reveal that high frequency traders first provide liquidity to institutional investors by acting as their trade counterparties, and then turn around to compete on order flows with institutional investors for orders that last for a long time.

2.2.3 Asymmetry between the Price Impact of Block Purchases and Sales: Theoretical Evidence

Empirical studies, conducted by Keim and Madhavan (1995), and Chan and Lakonishok (1993), examine the trading behaviour of institutional investors and provide incentives for the theoretical model proposed in Saar (2001). Saar (2001) develops a theoretical framework to interpret the asymmetry between the permanent price impact of large sells and large buys. Saar (2001) identifies three factors that underlie the asymmetry: (1) the way in which prototypical institutions gather and analyse information; (2) the dynamic portfolio rebalancing of institutions; and (3) trading constraints adhered to institutional investors.

In general, institutional investors sell stocks that are expected to generate negative or zero returns in the future, and, at the same time, buy stocks with favourable information that are expected to rise in the future. However, this simple strategy is sometimes restricted by factors such as inability to use leverage to fund trading, short selling constraints and diversification requirements to reduce portfolio risks. Saar (2001) predicts that for stocks with a history of insignificant price improvements, block purchases are associated with greater permanent price impacts than block sales. The reasoning behind this proposition is that investors are less likely to hold portfolios of companies with no favourable information; therefore, a market with uncertainty and unfavourable news reduces the probability of informed selling due to the presence of short selling constraints. To model the behaviour of institutional investors, Saar (2001) assumes that investors would prefer holding cash than buying stocks without favourable information. Conversely, Saar (2001) predicts that for stocks with a history of continuous price increases, block sales are associated with greater permanent price impacts than block purchases.

To explain the observed asymmetry between purchases and sales, Saar (2001) argues that the magnitude of the asymmetry is linked with the associated trading environment, i.e. favourable or unfavourable news. Furthermore, the asymmetry is positively correlated with the level of institutional trading and the frequency of information events. Saar (2001) then calibrates his model using daily data on NYSE stocks and provides empirical support for his model, suggesting future research to investigate the information asymmetry involving a control for different trading environments. Chapter 3 extends the framework of Saar (2001) by modelling the information asymmetry across different market conditions and verifying the theoretical model with intraday data on S&P 500 index futures and ETF. Further, the model in Saar (2001) does not necessarily transcend to futures markets, where short selling constraints are not imposed. The sequential trading model, developed in Chapter 3, allows traders to transact in large or small quantities with no short-selling constraints. And the model is then calibrated with data on index futures, a type of financial instruments with no short-selling restrictions.

2.2.4 Bull and Bear Market Conditions

Bull and bear market settings have isolated a number of asymmetric responses in the market microstructure literature. Consistent with previous literature, Chiyachantana et al. (2004) observe an asymmetric relationship in the total price impacts of large buys and large sells. In contrast, however, Chiyachantana et al. (2004) provide a new explanation in their reporting of the asymmetric total price impacts. The authors suggest that liquidity available to purchasers is higher in bearish markets, whereas in bullish markets the available liquidity is higher for sellers. They also argue that block sales have relatively little impact on prices in bull markets due to the large quantity of buy orders available. On the other hand, investors are relatively more motivated to sell in bear markets, and hence it is easier to buy stocks. The authors use these insights to predict that large buys will have a greater total price impact in bull markets whilst large sells will have a greater total price impact in bear markets. They therefore conclude that the impact of large transactions varies with market conditions. However, their study is limited to the total impact of large buys and large sells, but ignores the permanent price impact, which measures the informational content of large transactions.

Futures markets also exhibit asymmetric trading behaviour across bull and bear market settings. Chiang, Lin and Yu (2009) provide evidence of an asymmetry between transient volatility and depth for bullish and bearish periods. The authors demonstrate that in a bullish period, transient volatility is positively correlated with both market depth and trading volumes, but the correlation does not exist for a bear period. The predictability of returns is also different between bullish and bearish market conditions in precious metal futures markets.

Pradkhan (2015) demonstrates there are more non-informational trades in bullish periods, whereas there are more informational trades in bearish periods. Specifically, the predictability of returns is strong during bullish periods and weak during bearish periods for palladium.

In summary, the existing literature demonstrates an asymmetric relationship between price impacts of block purchases and sales. Most previous studies primarily use data from bull periods and examine equity markets, which suffer from short selling limitations. In addition, the extant literature has focused on the total price impact of trade, and ignored the permanent price impact asymmetry in light of market sentiments.

2.3 Commonality in Liquidity across International Borders: Evidence from Futures Markets

2.3.1 Evidence of Liquidity Commonality

Commonality in liquidity described by Chordia, Roll and Subrahmanyam (2000) refers to the liquidity of individual securities co-moving with market-wide liquidity. This concept first tested in the U.S. market has received wide attention in the literature and has been replicated for a number of different international markets with opposing market structures. The following section of the thesis reviews evidence of commonality in liquidity in other international markets and identifies the causes of common components in liquidity.

Brockman and Chung (2002) provide evidence of liquidity commonality for an order-driven market, the Hong Kong Stock Exchange. Their study demonstrates that liquidity commonality consists of both industry and market factors and the commonality is evident across stock portfolios sorted by size. In contrast to previous research, Fabre and Frino (2004) show that the liquidity commonality is less evident for stocks listed on the Australian Stock Exchange (ASX), compared to stocks in other markets. They suggest the difference in the degree of liquidity commonality may result from the market structure difference between Australia and the U.S..

Mancini, Ranaldo, and Wrampelmeyer (2013), was among the first studies to systematically examine liquidity in the FX market. The study discovers significant liquidity commonality across various currencies and with bond and equity markets. The study also demonstrates that the liquidity risk is strongly correlated with carry trade returns and therefore liquidity should be priced in currency returns, as has been the case in equity markets (Acharya and Pederson, 2005).

As capital markets become increasingly globalized due to low costs of information technology and a tendency towards free-trade and deregulation, it is necessary to understand the co-movements of capital and liquidity across countries. Brockman, Chung, and Perignon (2009) extend previous literature by examining liquidity commonality across exchanges. It is one of the first studies to investigate the commonality issue across international borders and to introduce the concept of "global liquidity commonality". The authors uncover a distinct, global component in liquidity measures. The commonality within each exchange represents around 40% of a company's total liquidity commonality, and the global component contributes to another 20% of the total commonality. In terms of the determinants of commonality, the study demonstrates that liquidity commonality is driven by movements in both the local and the U.S. macroeconomic environments.

Although extensive studies have documented the existence of commonality in liquidity among equity securities, relatively little is known about commonality in liquidity among derivative markets. Cao and Wei (2010) demonstrate the existence of liquidity commonality in the option market. They show that the liquidity of an individual option co-moves with both the options' market-wide liquidity and the underlying stock liquidity. In addition to findings on liquidity commonality, they unveil important liquidity characteristics for options. Specifically, the options liquidity reacts asymmetrically to upward and downward market conditions, with call options responding more in an upward market and put options responding more in a downward market.

The commodity market is an important asset class as it provides diversification benefits to stock and bond portfolios. Marshall and Nguyen (2013) report evidence of liquidity commonality among 16 different U.S. commodity futures, covering agricultural, energy, metal and livestock sectors. Furthermore, the authors examine commonality in liquidity for two sub-periods to determine whether the commonality only exists in the later period with escalating commodity prices. They find that liquidity commonality is present for both sub-periods, but the degree of the commonality increases across the two periods.

2.3.2 Determinants of Liquidity Commonality

After establishing the widespread existence of liquidity commonality, the next stage in the research agenda is to determine the drivers of commonality. The determinants of liquidity commonality have important implications for international asset pricing (Chordia, Roll, & Subrahmanyam, 2000, 2011). Two new research questions have been raised with regards to the determinants of liquidity commonality. First, what are the driving forces behind liquidity commonality, and what are the market-level and firm-level factors that can explain the variations in global liquidity commonality? Second, should liquidity commonality be priced, and how is it priced? Understanding the determinants of liquidity and the role of liquidity commonality in asset pricing would change the structure of existing asset pricing models (Acharya & Pedersen, 2005) and also the trading behavior of market participants.

Several specific drivers of liquidity commonality have been identified in the literature, with the most common ones being industry and firm size effects. In addition, Coughenour and Saad (2004) examine the importance of trading by the same specialist firm as a source of commonality in liquidity for stock portfolios transacted on the NYSE. The authors argue that the liquidity of stocks held by the same specialist firm tend to co-move with each other, with magnitude increasing with the risk of liquidity provision. Brockman and Chung (2006) focus on one single driver of commonality in liquidity, equity index inclusion, and demonstrate that it is a significant source of a firm's liquidity commonality. Dang et al. (2017) examine commonality in liquidity for cross-listed stocks and discover an asymmetric impact of cross-listings on the local and the host markets. Specifically, cross-listings reduce the co-movements between the stocks' liquidity with the local market liquidity, meanwhile, cross-listings increase the co-movements between the stocks' liquidity with the host market liquidity.

Karolyi, Lee and Dijk (2012) analyze a wide range of market-level factors affecting liquidity commonality and categorize them into demand-side and supply-side components. They use these factors to explain how and why liquidity commonality differs across countries. The supply side factors include elements that affect financial intermediaries' funding liquidity, such as short term interest rates, bank deposits, market volatility and market capitalization; while the demand side factors cover elements that affect connected trading behaviour of institutional investors and international investors, and trade incentives, such as foreign institution ownership, financial disclosure, market turnover and investor sentiment. Their results show that both supply-side and demand-side sources significantly affect liquidity commonality. Specifically, liquidity commonality is greater when the market is more volatile (supply side) and when there are more international investors in the market (demand side).

Using transaction data from 39 markets over the period of 1996-2010, Moshirian et al. (2017) extends Karolyi, Lee and Dijk's study (2012) by considering both firm-level and market-level factors that drive liquidity commonality across countries. The paper investigates determinants of liquidity commonality, and examines factors including economic and financial conditions, the quality of investor protection, the information environment and the cultural and behavioral characteristics of investors. Their results show that commonality in liquidity is driven by both market-level and firm-level factors; specifically, liquidity commonality is higher in weaker and more volatile economic and financial environments, in areas with poor investor protection, and in opaque information environments.

With respect to the determinants of commonality in liquidity for derivatives markets, Marshall and Nguyen (2013) test both supply-side and demand-side drivers of liquidity commonality. The study provides evidence to support both supply-side and demand-side explanations of commonality, and the study finds that fund ownership is positively correlated to liquidity commonality with the Amihud liquidity measure; while market return is negatively correlated with liquidity with the relative spread measure. However, their study did not find consistent results across liquidity measures.

2.3.3 Liquidity Risk and Asset Pricing

A number of studies have investigated the relationship between market liquidity and expected returns, and found evidence suggesting pricing liquidity as a characteristic or as a risk factor. Liquidity is a latent concept, and cannot be fully captured by a single measure. A market is liquid if investors can trade stocks in large quantities, with low transaction costs (Huberman & Halka, 2001)[2]. The possibility that liquidity might disappear from a market, and so not be available when it is needed, is a significant source of risk to an investor. Acharya and Pederson (2005) derived a liquidity-adjusted capital asset pricing model that helps explain price effects associated with the risk of changes both in the liquidity of individual stocks and the market-wide liquidity. The model can be seen as a unified approach for understanding liquidity risk and how it affects asset prices. Their study finds that most of the pricing effect is derived from the sensitivity of liquidity to market returns and that the covariance of stock liquidity and market liquidity has no effect on pricing.

Lee (2011) provides empirical evidence for the liquidity-adjusted capital asset pricing model, developed by Acharya and Pederson (2005), using global market data. The study finds consistent results with conclusions of the theoretical model. Specifically, the analysis demonstrates that the required return of a security is partly determined by the correlation between the security's liquidity and the overall market liquidity, and partly depends on the correlation between the security's liquidity with the local and the global market returns. In

[2] Liquidity refers to the ability to transact a large amount of financial securities rapidly at low costs, and it can be measured through different dimensions. Borio (2000) defines liquidity from four dimensions: 1) depth, measured as the maximum number of shares that can be executed without affecting the best quoted mid-price; 2) tightness, measured by the bid-ask spread, indicates how far transaction price diverges from the quoted mid-price; 3) immediacy, measured by the time required for the market to execute an order, and 4) resiliency refers to the ease with which prices return to "normal" after temporary order imbalances.

addition, the analysis also finds that the global liquidity risk is mainly driven by the U.S. market. However, the study finds little evidence that the liquidity co-movements affect future stock returns.

Pastor and Stambaugh (2003), Sadka (2006), and Korajczyk and Sadka (2008) examine whether market-wide liquidity is a state variable important for asset pricing and conclude that the market-wide liquidity is a latent priced factor for common stock markets. Similar to stock returns, the studies discover a liquidity beta for each stock. Such a beta factor measures the stock's sensitivity to movements in the overall market liquidity, and significantly affects asset pricing, i.e. a higher liquidity beta is associated with a higher expected return.

In fact, exchange-level liquidity risks are empirically even more important compared to exchange-level market risks as for emerging markets, according to Bekaert, Harvey and Lundblad (2007). Consistent with liquidity being a priced factor, as documented in previous studies, the authors show that for emerging markets there is a positive correlation between the unexpected liquidity shocks and the shocks to contemporaneous returns, and a negative correlation between the unexpected liquidity shocks and the shocks to dividend yields. Furthermore, they also suggest that for emerging markets, stocks returns are driven by the local market liquidity and the importance of market liquidity is not affected by their liberalization process.

As for derivatives, option price is significantly affected by liquidity risk and the impact of liquidity risk increases quadratically as the size of hedged options goes up. Cetin, Jarrow, Protter and Warachka (2006) provide the first theoretical evidence of the impact of illiquidity of the underlying asset market on option pricing. Furthermore, the study addresses the importance of illiquidity and the need to consider liquidity cost in option pricing.

Recent studies show not only that liquidity itself can be seen as a priced factor, the co-movements in liquidity also has pricing implications. Huh (2011) argues that high liquidity commonality implies high liquidity risk, which in turn affects asset prices. Huh (2011) explains this relationship between liquidity commonality and asset pricing as follows: When global liquidity commonality is high, liquidity drying up in one market will also damage the liquidity in other markets, especially during economic downturns, which causes higher losses for investors who have to liquidate; as a result, investors would demand a higher rate of return when the systematic liquidity risk is higher and the global market is more integrated.

Moshirian et al. (2017) provide further evidence that the liquidity risk arising from liquidity commonality is priced across global stock markets. Different from previous studies conducted by Acharya and Pedersen (2005) and Lee (2011), Moshirian et al. (2017) uses bid-ask spreads rather than low-frequency liquidity proxies. The bid-ask spread may capture total transaction costs more directly and accurately than low frequency proxies on liquidity. Using high frequency liquidity measures, the study finds that liquidity commonality is priced in the global stock markets and that the pricing effect is stronger in developed markets.

In summary, previous studies in the literature demonstrate that commonality in liquidity exists in stock markets both at a local exchange level and a global level. Such liquidity risk has a significant predictive power on equities' expected returns, which gives rise to a liquidity adjusted capital asset pricing model. Despite the progress made in stocks markets, it remains an open issue to examine the existence of global commonality in liquidity in futures markets.

The contribution of this present study to the existing literature will be twofold. First, this analysis examines whether changes in liquidity in one country affects the liquidity in other countries by analysing data from nine index futures markets in five different MSCI regions. Three liquidity measures, intraday quoted bid-ask spread, relative bid-ask spread and depth, are employed to investigate these co-movements in liquidity. Second, this analysis tests whether liquidity commonality varies over a 10-year period. The study first divides time series data into five equal periods and then conducts a comparison analysis among these periods in order to capture the changes in the degree of liquidity commonality.

2.4 High Frequency Trading and Market Liquidity around Macroeconomic Announcements

2.4.1 Market Behaviour around Macroeconomic Announcements

The two main drivers of market price movements are new information and market fundamentals. Section 2.2 documents evidence of an asymmetry in the permanent price impact of block purchases and sales, which resulted from different information levels contained in buy and sell orders. Section 2.3 provides evidence of global commonality in liquidity and demonstrates how the global market liquidity could affect the total price impact of trades in the individual capital market. The liquidity commonality is partly explained by the co-movements in market fundamentals across international borders. This section reviews the literature related to HFT and the price impact of trades during announcement periods, representing a very different informational environment relative to normal times.

A number of early studies, (Bernard & Thomas, 1989, Kross & Schroeder, 1984), have investigated the real-time asset price dynamics in the U.S. stock market on earnings announcement days. The studies have received wide attention in the literature and subsequent studies have extended the sample data to other international stock markets and to scheduled macroeconomic releases. The existing literature reveals diversity in intraday responses. Andersen, Bollerslev and Cai (2000) investigate this topic in an order driven market, Japan, and find that macroeconomic announcements do not explain most variations in intraday volatility for the Japanese stock market. Furthermore, Erenburg and Lasser (2009) study the intraday patterns of a limit order book market, the Island stock market, around macroeconomic announcements. The authors find that liquidity reduces for intervals surrounding news releases, as evidenced by a thinner depth and wider spreads. Furthermore, the order book exhibits higher volatility and more aggressive order submissions for announcement periods, relative to normal times.

To determine how futures markets process information on an intraday basis, early literature first assessed returns and volatility for the U.S. futures market, as well the London futures market. Ederington and Lee (1993), a seminal work, examine futures markets' intraday behavior around announcements and study the impacts of scheduled macro releases on the U.S. interest rate and foreign exchange futures markets. In contrast to equity markets, the futures markets appear to exhibit a relatively stable intraday pattern in general, but respond substantially to news arrivals. The study uses five-minute and one-minute intervals and reveals that the price adjustment occurs in the first minute following releases; however, volatility remains significantly larger than normal for around 15 minutes. Ederington and Lee (1995) extend their previous work by examining finer intervals, 10-second intervals. They document that the price overreacts in the first 40 seconds of announcements, but it is then corrected in the second or third minute following announcements.

Similar evidence has been found in the Australian futures market. Frino and Hill (2001) examine intraday market behavior of the Australian index future contract, SPI 200, surrounding scheduled macro releases. The authors find that bid-ask spreads dramatically widen in the 20 seconds prior to release times and stay substantially wider for 30 seconds following releases. Market participants tend to quote wider spreads around information announcements to avoid adverse selection costs. The interest rate futures market also displays pronounced movements following macroeconomic announcements. Smales (2013) reports that intraday patterns of interest rate futures are likely to be dominated by public information releases, vis-à-vis their underlying cash markets.

Fleming and Remolona (1999) analyze the U.S. Treasury spot market and uncover two stages of market adjustments to new arrivals of public information for price formation and liquidity provision at an intraday level. After regressing government bond returns on announcement surprises, Balduzzi, Elton and Green (2001) differentiate between existing macro announcements and identify the types of announcements that have significantly affected market prices. Furthermore, the authors discover wide spreads at the time of announcements and revert slowly to normal five to fifteen minutes following announcements. A recent study by Jiang, Lo and Valente (2015) extends previous literature by examining HFT around major macroeconomic announcements in the U.S. treasury market. They find that HFT increases after macro news releases and HFT improves price efficiency around information arrivals.

A comprehensive study on the commodity futures market, conducted by Cai, Cheung and Wong (2001), reveals evidence of long-memory volatility dependencies caused by major announcements in the gold market. Using intraday data for the period 2002 through 2008, Elder, Miao and Ramchander (2012) assess the impact of U.S. macroeconomic news on three commodity futures: gold, silver and copper. The authors find that the three metal futures respond to news surprises rapidly; however, the impact of new information is different across the three metal futures. Specifically, the unexpected improvement in the economy tends to be negatively related to gold and silver prices, but positively related to copper prices.

A number of studies argue that public information releases are linked to the largest returns observed in foreign exchange markets. According to Andersen and Bollerslev (1998), major macroeconomic announcements dominate the price movements in the Deutsche mark-dollar foreign exchange market immediately following the release time, but with a smaller response than other markets. Chen and Gau (2010) provide further evidence of price discovery for both spot and futures rates for two currency pairs, USD-JPY and USD-EUR, around scheduled macro releases. The authors find that the spot rates exhibit more price discovery than the futures rates do in general, but during a macro news release period, the futures returns are more sensitive to announcements than the spot returns are.

Many market participants believe that macroeconomic announcements impact the financial market significantly. As documented in previous literature, the intraday patterns appear to be largely driven by macro announcements, especially around the news release time. This finding is consistent across major financial markets, such as various equity markets, interest rate futures markets, index futures markets, treasury markets, commodity futures markets and foreign exchange markets. The impact of macro announcements is weak in equity markets, but more significant in other markets.

2.4.2 High Frequency Trading

Financial markets have been transformed over the last decade due to the introduction and development of Algorithmic Trading (AT). AT is commonly defined as "the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission" (Hendershott, Jones and Menkveld 2011, Page 1). The growing prevalence of AT is attributed to the competition for the speed at which market participants are able to interact with other participants and also with the exchange.

High frequency trading forms a subcategory of AT, i.e. not all algorithmic trading is associated with HFT. Specifically, the U.S. Securities and Exchange Commission (SEC) defines HFTs as, "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis" (SEC 2010, p.45). SEC identifies HFTs to be associated with the following characteristics: "(1) extraordinarily high speed and sophisticated computer programs for generating, routing, and executing orders; (2) use of co-location services and individual data feeds to minimize latency; (3) very short time-frames for establishing and liquidating positions; (4) submission of numerous orders cancelled shortly after submission; and (5) ending the trading day in as close to a flat position as possible" (SEC 2010, 45). These characteristics of HFTs are in line with a variety of trading strategies used by a mixed group of market participants, from quantitative hedge funds to proprietary market-making firms. The trading strategies adopted by these participants include statistical arbitrage and pseudo market-making which do not require human interventions. In contrast to HFT, algorithmic trading is more commonly used by agency traders. The strategies adopted by algorithmic traders aim to achieve certain outcomes, for example to acquire liquidity, or to minimise information leakage for block trades and therefore to reduce the costs of implementation shortfall[3].

At the beginning of the 2000s, HFTs represented less than 10% of equity trading volume in the U.S. By the end of 2012, around 50% of the U.S. equity trading volume was transacted by HFTs, and 40% and 60% of trading volume across stocks, options and forex in the U.S. was transacted by HFTs[4]. Besides the U.S. market, HFTs are also rapidly expanding in Asia and Europe: representing roughly 40% stock trading volume in Japan, 12% in the rest of Asia, and 45% in Europe, at the end of 2012. Due to persistent investments in technological upgrades and competitiveness among HFT players, trading speed has been dramatically increasing over the last 15 years. As specified in Goldstein, Kumar and Graves (2014), HFTs initially had an average latency (execution time for round trips) of several seconds, and in recent years, the latency has significantly reduced to milliseconds and even microseconds.

2.4.2.1 High Frequency Trading – Theoretical Literature

The widespread interest in algorithmic trading and HFT has stimulated the growth in studies examining the consequences of this development in trading speed, especially the impacts of the improved speed on market liquidity. Previous theoretical literature demonstrates that liquidity is affected by trading speed through two channels: inventory management and

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[3] Implementation shortfall refers to the difference between the prevailing price of an order and the final execution price of the order after taking into consideration of all commissions, fees and taxes.

[4] Source: http://www.businessinsider.com/how-high-frequency-trading-has-changed-the-stock-market-2017-3/?r=AU&IR=T and https://en.wikipedia.org/wiki/High-frequency_trading#cite_note-speedPays-26 and SEC (2014).

adverse selection. This section documents the existing literature that theoretically examines how an improvement in trading speed could affect a financial market.

Cvitanic and Kirilenko's (2010) research is amongst the first group of theoretical studies conducted on algorithmic trading and HFTs. Their model analyses the impact of the entry of machine traders on transaction costs faced by human traders in a limit order market, and the authors demonstrate that the introduction of HFTs affects market prices, even in periods without any new information. In terms of profitability, HFTs gain profits by pushing non-HFT orders away from the top of the order book.

Hoffmann (2014) emphasizes the adverse selection channel through which trading speed may influence market quality. The study analyses the role of HFTs in a dynamic limit order market and shows that market makers are more willing to provide liquidity on the condition that they are able to react fast and to avoid being selected adversely. In addition, the study demonstrates that superior speed enables fast traders to extract rents from other market participants and therefore stimulates a costly speed competition that reduces social welfare.

Foucault, Kozhan, and Tham (2017) report that the adverse selection costs become larger as news-traders and arbitrageurs are fast, and therefore market makers are forced to lower their liquidity provision. In contrast to the standard view that competition among market participants increases price efficiency, the authors claim that a crowding effect, generated by HFTs competing with each other to explore an arbitrage opportunity, may push prices away from their fundamental values. Furthermore, Foucault, Kozhan, and Tham (2017) examine high frequency triangular arbitrage opportunities in the real world using data from the FX market and provide evidence to support their theoretical predictions. Based on their empirical sample, a 1% increase in the likelihood that an arbitrage opportunity terminates with an arbitrageur's trade raises bid-ask spreads by about 4%.

Following previous studies on the speed competition between HFTs, Budish, Cramton and Shim (2015) use millisecond-level direct-feed data from exchanges and report that the continuous limit order book market design leads to obvious mechanical arbitrage opportunities at high-frequency time horizons. Furthermore, the authors build a theoretical model to explain the empirical facts and demonstrate that the arbitrage opportunities dampen liquidity supply and cause a continuous speed competition between HFTs. More importantly, they show frequent batch auctions directly correct the weakness of the continuous limit order book through eliminating arbitrage opportunities, enhancing liquidity and preventing an HFT arms race.

Jovanovic and Menkveld (2016) are also in favour of a double auction market design, relative to the current continuous limit order book market design. The authors develop a theoretical model where computerised traders act as middlemen who are informed about machine readable hard information on common values in an electronic limit order market. They show that HFTs reduce welfare if they are the only ones with such information; however, the entry of HFTs could raise welfare if other investors also possess such information. Furthermore, they examine the theoretical impacts of the introduction of a double auction and show that welfare rises even more than with the entry of the HFTs following the introduction of a double auction.

Cartea and Panelva (2012) model a market with HFTs, market makers and liquidity traders. The authors report that liquidity trades induce high price impact when HFTs are present.

Market makers also lose revenue to HFTs but are compensated for these losses by a higher liquidity discount. Furthermore, they show that HFTs increase price volatility but improve trading volume.

Foucault Hombert and Rosu (2016) provide a theoretical dealer-speculator model based on Kyle (1985) and extend it by differentiating degrees of speed of the speculator. Their model involves both private information and news, which is different to existing theoretical literature and allows others to understand HFTs' aggressive orders. Based on this model, the authors find that assuming symmetric information, the speed advantage of HFTs increase adverse selection costs without increasing the price informativeness. Moreover, fast speculators make profits from trading on long-term price changes.

Further research related to adverse selection is that of Biais, Foucault, and Moinas (2015). The study is in line with the seminal analysis of private information acquisition in financial markets by Grossman and Stiglitz (1980). The study shows that on one hand, fast trading technology provides advanced access to new information, which creates adverse selection and lowers welfare; on the other hand, the technology enhances the financial institutions' ability to receive mutual profits from trades and improves social welfare.

The other channel, the inventory cost channel, is explored by Rosu (2016). Similar to Foucault Hombert and Rosu (2016), Rosu (2016) also develops an extended model based on Kyle (1985), which allows inventory management through including an additional trader with inventory costs. The model considers fast and slow traders defined by their information processing speed. The study makes predictions towards the aversion of fast traders to hold inventory. After trading on information, fast traders rapidly transfer part of their inventory to slower traders and thus realize their profits.

In summary, the theoretical literature details that HFTs affect market liquidity through two channels, inventory costs and adverse selection costs, and the net effects of these two costs are determined by the employed trading strategies. When looking at the effects of HFTs on welfare implications, most theoretical models conclude negative consequences to other market participants. In particular, fast traders pose increased adverse selection risk to other market participants and they also increase market volatility, which leads to undesirable outcomes to liquidity suppliers. When looking at the effects of HFTs on market liquidity, most theoretical literature suggests that fast market makers improve liquidity (Foucault, Kozhan, and Tham 2017; Hoffmann, 2014; Sahalia and Saglam 2014). Studies show that the latency advantage of market makers reduces their inventory costs, and therefore increases their incentives to supply liquidity in the market.

2.4.2.2 High Frequency Trading – Empirical Literature

There has been a widespread interest in the literature on understanding the potential impact of HFTs on market dynamics. The empirical literature provides evidence for the theoretical debate over the pros and cons of the development of HFTs. Some have emphasized the possibility of a faster price discovery, an improvement in liquidity and a reduction in volatility; while others have expressed concerns that HFTs may exacerbate volatility, consume liquidity and induce higher adverse selection costs and profit at the expense of non-HFT participants. This section describes the existing literature that empirically examines the development of HFTs and how they affect market quality. In general, positive implications have been suggested for financial markets based on existing literature in regards to the effects of algorithmic trading; however, not all researchers hold the same view.

Brogaard (2010) conducts one of the first empirical studies that investigate the characteristics of HFTs with direct traders' identifications by the exchange. The research documents HFTs' trading strategies, profitability, as well as their impact on market liquidity, price discovery and volatility. Using a unique dataset provided by NASDAQ that directly identifies 26 HFT firms, the study finds that during volatile times, HFTs supply more liquidity and demand less liquidity. Furthermore, there is no evidence showing HFTs increase volatility and they may in fact reduce it. In relation to price discovery, HFTs contribute more to the price discovery process than do non-HFTs from both trading and quoting activity, with quotes contributing more to price discovery than trades.

Using the same dataset, Brogaard, Hendershott and Riordan (2014) focus on the role of HFTs in price discovery and price efficiency. HFTs are found to improve pricing efficiency by trading in the same direction of permanent price changes and in the opposite direction of transitory pricing errors, both on normal and high volatility days. On normal trading days, HFTs demand liquidity towards the direction of public information, such as macroeconomic announcements, overall market price movements and order book imbalances. In other periods, HFTs provide liquidity for high volatility days and for intervals around macroeconomic news releases.

With a primary interest in the relationship between HFTs and market liquidity, Hendershott and Riordan (2013) investigate the role of HFTs in demanding and supplying liquidity in the

30 Deutscher Aktien Index stocks on the Deutsche Boerse. In terms of market and limit order volumes, HFTs represent 52% of total market order volume and 64% of total limit order volume. In addition, HFTs consume liquidity when the bid-ask quotes are narrow and supply liquidity when the spreads are wide. In respect to responses to events (insert, cancel, trade) in the order book, HFTs react faster to events than human traders and even more so when spreads are wide.

Chaboud et al. (2014) is the first empirical HFT study in foreign exchange markets. Using a novel dataset that explicitly identifies the volume and trade direction of human and computer trades, the study analyses how HFTs and human traders affect the price efficiency of new information respectively. It finds that HFTs improve price efficiency through faster price discovery, but it also raises the adverse selection costs faced by human traders, which is consistent with theoretical predictions made by Martinez and Rosu (2013) and Biais, Foucault and Moinas (2015). In addition, the study also provides evidence that the strategies of algorithmic traders are highly correlated.

Viljoen, Westerholm and Zheng (2014) extend previous literature to the Australian index futures market. The authors examine the intraday price impact of HFTs on the SPI 200 futures markets, where HFT is proxied by negative of the dollar trading volume associated with each order-book update. Their results suggest that HFTs are informed and contribute to liquidity and price discovery in the Australian futures market. Their work has laid a solid foundation for future studies that intend to uncover the impact of HFTs on the Australian market. However, the study did not isolate the effect of latency on liquidity and price discovery through an exogenous event that changes the level of trading speed.

Opponents of HFT question the traditional view of liquidity provision by limit orders to the market made by high frequency traders, and also suggest that these fast participants have caused excess volatility in the financial markets. There are in general two sets of market makers: exchange-regulated market makers and undesignated market makers. In contrast to exchange-regulated market makers, undesignated market makers do not have the obligation to provide liquidity, i.e. an obligation to quote on both sides of the market. Therefore, they might withdraw from the market when uncertainties increase and conditions get difficult. With unique access to the audit trail data for the E-mini S&P 500 futures contracts, Kirilenko et al. (2014) are able to identify high frequency traders and then investigate their behaviour on May 6, 2010, the day of the "Flash Crash". They show that HFTs exacerbated the falling market but did not cause the "Flash Crash". The study finds that HFTs initially provided liquidity to fundamental sellers but subsequently contributed to the selling pressure that precipitated the incident.

Co-location events provide the best laboratory to isolate the effect of latency on liquidity and price discovery, and also to identify the causal effect of a change in algorithmic trading on liquidity. Co-location provides a faster speed of trading for co-located institutions and allows them to react faster to changes in market conditions. Co-location also stimulates the growth of HFTs in the market. As more market participants are able to trade fast, the competition for speed become more severe. Consequently, the introduction of co-location is expected to improve liquidity by heightening the level of HFTs and encouraging speed competitions among market participants. Co-location event studies in general suggest that the net effect for market quality is moderately positive.

Riordan and Storkenmaier (2012) isolate the effect of trading speed on liquidity and information processing in a limit order market. The trading system upgrade at Deutsche Boerse in 2007 is used as a natural experiment to test whether a reduction in latency improves liquidity in the stock market. The results show that trading costs are reduced by one to four basis points and liquidity increases following the speed upgrade. In terms of information processing, results show that market prices are more efficient and better reflect public information following the upgrade. Their findings demonstrate the importance of latency in the stock market; however, the role of latency around public information releases in futures markets remains unclear.

On February 20, 2012, the Australian Securities Exchange allowed futures traders to co-locate their servers to the exchange data centre (Frino, Mollica & Webb, 2014). This action has attracted more HFTs in the futures market, proxied by a higher message traffic measure, and improved market liquidity, evidenced by a lower bid-ask spread and a thicker market depth for interest rate futures contracts.

To determine the causality between the growth of HFTs and the improvements in liquidity in the U.S. stock market, Hendershott, Jones and Menkveld (2011) introduce an exogenous variable, the introduction of 'autoquote', as an instrument. The study shows that HFTs improve liquidity for stocks with a large market capitalization. The size of quoted and effective spreads becomes smaller following the autoquote event, as a result of the heightened level of HFTs. Furthermore, HFTs stimulate the price discovery of quotes, and as a result, quotes become more informative than trades.

As theoretical literature has documented, the speed of trading may affect liquidity through inventory management or adverse selection. Brogaard, et al. (2015) seek to find empirical evidence to support the view. The study examines the impact of trading speed on market liquidity by exploiting an optional co-location upgrade at NASDAQ OMX Stockholm. In September 2012, NASDAQ OMX provided an optional service that allowed market participants to upgrade their existing co-location server for a faster trading speed with an additional fee. The speed advantage of market makers reduces the cost of holding inventory. Consequently, market makers are more motivated to provide liquidity. The empirical results suggest that market liquidity is improved when market makers become faster, which is consistent with existing theoretical models.

With a special focus on whether HFTs increase the execution costs of institutional investors, Brogaard el al. (2014) use technology upgrades that lower the latency of the London Stock Exchange as an instrument variable to examine the variations in the level of HFTs and the impacts of HFTs on institutional execution costs. The study shows that HFT activity increases following improvements in exchange trading speed; however, no relationship is found between a heightened level of HFT activity and higher institutional execution costs.

Boehmer, Fong, and Wu (2014) add to the empirical findings on the impacts of speed upgrades on market quality, using data from 39 equity exchanges. However, their findings are mixed. In this international study, the authors employ the introduction of the co-location service as an instrumental variable to identity the causality between greater intensity of HFTs and improved liquidity. Consistent with other empirical work on the introduction of co-location facilities, they find that a greater presence of HFTs improves liquidity and informational efficiency. In contrast to previous empirical literature, they show that the heightened level of HFTs increases volatility, especially for small stocks.

In summary, existing empirical literature finds mixed results on the impact of HFTs. On one hand, HFTs contribute to more efficient price discovery, and improve market liquidity. On the other hand, they may exacerbate volatility and induce higher adverse selection costs for other market participants. This dissertation contributes to the literature on the causality between a latency reduction and an improvement in liquidity in the futures market. The speedup of a few milliseconds, resulting from co-location, may produce critical values to algorithms, but may not be useful to slower human traders. Therefore, the introduction of co-location provides the best laboratory to isolate the effect of latency on liquidity, and also to identify the causal effect of a change in algorithmic trading on liquidity around public information arrivals.

2.4.3 High Frequency Trading and Information Announcements

As documented in the previous section, the speed of trading has increased substantially in the recent decade, due to the group of high frequency traders who seek to enhance speed by investing in technology upgrades and co-locating their trading servers next to stock exchanges. HFTs may be able to make profits from their speed advantage through rapidly responding to scheduled news releases. The market reaction time to new information may be significantly shortened for HFTs as a result of their advantage in consistency and speed.

Jiang, Lo and Valente (2015) focus on fixed income markets and examine HFTs in the U.S. treasury market around major macroeconomic announcements. The authors show that HFT activity substantially increases following news releases and generally improves price efficiency. HFTs harm market liquidity by widening bid-ask spreads before news releases and weakening market depth following the releases.

Chaboud et al. (2014) study the impact of HFTs in the foreign exchange market around macroeconomic news releases. The study finds that HFTs improve the price discovery process through rapidly incorporating new information into prices and eliminating arbitrage opportunities in the market place. Although computer trades tend to be correlated, the study finds no evidence that HFTs lead to excessive volatility in the foreign exchange market.

After confirming the role of HFTs in enhancing price efficiency and shortening response time following public information releases, Chordia, Green and Kottimukkalur (2016) extend previous work by examining whether HFTs are able to profit in the U.S. stock index ETF and the E-mini futures markets from two-second early access to macroeconomic releases with their advantageous trading speed. They find that HFTs do not earn excess profits from acquiring early access to the consumer sentiment data.

Scholtus, Dijk and Frijns (2014) also examine the market responsiveness to the U.S. macroeconomic releases in the S&P 500 ETF. Unlike previous studies, focus of this work is to determine whether speed is crucial for news based trading strategies. The authors find that the profitability of news based strategies is significantly reduced following a 300 milliseconds delay. And the impact of speed is more evident for days with high volatility or influential news. Positively, HFTs increase quoted depth at the best level and push up trading volume in the minute immediately after the announcement time. Negatively, HFTs deteriorate volatility and reduce the amount of the overall market depth. Furthermore, HTFs reduce quoted half-spreads throughout the order book, and increases quoted half-spreads at the top of the order book.

Using a unique dataset that identifies whether the liquidity suppliers and demanders are HFTs or not, Brogaard, Hendershott and Riordan (2014) investigate the impact of HFTs on price efficiency. The study reports that HFTs' supply liquidity more than the amount they demand for the time intervals immediately following macro releases, and therefore HFTs do not impose net adverse selection cost on other market participants for announcement periods.

A group of studies extend previous literature by investigating the impact of HFTs on the market responses to earnings announcements in the stock market for the U.S. and Australia. Zhang (2013) examines the role of HFTs in reacting to extreme price changes as well as to firm-specific news in the U.S. stock market. He examines whether HFT order flows impact the stock market returns more significantly relative to non-HFT order flows. The results show that HFTs dominate the price discovery for the short time horizon. However, in the longer run, non-HFTs contribute to more price discovery than HFTs.

Another public concern emerges from the argument that a financial market is unfair and favours those with access to advanced speed. Frino et al. (2016) shows algorithmic traders react much faster and more accurately to earnings announcements than non-algorithmic traders using Australian equity market data. Specifically, non-algorithmic volume imbalance leads algorithmic volume imbalance in the pre-announcement period and the lead-lag relation is reversed in the post-announcement period.

Academic studies further extend the price discovery literature to analyse the informativeness of order flows by using a state-space approach. New evidence suggests that HFT plays an important role in the price discovery process in a more general form. Brogaard et al. (2014) deconstruct the price movements of 120 U.S. stocks into permanent (information) and temporary (pricing errors) components and investigate the role of HFT in explaining each type of price change. They find that HFT's trading volume enhances price discovery by trading in the same direction of permanent price changes and in the opposing direction of transitory price changes, for both volatile and non-volatile periods.

Benos and Sagade (2013) provide evidence of the impact of HFTs on market quality, in particular price discovery measures for the U.K. stock market. They analyse the behaviour of HFTs and their impact on four U.K. stocks in a randomly selected one-week period, and find that elevated price volatility leads to increased HFT activity. Furthermore, the authors demonstrate that in general HFTs have a higher information-to-noise ratio than non-HFTs, with some instances where the contribution to information by HFTs is accompanied by a large absolute noise.

In summary, existing literature suggests that high frequency traders employ co-location upgrades to reduce latency and respond more rapidly to information releases (Jiang, Lo & Valente, 2015; Chaboud et al., 2014; Chordia, Green & Kottimukkalur, 2016; Brogaard, Hendershott & Riordan, 2014; Frino et al., 2016). The improvement in latency enables algorithmic traders to adjust their prices more rapidly when new information arrives and therefore improves price discovery efficiency. As futures markets have different participants, speeds of trading, market structures and trading rules relative to equity markets, it is important to assess how HFTs affect liquidity, under different latency environments, around new information releases for futures markets.

2.5 Hypotheses Development

The literature review presented in the previous section identified a number of gaps in the current literature. In this section, a set of testable hypotheses are developed, and tests of these are reported in the following chapters. The hypotheses developed in this section relate to the impact of market conditions, liquidity in international markets and HFTs on the price effects associated with trades, which forms a theme to the dissertation.

2.5.1 Asymmetry in the Permanent Price Impact of Block Purchases and Sales: Theoretical and Empirical Evidence

A large body of research has examined the impact of block trades in equities markets, derivative markets and fixed-income markets. Section 2.2.1 identifies three hypotheses in the literature that predict the price effects associated with block trades: (1) short-run liquidity costs, (2) information asymmetry, and (3) imperfect substitution (Demsetz, 1968; Amihud & Mendelson, 1980; Glosten & Milgrom, 1985; Easley & O'Hara, 1987; Scholes, 1972; Shleifer, 1986; Biais, Hillion & Spatt, 1995; Levin & Wright, 2002), and also provides empirical evidence measured by temporary, permanent and total price impacts respectively, for the U.S. markets (Kraus & Stoll, 1972; Holthausen, Leftwich & Mayers, 1987, 1990; Dann, Mayers & Raab, 1977; Kumar, Sarin & Shastri, 1992; Koski & Michaely, 2000) and other international markets (Ball & Finn, 1989; Aitken, Frino & Sayers, 1994; Gemmill, 1996). Section 2.2.2 further identifies an asymmetric relationship between the price impacts of block purchases and sales using institutional transaction data (Chan & Lakonishok, 1993, 1997; Keim & Madhavan, 1995, 1997; Saar 2001; Bozcuk & Lasfer, 2005; Chiyachantana et al., 2004). Section 2.2.3 identifies that bull and bear market settings have isolated a number of asymmetric responses in the microstructure literature (Chiyachantana et al., 2004; Chiang, Lin & Yu, 2009; Pradkhan, 2015). Most previous studies were conducted using data primarily from bullish markets; however, studying the intricacies of transaction costs in a bearish market is also valuable as cost-cutting measures are particularly important in down markets. Chiyachantana et al. (2004) is one of the few studies that investigate block transaction costs across different market sentiments, with a pure focus on the total price impact of block trades. Chapter 3 extends their work by providing theoretical and empirical evidence on the permanent price impact of block trades, across different market conditions.

The hypothesis (H3) examined in this analysis is that the permanent price impact of block trades is asymmetric between purchases and sales transacted on the E-Mini index futures and the EFT shares. The asymmetric relationship varies across different market sentiments. Specifically, the hypothesis contains two parts that are related to bull and bear markets respectively:

> $H_{3,1}$*: The permanent price impacts associated with block sales are larger than those associated with block purchases in a bull market period.*

> $H_{3,2}$*: The permanent price impacts associated with block purchases are larger than those associated with block sales in a bear market period.*

2.5.2 Commonality in Liquidity across International Borders: Evidence from Futures Markets

Commonality in liquidity refers to the liquidity of individual securities co-moving with market-wide liquidity. Sections 2.3 in Chapter 2 identifies evidence of liquidity commonality in the U.S. stock market (Chordia, Roll & Subrahmanyam, 2000), the FX market (Mancini, Ranaldo & Wrampelmeyer, 2013) and non-U.S. exchanges (Brockman & Chung, 2002; Fabre & Frino, 2004). After confirming the pervasive role of commonality within individual exchanges, Brockman, Chung, and Perignon (2009) extend previous literature by examining commonality in liquidity across exchanges and discover a distinct and significant global component in an individual firm's total liquidity commonality. Section 2.3 identifies a gap in the literature in global commonality in liquidity for index futures markets. Index derivatives have substantially higher trading values compared to their underlying cash markets (Schoenfeld, 2004). With faster responses to new information, the index future's price tends to lead its underlying indexes (Frino & West, 2003), which highlights the importance of stock index futures as a useful price discovery vehicle. Given the importance of index futures markets and their different trading behaviour and liquidity features relative to the underlying stock markets, it is crucial for researchers and policy makers to understand the liquidity of index futures markets, more importantly, the commonality in liquidity across index futures markets. Chapter 4 extends previous studies by examining global commonality in liquidity across nine stock index futures markets for a 10-year period.

The first hypothesis ($H4_1$) tests whether global commonality in liquidity exists for index futures markets, i.e. whether the liquidity in an individual market co-moves with the global wide liquidity. Liquidity is measured by quoted bid-ask spreads, relative spreads, effective spreads and market depth.

$H_{4,1}$: The movements of liquidity in an individual index future's market are correlated with the movements of liquidity in the global index futures market

Similarly, the second hypothesis ($H4_2$) tests whether regional liquidity commonality prevails within each GMT time zone for index futures markets. All international markets are divided into three different regions based on the associated GMT time zone. Markets located in the same or similar GMT time zones are grouped into one geographical region and the hypothesis is tested for each region over a 10-year period:

$H_{4,2}$: The movements of liquidity in an individual index future's market are correlated with the movements of liquidity in the regional index futures market

2.5.3 The Impact of High Frequency Trading on Market Liquidity around Macroeconomic Announcements: Evidence from Australian Futures Market

Section 2.4.1 identifies that announcement periods represent a very different informational environment relative to normal times. The intraday patterns appear to be largely driven by macro announcements across major financial markets, such as interest rate futures markets, index futures markets, treasury markets, commodity futures markets and foreign exchange markets (Ederington & Lee, 1993, 1995; Frino & Hill, 2001; Cai, Cheung & Wong, 2001; Andersen & Bollerslev, 1998). Given the importance of macro news and the widespread use of news embargoes, understanding the consequences of these releases is important to ensure market integrity.

Over the last decade, financial markets have been transformed due to the introduction and development of HFT. Section 2.4.2 identifies there is a debate in the extant literature over the pros and cons of the development of HFT. Some researchers have highlighted the potential for more efficient price discovery and improvement in liquidity (Brogaard, 2010; Brogaard, Hendershott & Riordan, 2014; Riordan & Storkenmaier, 2012; Frino, Mollica & Webb, 2014; Brogaard et al., 2015; Hendershott, Jones & Menkveld, 2011); others have expressed concerns that it may exacerbate volatility, consume liquidity and induce higher adverse selection costs and profit at the expense of non-HFT participants (Boehmer, Fong & Wu, 2014; Kirilenko et al., 2014; Chaboud et al., 2014; Rosu, 2016; Cartea & Panelva, 2012). Therefore, it is crucial for researchers and policy makers to understand the behaviour of high frequency traders in futures markets, especially how they impact market quality around macro news releases.

Co-location is an important technology upgrade for high frequency traders since it significantly reduces latency and allows traders to response more rapidly to information releases (Jiang, Lo & Valente, 2015; Chaboud et al., 2014; Chordia, Green & Kottimukkalur, 2016; Brogaard, Hendershott & Riordan, 2014; Frino et al., 2016). As documented in Section 2.4.3, there is still a gap in the literature on the impact of co-location on HFT around macroeconomic announcements in the futures market. Chapter 5 intends to fill this gap by examining how HFT behaves around public information releases under different levels of latency.

The first hypothesis ($H5_1$) tests whether the introduction of co-location at ASX leads to an increase in HFT surrounding macro news releases.

$H_{5,1}$: The introduction of co-location leads to an increase in high frequency trading activity in futures markets around macro news releases.

The reduced latency associated with co-location service would provide critical new information to algorithms, but would be unlikely to directly affect the trading behaviour of slower human traders. Chapter 5 uses the introduction of co-location as an exogenous event to isolate the effect of latency on liquidity, and also to identify the causal effect of a change in HFT on liquidity. These two important issues have not been resolved in the existing literature, and Chapter 5 aims to uncover these issues. The second hypothesis of Chapter 5 is as follows:

$H_{5,2}$: The heightened level of high frequency trading leads to improved liquidity in futures markets around macro news releases.

2.6 Summary

This chapter reviews related literature and develops a number of hypotheses. Tests of these hypotheses are presented in the following chapters. Chapter 3 examines the impact of market conditions on the price effects associated with block trades for E-mini S&P 500 index futures and SPDR S&P 500 ETF. Chapter 4 tests the impact of liquidity in the global index futures market on the price effects associated with trades transacted in the local share price index futures market. Chapter 5 investigates the impact of HFTs on the price effects associated with trades in the Australian futures market around scheduled macroeconomic announcements.

CHAPTER 3. Asymmetry in the Permanent Price Impact of Block Purchases and Sales: Theoretical and Empirical Evidence

3.1 Introduction

The first examination in this dissertation develops and tests a model of the price effects of block trades in derivatives markets conditioned on market sentiments, using the E-mini S&P 500 share price index future and SPDR S&P 500 exchange traded fund (ETF). The findings of the existing literature discussed in Section 2.2 identify an asymmetric relationship between the price effect of block purchases and sales (Chan & Lakonishok, 1993, 1997; Keim & Madhavan, 1995, 1997; Saar, 2001; Bozcuk & Lasfer, 2005; Chiyachantana et al., 2004) and that bull and bear market settings may explain a number of asymmetric responses in the microstructure literature (Chiyachantana et al., 2004; Chiang, Lin & Yu, 2009; Pradkhan, 2015). This chapter addresses this lacuna in the literature specifically focusing on the permanent price effects of trades, a proxy for information content.

The remainder of this chapter is structured as follows. Section 3.2 details a sequential trading model that allows traders to transact in block (large) or small quantities with no short-selling constraints. In Section 3.3, theoretical propositions are derived for the asymmetric price impact between block sales and block buys in bear and bull markets. Sections 3.4 and 3.5 describe the data on the E-mini S&P 500 index futures contracts and the SPDR EFT shares and the research design adopted to test the hypothesis H_3. Section 3.6 demonstrates the first empirical evidence of the permanent price effects of block purchases and sales under bull and bear markets. Section 3.7 concludes the chapter.

3.2 Model

3.2.1 The Market

The model employed is a standard sequential trading model similar to Easley and O'Hara's (1987), simplified for no event uncertainty. The market is for a single risky asset that has a liquidation value $\tilde{V}$ that can be low ($\tilde{V} = \underline{V} = 0$) or high ($\tilde{V} = \overline{V} = 1$). π_0 denotes the ex-ante probability of $\tilde{V} = \overline{V}$, and assume that it is non-degenerate, that is, $\pi_0 \in (0, 1)$. The asset is exchanged among a sequence of risk neutral traders and risk neutral competitive market makers who are responsible for quoting prices.

Trades occur sequentially in discrete time, and at any point in time only one trader is allowed to transact. A trader arriving in the market may buy or sell either a small quantity, Q_S , or a large quantity, Q_L. SQ_i and BQ_idenote a sell and a buy order respectively, for quantity Q_i, with $i = S, L$.

A fraction μ of traders are informed traders, while a fraction $1 -$ μ are liquidity traders.[5]

Informed traders are price-taking agents who privately observe a signal $\theta \in \{\underline{\theta}, \overline{\theta}\}$ perfectly correlated with the final asset value.[6] They trade to maximize their expected profit.

Liquidity traders transact for reasons exogenous to the model. To simplify the analysis, it is assumed that they choose any action with equal probability and denote the likelihood that a liquidity trader submits a given order as $\gamma = (1 - \mu)/4$.

[5] Liquidity traders are needed to guarantee that trading occurs. In the absence of traders who transact for reasons other than speculation, the no-trade theorem of Milgrom and Stokey (1982) applies and the market breaks down.
[6] All results remain true even if private signals are imperfect.

Both market makers and traders are Bayesian agents who understand the market structure. π_t denotes the public belief—the probability that the market makers attach to $\overline{V}$ at time *t*, $E_t[\tilde{V}]$ denotes the market makers' expectation, and $E[\tilde{V}|\ \theta]$ denotes the expectation of an informed trader observing signal θ. Since $\underline{V}$= 0 and $\overline{V}$= 1, $E_t[\tilde{V}] = \pi_t$. Since private signals are perfect, $E[\tilde{V}|\ \theta]$ is equal to 1 if $\theta = \overline{\theta}$ and to 0 in the other case.

The market is defined as flat when low and high liquidation asset values are equally likely, that is, $\pi_t = 1/2$, as bearish when the low is more likely than the high asset value $\pi_t < 1/2$, and as bullish when the high is more likely than the low asset value $\pi_t > 1/2$.

3.2.2 Equilibrium Prices and Strategies

Before each trading round *t*, market makers simultaneously announce their price-quantity quotes. After prices are set, a trader observes the price schedule and executes his strategy at the best price. If he is informed, he submits a quantity and order that maximizes his expected profit. If he is a liquidity trader, he acts in the probabilistic way specified above.

Bertrand competition restricts the market makers to earn zero expected profit. This condition requires a price for any quantity equal to the market maker's expectation of $\tilde{V}$, given a transaction of that quantity; the conditional expectation depends on the informed traders' strategy.

$B_{L,t}$ and $A_{L,t}$ denote the competitive bid and ask prices for large orders at time t, respectively, and $B_{S,t}$ and $A_{S,t}$ the competitive bid and ask prices for small orders, respectively. The trader arriving at t faces price-quantity quotes that satisfy:

$$B_{i,t} = E_t[\tilde{V}|SQ_i] = \frac{\Pr(SQ_i|\overline{V})\pi}{\Pr(SQ_i|\overline{V})\pi+\Pr(SQ_i|\underline{V})(1-\pi)},$$
$$A_{i,t} = E_t[\tilde{V}|BQ_i] = \frac{\Pr(BQ_i|\overline{V})\pi}{\Pr(BQ_i|\overline{V})\pi+\Pr(BQ_i|\underline{V})(1-\pi)},$$

for all $i \in \{S, L\}$.

Since market makers are imperfectly informed about the liquidation asset value, competitive prices are always between 0 and 1. If the true asset value is high, informed traders receive the good signal and buy. On the other hand, if the true asset value is low, informed traders receive the bad signal and sell. Since private signals are perfect, the probability of an informed buyer conditional on a low asset value, and the probability of an informed seller conditional on a high asset value are both zero. This implies that $\Pr\left(BQ_i|\underline{V}\right) = \Pr\left(SQ_i|\overline{V}\right) = \gamma$ for both small and large orders.

Based on Easley and O'Hara (1987), only two forms of equilibria can occur. If informed traders prefer to trade only a large quantity, they are separated from small liquidity traders and a separating equilibrium exists. If informed traders submit either small or large orders with strictly positive probability, a pooling equilibrium occurs.

This chapter first examines the market in a separating equilibrium. In this market, the competitive price schedule, $P^{se} = \{B_L^{se}, B_S^{se}, A_S^{se}, A_L^{se}\}$, is such that informed traders place only large orders. Thus, small trades are not information-based and do not affect the public belief about the true asset value, while the information content of large trades is very strong.

This implies that the competitive price for small orders is $B_S^{se} = A_S^{se} = E[\tilde{V}] = \pi$ and the competitive prices for large orders is:

$$B_L^{se} = \frac{\gamma\pi}{\gamma\pi + (\gamma+\mu)(1-\pi)} = \frac{\gamma\pi}{\gamma + \mu(1-\pi)},$$
$$A_L^{se} = \frac{(\gamma+\mu)\pi}{(\gamma+\mu)\pi + \gamma(1-\pi)} = \frac{(\gamma+\mu)\pi}{\mu\pi + \gamma},$$

where $(\gamma+\mu)$ and γ are probabilities of a large sell order conditional on $\tilde{V} = \underline{V}$ and $\tilde{V} = \overline{V}$, respectively, and the probabilities of a large buy order conditional on $\tilde{V} = \overline{V}$ and $\tilde{V} = \underline{V}$, respectively.[7] The price schedule P^{se} determines the separating equilibrium only if, informed traders prefer to trade in large quantities. This occurs when the gain from the larger quantity outweighs the price available for small trades, that is when

$$\Pi_{\theta,L}^{se}(\pi)Q_L \geq \Pi_{\theta,S}(\pi)Q_S, \tag{3.1}$$

where $\Pi_{\underline{\theta},L}^{se}(\pi) = B_L^{se}$ and $\Pi_{\overline{\theta},L}^{se}(\pi) = 1 - A_L^{se}$ are the separating marginal profits of an informed trader when the asset value is low and high, respectively, and $\Pi_{\underline{\theta},L} = E[\tilde{V}]$ and $\Pi_{\overline{\theta},L} = 1 - E[\tilde{V}]$ represent the deviation marginal profits, that is, the marginal profits of an informed trader who deviates from the "separating" strategy when the asset value is low and high, respectively.[8] Rearranging terms and substituting the price schedule P^{se}, Condition (3.1) becomes

$$\frac{Q_L}{Q_S} \geq \frac{\pi}{B_L^{se}} = 1 + f_{\underline{\theta}}(\pi), \tag{3.2}$$

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[7] To simplify notation hereafter the t subscript will be omitted.

[8] Recall that $E[\widetilde{V|\underline{\theta}}]$=0 and $E[\widetilde{V|\overline{\theta}}]$=1.

with $f_{\underline{\theta}}(\pi) = (1-\pi)\mu/\gamma$, for the bid side of the market, and

$$\frac{Q_L}{Q_S} \geq \frac{1-\pi}{1-A_L^{se}} = 1 + f_{\overline{\theta}}(\pi), \tag{3.3}$$

with $f_{\overline{\theta}}(\pi) = \pi\mu/\gamma$, for the ask side of the market. The left side of Conditions (3.2) and (3.3) represents the market width. For the separating equilibrium to exist, it has to be larger than the ratio between the deviation and separating marginal profits on each side of the market.

Conditions (3.2) and (3.3) highlight firstly, that the ratio between deviation and separating marginal profits of an informed seller reduces when public belief increases and, then, on the bid side the separating equilibrium is more likely to exist in bull markets rather than bear markets ($f_{\underline{\theta}}(\pi)$ is decreasing in π), and secondly, that the ratio between deviation and separating marginal profits of an informed buyer reduces when public belief decreases and, then, on the ask side it is more likely to exist in bear markets rather than in bull markets ($f_{\overline{\theta}}(\pi)$ is increasing in π). Intuitively, consider the ask side of the market; the difference between the profit from buying large and small quantity can be written as

$$(1 - A_L^{se})(Q_L - Q_S) - (A_L^{se} - \pi)Q_S. \tag{3.4}$$

The first term represents the separating profit due to the larger quantity purchase and the second term is the loss due to the higher price paid to purchase the first Q_S units of the asset. An informed trader observing a good signal buys large with probability 1 if this difference is positive. When market makers attach a very low probability to $\tilde{V} = \overline{V}$ (i.e., π is near to 0), the gain due to the larger quantity of asset bought is high, whilst the loss due to the higher price paid to purchase the first Q_S units of the asset tends to zero, since both ask price and public belief are near to $\underline{V}$. Therefore, the difference in expression (4) is positive and the separating equilibrium exists. An increase in the public belief affects the difference in expression (4) in two ways. First, the greater the probability that market makers attach to $\tilde{V} = \overline{V}$, the smaller is the profit due to purchasing the larger quantity. This inverse relationship of a separating gain to public belief arises because the expected asset value of an informed buyer is always equal to 1, and the larger the public belief, the nearer to 1 is the market makers' expectation. Second, the public belief also affects the loss due to the higher price paid to purchase the first Q_S units of the asset. This influence is inversely U-shaped. Indeed, when π is 0 or 1 the ask price and public belief are equal; whilst their distance grows as the uncertainty in the market increases (i.e., π moves toward 1/2). Therefore, starting from 0, an increase in public belief reduces the incentive to buy large since the profit due to a larger quantity purchase decreases, and the loss due to the higher price paid to buy the first Q_S units of the asset increases. However, if public belief grows enough, the impact on the separating loss becomes negative, and may offset the negative effect on the separating gain of a larger π. Thus, if the market is wide enough, then a separating equilibrium on the ask side exists both in a bear and bull market. But, if the market is narrow, then a buying separating equilibrium exists only in a bear market.

If Conditions (3.2) and (3.3) are not satisfied on either side of the market, then there can be no separating equilibrium, and a pooling equilibrium will exist. In a pooling equilibrium there is a positive probability of informed trading in both large and small quantities. Denote $\sigma_{\underline{\theta}} = \{\sigma_{\underline{\theta},S}; \sigma_{\underline{\theta},L}\}$, defined on the simplex $\Delta(SQ_S, SQ_L)$, the mixed strategy of an informed trader observing the bad signal, and $\sigma_{\overline{\theta}} = \{\sigma_{\overline{\theta},S}; \sigma_{\overline{\theta},L}\}$, defined on the simplex $\Delta(BQ_S, BQ_L)$, the mixed strategy of an informed trader observing the good signal.

For any $\sigma_{\underline{\theta}}$ and $\sigma_{\overline{\theta}}$, the competitive prices are given by:

$$B_i^{pe} = \frac{\gamma\pi}{\gamma+\mu\sigma_{\underline{\theta},i}(1-\pi)},$$
$$A_i^{pe} = \frac{(\gamma+\mu\sigma_{\overline{\theta},i})\pi}{\mu\sigma_{\overline{\theta},i}\pi+\gamma},$$

for all $i \in \{S, L\}$. For the competitive price schedule $P^{pe} = \{B_L^{pe}, B_S^{pe}, A_S^{pe}, A_L^{pe}\}$ to exist, informed traders must be indifferent between trading the large and the small quantity. This condition requires:

$$\left(B_L^{pe} - E\left[\tilde{V}|\underline{\theta}\right]\right)Q_L = \left(B_S^{pe} - E\left[\tilde{V}|\underline{\theta}\right]\right)Q_s, \tag{3.5}$$

$$\left(E\left[\tilde{V}|\overline{\theta}\right] - A_L^{pe}\right)Q_L = \left(E\left[\tilde{V}|\overline{\theta}\right] - A_S^{pe}\right)Q_s. \tag{3.6}$$

It is easy to see that Conditions (3.5) and (3.6) can be satisfied only if the price schedule is such that $B_L^{pe} \leq B_S^{pe}$ and $A_L^{pe} \geq A_S^{pe}$. This, in turn, implies that informed traders are more likely to place a large than a small order.

The pooling equilibrium exists only if the better price available for a small trade outweighs the advantage of trading a large quantity. It is known that private signals are more valuable when they indicate opposing asset values with respect to the public belief. More precisely, if the final asset value is low, the distance between deviation and separating profits of informed traders (sellers) is larger when public belief (and, then, the bid price) is higher, whilst if the final asset value is high, the distance between deviation and separating profits of informed traders (buyers) is larger when public belief (and, then, the ask price) is lower. As a consequence, informed sellers are more prone to separate themselves from small liquidity traders in bullish markets and the probability of a large information-based sell, $\sigma_{\underline{\theta},L}$, is increasing in π, whilst informed buyers are more prone to separate themselves from small liquidity traders in bearish markets and the probability of a large information-based buy, $\sigma_{\overline{\theta},L}$, is decreasing in π.

Another aspect that should be noted is the condition for a pooling equilibrium is the reverse of any necessary condition for the separating equilibrium, and there is always a separating or a pooling equilibrium on each side of the market.

3.2.3 Price Impact of Large Orders

In this study's model, the price impact of a trade is the change in public belief about the asset liquidation value due to a trade. Since informed traders never sell when observing a good signal and never buy when observing a bad signal, the price impact of a sell is always negative and the price impact of a buy is always positive. The magnitude of price impact depends both on the information content of a trade and the weight market makers attach to this information.

The information content of a trade is related to its likelihood ratio, given by the ratio between the probability of trade condition $\tilde{V} = \underline{V}$ and the probability of trade condition $\tilde{V} = \overline{V}$. If a trade is totally uninformative about the true asset value, then its likelihood ratio is equal to 1. The more informative a trade is, the more its likelihood ratio differs from 1. Specifically, the more informative a sale is, the more its likelihood ratio is higher than 1 and the more informative a buy is, the more its likelihood ratio is lower than 1. Consequently, the information content of a sell is defined as its likelihood ratio, and the information content of a buy is defined as the reciprocal of its likelihood ratio.

The weight attached by the market maker to the information content of a trade is related to uncertainty in the asset's fundamental value. When the market is characterized by high uncertainty regarding the true asset value (that is, when π is sufficiently far from 0 and 1), then the market maker attaches a high weight to the information content of a trade. But, when public belief converges to the low or to the high asset value, then the weight is lower.

Given the unconditional public belief π, the price impact measure of a large sell is

$$\Delta S(\pi) \equiv |B_L - \pi| = \frac{\pi(1-\pi)(\lambda_S(\pi)-1)}{\pi+(1-\pi)\lambda_S(\pi)},$$

where $\lambda_S(\pi) \equiv \Pr(SQ_L|\pi,\underline{V})/\Pr(SQ_L|\pi,\overline{V})$ is the information content of a sale, conditional on public belief, and the price impact measure of a large buy is

$$\Delta B(\pi) \equiv |A_L - \pi| = \frac{\pi(1-\pi)(\lambda_B(\pi)-1)}{\pi\lambda_B(\pi)+(1-\pi)},$$

where $\lambda_B(\pi) \equiv \Pr(BQ_L|\pi,\overline{V})/\Pr(B|\pi,\underline{V})$ is the information content of a purchase, conditional on public belief. Notice that, on both sides of the market, the price impact of a large trade is increasing on its information content, and that both $\Delta S(\pi)$ and $\Delta B(\pi)$ are zero when π is equal to 0 or 1.

Let the price impact asymmetry between large trades can be defined as

$$J(\pi) \equiv \Delta B(\pi) - \Delta S(\pi).$$

$J_i(\pi)$ is larger than, equal to, or lower than 0 if and only if the price impact of a large buy is, respectively, larger than, equal to, or lower than the price impact of a large sell.

Proposition 1a. *In a bull market the price impact of a large sell order is larger than the price impact of a large buy order.*

Proposition 1b. *In a bear market the price impact of a large buy order is larger than the price impact of a large sell order.*

The rationale for Proposition 1a and 1b is that equilibrium bid and ask prices for large trades can be viewed as the weighted average between public belief and asset assessment of informed sellers or buyers. In a bull market, public belief is closer to the asset assessment of informed buyers than to the asset assessment of informed sellers, whilst the opposite is true in a bear market. As a consequence, ceteris paribus, in a bull market the price impact of a large buy (i.e., the distance between the ask price and the public belief) is lower vis-à-vis a large sell (i.e., the distance between the public belief and the bid price), whilst in a bear market the price impact of a large buy is larger.[9] This issue is amplified by the fact that in a bull market the information content of large buys cannot exceed that of large sells, and in a bear market the information content of large sells cannot exceed that of large buys. Indeed, the profit for traders observing a signal contrary to the price path— (a good signal in a bear market or a bad signal in a bull market) is larger and encourages them to be more aggressive, and trade the large quantity with higher probability.

[9] In a companion paper, Frino et al. (2013) examine the impact of transaction costs on the trading strategy of informed institutional investors. They show that this asymmetry disappears during strong bearish or bullish phases, when information-based orders stop because the informational advantage of institutional investors becomes too small with respect to transaction costs.

3.3 Institutional Detail

The S&P 500 E-mini futures contract was introduced by Chicago Mercantile Exchange in September 1997. The contract is traded on the CME GLOBEX platform where a limit order book is employed. Limit orders submitted to the electronic platform are prioritized by their price and then by time. In GLOBEX, the best five levels of the order book are publicly available to all market participants. In the case that a market order is partially filled in GLOBEX, it then becomes a limit order at the submitted price. The trading hours of E-mini futures are almost 24 hours a day and five days a week with a short break every day between 3:15pm and 3:30pm and then between 4:15pm and 5:00pm for technical maintenance. The weekly trading starts from 5pm (CST) on Sunday and ends at 3:15pm on Friday. Each E-mini contract has a notional value of USD$50 times the index points of S&P 500, with the minimum tick size being 0.25 index points or USD$12.50. At any given time, there are a number of E-mini contracts trading simultaneously with different expiration dates. E-mini futures use quarterly expirations—March, June, September, and December. For each quarterly contract, the last trading day is the third Friday of the expiry month. On any given day, this dissertation selects the future contract with the highest trading volume to establish a time-series. The E-mini futures contract charges an initial margin for hedging and speculation at the rate of $4,500 and $5,625 respectively, and a maintenance margin at the rate of $4,500 for both hedging and speculation.

Exchange Traded Fund (ETF) was first introduced by the American Stock Exchange (AMEX)[10] in 1993. The primary purpose of an ETF is to allow investors to track the performance of a particular index. The trading of SPDR ETF started with AMEX in January

[10] American Stock Exchange (AMEX) was acquired by NYSE Euronext on October 1, 2008, and renamed as the NYSE Alternext U.S. In March 2009, it was renamed again to NYSE Amex Equities. On May 10, 2012, NYSE Amex Equities changed its name to NYSE MKT LLC.

1993. SPDR ETF is designed to track the S&P 500 index and is traded at 1/10 of the S&P 500 index. The SPDR ETF represents ownership of shares in State Street, the trust that manages the ETF, rather than ownership of the S&P 500 index. Market participants invest in the SPDR ETF for different purposes, such as acquiring an exposure to the U.S. equity markets, transacting the S&P 500 index with a single security, and diversifying existing portfolios.

3.4 Data

This chapter uses trades and quotes data for the E-mini S&P 500 futures contract and SPDR ETF over a two-year sample period extending from 1 February 2014 to 31 January 2016, sourced from the Thomson Reuters Tick History (TRTH) database. The data is sampled between 9.30 am and 4.00 pm (N.Y. Time), during which time both instruments are traded. In order to identify bull and bear market periods, two methods have been applied. The first method compares cumulative returns in the S&P 500 index over a 60-trading-day rolling window. A bull market is defined as the period with the largest cumulative return, and a bear market is defined as the period with the smallest cumulative return. In the event of a tie, the period with the highest proportion of positive/negative return days is selected as the bull/bear market. The identified bull market period extends from 10 October 2014 to 08 January 2015, and the selected bear market period extends from 23 October 2015 to 20 January 2016.

The second method, considers market sentiment by categorizing macro-economic news releases, sourced from Bloomberg, into good or bad news days. Only macro-economic releases that have a major impact on the financial market are considered in this analysis. Following Chordia, Green & Kaottimukkalur (2015) and Balduzzi, Elan & Green (2001), the pre-announcement returns, measured as the percentage mid-quote change from five-minutes before an announcement to the release time, are compared with the post-announcement returns, measured as the percentage mid-quote change from the release time to five-minutes after an announcement. A major announcement is defined as one where the post-announcement return is two times the magnitude of the pre-announcement return. The selected major announcements in this dissertation are consistent with those identified in Chordia et al. (2015).

To account for the large number of macro-economic announcements released at 8.30 am, the sample period is extended one-hour and five minutes earlier to identify bullish and bearish announcement days.[11] A total of 171 news releases are identified and categorized as bullish/bearish if the post-event return is positive/negative.[12]

3.5 Research Design

This section presents the research design used in this chapter. Outlined are methods used to: (1) classify buyer-initiated and seller-initiated trades; (2) package trades that stem from one large order submission; (3) calculate the net price effects of block trades; and (4) evaluate the price effects of block purchases and sales for both bull and bear market conditions.

Consistent with the extant literature, Lee and Ready's (1991) method is used to partition transactions into buyer or seller initiated trades. The mid-quote price is determined as the

[11] A limited number of major announcements are released during ETF trading hours between 9.30 am to 4 pm.
[12] Seventy-seven trading days in the bullish information sample and 94 trading days in the bearish information sample.

average between the best bid and the best ask prices. If the transaction price is greater than the prevailing mid-quote price, then it is classified as a buyer initiated trade. Alternatively, if the transaction price is below the prevailing mid-quote price, it is classified as a seller initiated trade. If the transaction price is equal to the prevailing mid-quote price, the tick rule is adopted for the trade classification. The tick rule is defined as follows: if the transaction price is higher than the previous trade price, then it is an uptick and is classified as a buyer initiated trade; otherwise it is a downtick and is classified as a seller initiated trade.

In order to test the proposition specified in Section 3.3, the largest 1% of transactions are used to identify block orders for each instrument (i.e. S&P 500 index futures and SPDR ETF) over the sample period. Additionally, the smallest 50% of transactions are sampled to measure the impact of non-block trades for each instrument. A block is defined as any 200+ contracts trade in the E-mini and 6000+ shares trade in the SPDR. Non-block trades[13] represent one to two index futures contracts for the E-mini and one-to-200 shares for the ETF.

Consecutive trades in the same direction and within the millisecond are packaged, to account for instances where large orders are executed against multiple standing limit orders at different price levels. If a quote update is observed within the same millisecond, a new trade package is initialized. The size of the order is given by the sum of all transaction records in the package, while the price is determined as the volume weighted average price of the packaged trades.

Following Berkman, Brailsford and Frino (2005), the information or permanent price effect of a trade is measured as follows:

[13] Non-block trades immediately following a block trade are excluded from the sample to avoid double counting of price effects.

$$Permanent\ Price\ Impact \ = 100 * \mathrm{D} * Ln\ (P_{post}/\ P_{prior}) \quad (3.7)$$

where P_{prior} is the equilibrium market price prior to the block transaction, and P_{post} is the equilibrium price after a block order has been executed. D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. Consistent with Berkman et al (2005), prices are sampled in calendar time, rather than transaction time as in Holthausen et al (1990). The prevailing mid-quote price preceding the block is used as a proxy for P_{prior}, while the mid-quote price five minutes after the block is used as a proxy for P_{post}.

As the analysis is conducted on sub-samples, defined by market conditions, the distribution of returns is expected to be right skewed in bull markets and left skewed in bear markets. To account for the asymmetric return distribution, Chapter 3 measures the incremental price impact of large trades, which is equivalent to the abnormal returns induced by block trades. The average price impact of non-block orders is also measured, and the incremental/net effect of block trades is defined as the mean difference in the permanent price impacts between the smallest (1-2 futures contracts/less than 200 ETF shares) and the largest (200+ futures contracts/6000+ETF shares) trade size groups.[14]

The hypothesis examined in this analysis (H3) is that the permanent price impact of block trades is asymmetric between purchases and sales transacted on the E-Mini index futures and the EFT shares. The asymmetric relationship varies across different market sentiments. Specifically, the hypothesis contains two parts that are related to bull and bear markets respectively. The first part states that:

[14]Barclay and Warner (1993) and Chakravarty (2001) find medium-size trades as opposed to the larger trades are associated with the greatest information effect. Results reported in Appendix A for the sample periods suggest this is not the case with the permanent and total price effect increasing in trade size.

$$H3_{1Null}: Permanent\ Price\ Impact\ (of\ Sales)$$
$$= Permanent\ Price\ Impact\ (of\ Purchases)\ in\ a\ Bull\ Market$$

$$H3_{1Alt}: Permanent\ Price\ Impact\ (of\ Sales)$$
$$> Permanent\ Price\ Impact\ (of\ Purchases)\ in\ a\ Bull\ Market$$

The second part states that:

$$H3_{2Null}: Permanent\ Price\ Impact\ (of\ Purchases)$$
$$= Permanent\ Price\ Impact\ (of\ Sales)\ in\ a\ Bear\ Market$$

$$H3_{2Alt}: Permanent\ Price\ Impact\ (of\ Purchases)$$
$$> Permanent\ Price\ Impact\ (of\ Sales)\ in\ a\ Bear\ Market$$

3.6 Empirical Results

Table 3-1 reports descriptive statistics for the sample of block transactions examined in this chapter. In Table 3-1 Panel A, 166,937 block purchases and 171,760 block sales are identified across the two-year sample period for index futures. The average trade size of a block purchase is equivalent to approximately \$30.93 million in exposure, or 315 contracts; and the average size of a block sale is equivalent to \$30.88 million in exposure, or 315 contracts. Similar sized trades are identified during the bull and bear market periods. As seen in Table 3-1 Panel A, block trades sampled during the bear market period are larger (in dollar value terms) than those in the bull market period for both purchases and sales. Furthermore, Table 3-1 Panel A reports a greater frequency of block trades in bull markets vis-à-vis bear markets for the E-mini index futures.

Table 3-1 Panel B documents the mean transaction size of block and non-block trades in the SPDR ETF. The average trade size of a block purchase is approximately \$2.39 million, or 12,005 shares, and the average size of a block sale is \$2.30 million, or 11,609 shares. In comparison, a non-block purchase/sale is on average \$22,481/ \$22,623, or approximately 100 times smaller than a block trade. In contrast to results reported for the E-mini index future, more block trades are reported in the bear market than in the bull market for the ETF. Further, block trades are bigger in the bear market relative to bull markets, in terms of both quantity and dollar values for the EFT.

Table 3-A

TABLE 3-1

Descriptive Statistics of Block Transactions and Non-block Transactions

This table reports the mean transaction size of the largest buy and sell trades for E-mini S&P500 index futures and SPDR ETF during: (1) the combined sample period extending 1 February 2014 to 31 January 2016, (2) the bear market from 23 October 2015 to 20 January 2016 and (3) the bull market from 10 October 2014 to 8 January 2015. The non-block transaction group includes trades with 1-2 contract size and accounts for 50% of the trade frequency. The non-block group is used as a benchmark to compute the incremental effect of block trades. All transactions are categorized into buyer or seller initiated trades using a quote-based rule.

	All sample		Bear markets		Bull markets	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
Panel A: E-Mini Index Futures						
Block trade number	166,937	171,760	13,091	13,390	19,701	19,476
Block trade size	315	315	309	309	309	311
Block value	30,931,618	30,880,601	31,440,710	31,324,297	30,773,665	30,912,825
Non-block value	126,542	126,533	127,450	127,649	131,071	130,720
Panel B: SPDRs ETF						
Block trade number	218,373	212,487	29,158	28,272	26,397	24,983
Block trade size	12,005	11,609	12,851	12,227	11,713	11,598
Block value	2,389,946	2,304,616	2,606,376	2,470,243	2,336,716	2,303,393
Non-block value	22,481	22,623	23,084	23,342	22,976	23,089

Table 3-2 reports the net permanent price effect of block trades executed in bull and bear markets for index futures and ETF shares. The bull market months extend from October 10, 2014 to January 8, 2015; and the bear market months extend from November 20, 2015 to January 20, 2016. “Sales” and “Purchases” indicate the incremental/net effect of block sales and purchases respectively, where the net effect is defined as the mean difference in the permanent price impacts between the largest (200 futures contracts/6,000 ETF shares) and the smallest (one to two futures contracts/less than 200 ETF shares) trade size groups. The number of block sales and purchases examined for each sample period are reported in the third and fifth columns respectively. The column labelled “Difference” reports the mean difference in the net effects between block sales and block purchases. A positive value indicates that the net effect of sales is bigger than that of buys; the opposite is true for a negative value. Panel A reports the incremental price impact of block trades for index futures and ETF during a bull market period; Panel B shows the incremental effect of block trades during a bear market time. T-Statistics are in parentheses for the null hypothesis that the net price impacts of block orders are zero($H3_{1Null}$), reported in “Sales” and “Purchases”, and the null hypothesis that the price impacts between block sales and purchases are the same for bull($H3_{2Null}$) and bear($H3_{3Null}$) market periods, reported in “Difference” for Panel A and Panel B respectively.

Table 3-2 Panel A reveals the fact that both block sales and purchases induce significant price impacts to the market. It suggests that prices continue to drift downwards following block sales and upwards following block purchases. As for E-mini futures, block sales permanently move prices down on average by 0.0084 percent; meanwhile, block purchases permanently move prices up on average by 0.0010 percent, which is much smaller than the price impacts of block sales. Table 3-2 Panel A also documents that the permanent price effect is larger for sales vis-à-vis purchases in bull markets, which supports the first part of the hypothesis ($H3_1$) that a significant asymmetry exists between seller-initiated and buyer-initiated block transactions in bull markets.

Similarly, Table 3-2 Panel B demonstrates that in bear markets the permanent price effect of purchases is greater than the permanent price effect of block sales. Results are consistent across the E-mini futures contract and the SPDR ETF, and support $H3_2$ that the asymmetry between the informational effects associated with block purchases and sales are reversed in a bear market. At the one percent level of significance, tests of difference indicate in net terms, a block sale in the E-mini (SPDR) has 0.0074 (0.0029) percentage points greater impact than a corresponding block purchase in bull markets. In the case of bear markets, Table 3-2 Panel B reports the difference in net permanent price impact between block purchases and sales is -0.0065 in the E-mini and -0.0040 in the SPDR, both significant at the one percent level.

TABLE 3-2

Permanent Price Impact of Block Trades in Bull and Bear Markets

This table documents the net price effects of purchases and sales for E-mini S&P 500 index futures and SPDR ETF during bull and bear markets. The bull market months extend 10 October 2014 to 8 January 2015, and the bear market months extend 20 November 2015 to 20 January 2016. The incremental/net effect of block trades is defined as the mean difference in the permanent price impacts between the smallest (1-2 futures contracts/less than 200 ETF shares) and the largest (200+ futures contracts/6000+ETF shares) trade size groups.

Panel A reports the incremental price impact of block trades for E-Mini index futures and SPDRs ETF during a bull market period; Panel B shows the incremental effect of block trades during a bear market time. The permanent price impact of each trade is defined as follows: permanent price impact = 100*D*ln(MQAfter/MQBefore) where D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. MQBefore is the prevailing mid-quote at the time of the trade and MQAfter is the mid-quote five minutes after the trade. The mean difference between the sale and the purchase groups is computed and reported in the last column. T-Statistics are in parentheses for the null hypothesis that the net price impacts of block orders are zero, reported in Sales and Purchases, and the null hypothesis that the price impacts between sales and purchases are the same, reported in Difference. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level.

	Sales	No. of Block Sales	Purchases	No. of Block Purchases	Difference
Panel A. Bull market					
	0.0084		0.0010		0.0074
E-Mini	(9.79)***	19,476	(1.08)*	19,701	(6.05)***
	0.0051		0.0022		0.0029
SPDRs	(6.66)***	24,983	(2.94)***	26,397	(2.75)***
Panel B Bear market					
	0.0042		0.0107		-0.0065
E-Mini	(3.36)***	13,390	(8.84)***	13,091	(-4.66)***
	0.0024		0.0064		-0.0040
SPDRs	(8.84)***	29,158	(3.36)***	28,272	(-3.93)***

To further test theoretical predictions in Section 3.3 and hypotheses in Section 3.5, Table 3-3 documents the permanent price impact of purchases and sales on bullish and bearish information announcement days. Table 3-3 Panel A reports the incremental price impact of block trades for index futures and ETF on bullish information days; Table 3-3 Panel B shows the incremental effect of block trades on bearish announcements days.

On bullish announcement days, the mean net permanent price impacts of block sales are 0.0042 percent for index futures and 0.0041 percent for ETF. Both values are significantly different from zero at the 1% statistical level. Similar results are found for block purchases, permanent price impacts are significant for both index futures (0.0031 percent) and ETF (0.0020 percent). Together these results demonstrate that block trades produce significant price impacts.

Turning to the "Difference" reported in the last column of Table 3-3, the price impacts of block sales are greater in magnitude in comparison to block purchases for both index futures and ETF. Statistical tests confirm that the difference is statistically significant at conventional levels for ETF; however, this is not the case for the E-mini futures contract. This result provides further, albeit weaker, support for the hypothesis ($H3_1$) that an asymmetry exists between the informational effects associated with block purchases and sales on bullish announcement days. Table 3-3 Panel B reports block purchases in the E-mini futures contract and the SPDR EFT on days where bearish macro-economic news is announced. Block purchases are associated with significant net price effects of 0.0080 percent for index futures and 0.0055 percent for the SPDR ETF. The "Difference" is reported at -0.0034 percentage points for index futures and -0.0042 percent points for the SPDR ETF, both significant at the 1% statistical level. Together these results indicate that block purchases are more informative than block sales when market sentiment is bearish, which is consistent with hypothesis $H3_2$.

These additional tests and results support the theoretical model in Section 3.3, wherein the permanent price effect of block trades varies across market sentiment as measured by responses to macro-economic news announcements.

TABLE 3-3

Permanent Price Impact of Block Trades for Bullish and Bearish Announcements

This table documents the price impact of purchases and sales for E-mini S&P500 index futures and SPDR ETF during bullish and bearish information days. The incremental effect of block trades is defined as the mean difference in the permanent price impacts between the smallest (1-2 futures contracts/less than 200 ETF shares) and the largest (200+ futures contracts/6000+ETF shares) trade size groups.

Panel A shows the incremental price impact of block trades for E-Mini index futures and SPDRs ETF on bullish information days; Panel B shows the incremental effect of block trades on bearish announcements days. The permanent price impact of each trade is defined as follows: permanent price impact = 100*D*ln(MQAfter/MQBefore) where D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. MQBefore is the prevailing mid-quote at the time of the trade and MQAfter is the mid-quote five minutes after the trade. The mean difference between the sale and the purchase groups is also computed and reported in the last column. *T*-Statistics are in parentheses for the null hypothesis that the net price impacts of block orders are zero, reported in Sales and Purchases, and the null hypothesis that the price impacts between sales and purchases are the same, reported in Difference. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level.

	Sales	No. of Block Sales	Purchases	No. of Block Purchases	Difference
Panel A. Bullish announcements days					
	0.0042		0.0031		0.0012
E-Mini	(6.30)***	26,064	(4.50)***	25,800	(1.21)
	0.0041		0.0020		0.0021
SPDRs	(6.46)***	31,617	(3.21)***	31,797	(2.34)***
Panel B Bearish announcements days					
	0.0046		0.0080		-0.0034
E-Mini	(7.65)***	28,344	(13.60)***	28,861	(-4.05)***
	0.0013		0.0055		-0.0042
SPDRs	(2.44)***	33,663	(10.84)***	34,902	(-4.41)***

3.7 Conclusion

Previous research has identified a “puzzle” in the price impact of block trades, finding that the information effects of block buy trades are generally greater than the information effects of block sell trades. This chapter extends the literature by examining the information effects of block trades in bull and bear market conditions.

This chapter has developed a theoretical model which predicts that the magnitude of the information conveyed by sell trades is greater than buy trades in bull markets and lower in bear markets. In the model, contrarian signals are more valuable than confirming signals. Consequently, in a bullish market, where the information advantage of institutional buyers is lower than that of institutional sellers, the adverse selection problem is less severe on the ask side of the market, and buy orders have a lower price impact than sell orders. The reverse is true in a bearish market.

Using a sample of trades executed on the E-mini S&P500 index futures and the SPDR ETF, evidence is found consistent with the theoretical proposition.

CHAPTER 4. Commonality in Liquidity across International Borders: Evidence from Futures Markets

4.1 Introduction

The second examination in this dissertation tests the impact of global market liquidity on the price effects of trades transacted in individual share price index futures markets. Commonality in liquidity refers to the liquidity of individual securities co-moving with market-wide liquidity. This chapter identifies global commonality in liquidity across stock index futures markets for a 10-year period, and also studies the evolution of the commonality through time. Further, this chapter investigates regional commonality in liquidity for index futures markets within each GMT time zone.

The literature review in Section 2.3 of Chapter 2 documented that liquidity commonality exists in the U.S. stock market (Chordia, Roll & Subrahmanyam, 2000), the FX market (Mancini, Ranaldo & Wrampelmeyer, 2013) and non-U.S. exchanges (Brockman & Chung, 2002); Fabre & Frino, 2004). Additionally, previous literature detailed a distinct and significant global component in an individual security's total liquidity commonality and referred to it as “global liquidity commonality” (Brockman, Chung & Perignon, 2009). To date, there is still a scarcity of literature addressing the global commonality in liquidity for index futures markets. Furthermore, the role of liquidity commonality within a geographical time zone is also an unexplored issue for futures markets.

The remainder of this chapter is organized as follows. Section 4.2 details the intraday data and liquidity measures. The regression models employed to test hypothesis $H_{4,1}$ and $H_{4,2}$ are discussed in Section 4.3. Sections 4.4 and 4.5 report the empirical results and robustness tests, respectively. Section 4.6 provides a summary of the chapter.

4.2 Data and Liquidity Measures

4.2.1 Data

The stock index futures data used in this paper are obtained from Thomson and Reuters Tick History (TRTH) database, managed and distributed by the Securities Industry Research Centre of Asia Pacific. The data obtained from TRTH are transaction & quotation data including: (1) the best bid price, (2) the best ask price, (3) trade price, and (4) volume of trade; and end of day data including: (1) open interest, and (2) trading volume for each contract on each trading day. One challenge in studying liquidity at a global level is to obtain a comprehensive dataset across multiple markets. In international futures markets, the tick-by-tick transaction and quotation data do not normally cover a sufficiently long period, possibly explaining why many studies in this area employ a short or medium term sample period. For example, Brockman, Chung and Perignon (2009) studied global liquidity commonality in stock markets based on only two year's data. The present study requires tick-by-tick index futures data over a 10-year sample period to examine liquidity co-movements through time. While Brockman, Chung and Perignon (2009), examine 47 equity markets, these market do not necessarily have a corresponding index future, or sufficient back history or activity. Following the imposition of a 10-year sample period to measure bid-ask spreads, nine index futures for the period from October 2002 to September 2012 are identified. In terms of market depth data, TRTH are only able to provide data in the two years from July 2010 to September 2012 limiting the analysis of commonality in the depth of markets. The sample includes both emerging markets and developed markets, and covers popular and influential markets in four regions defined by MSCI. The nine index futures are Australia SPI 200, Canada S&P TSX 60, Germany DAX, Hong Kong Hang Seng, Hungary BUX, Japan Nikkei225, Norway OBX, U.K. FTSE 100 and U.S. S&P 500. And the four MSCI regions are Europe (Developed Markets in Europe and Middle East), Europe (Emerging Markets in Europe, Middles East and Africa), Americas (Developed Markets) and Pacific (Developed Markets).

In an attempt to evaluate regional liquidity commonality as defined by GMT time zones and include more markets the sample period is shortened to the period May 2006 to September 2012. The final sample for the regional commonality analysis consists of six additional markets, which are Brazil BOVESPA, France CAC-40, India Nifty 50, Italy FTSE-MIB, MSCI-Singapore and MSCI-Taiwan. These additional markets have poor data quality for the period prior to 2006 and therefore are only included in the regional commonality analysis, but not in the global commonality analysis which requires a 10-year sample period.

Given the various expiry dates on contracts that trade simultaneously, for each index future on each day, this analysis only includes the contract with the highest trading volume on that day[15]. By taking the most actively traded future contract, the liquidity fluctuations, caused by expiry cycle, are minimized[16]. The sample data includes the day trading sessions only, not all index futures have a night-time trading session. As opening and closing mechanisms differ across exchanges, all opening and closing sessions are identified and data during these periods are removed to ensure market liquidity is only captured during continuous trading. After sampling the continuous trading day session data at a 1-minute interval frequency, three liquidity metrics are calculated: quoted bid-ask spread, relative bid-ask spared and depth; these are then averaged to create daily time-series data for each market. Using tick-by-tick data for transactions and quotations, effective bid-ask spread/total price impact is computed for each trade and then averaged for each 1-minute interval weighted by the volume of the trade. The intraday one minute observations are then averaged to form the daily time-series data for each market. Regression analysis is conducted on consolidated daily data over a 10-year sample period, and results are reported in Section 4.4. The following outliers are filtered from the sample. Observations associated with less than 50 contracts trading volume within one trading day are deleted. Observations associated with zero or negative bid-ask spared or with spread that is smaller than the local tick size are deleted. Filters are also applied on unreasonable observations that are outside the range, defined as daily quoted spread three standard deviations away from the mean.

[15] The contract with the highest open interest is also the contract with the highest trading volume typically.
[16] Market participants normally roll over their positions a couple of days before the future's contract expires, not necessarily on the last trading day of the contract. Therefore, the activity of a future's contract is determined by its daily trading volume, not by its expiration date.

4.2.2 Liquidity measures

Flowing Chordia et al. (2000), three liquidity measures, quoted bid-ask spread, relative bid-ask spread and depth, are calculated for the last quote in each minute of the normal trading session. The three measures are defined as follows:

$$QS_t = \frac{\sum_{i=1}^{n} P_{A_i} - P_{B_i}}{n} \qquad (4.1)$$

$$RS_t = \frac{1}{n} \sum_{i=1}^{n} \frac{P_{A_i} - P_{B_i}}{P_{M_i}} \qquad (4.2)$$

$$DD_t = \frac{1}{2n} * \sum_{i=1}^{n} \left(P_{A_i} * Q_{A_i} + P_{B_i} * Q_{B_i}\right) \qquad (4.3)$$

Where $QS_t, RS_t\ and\ DD_t$ represent the quoted spread, relative spread and dollar depth on day *t*, respectively. The variable *P* denotes price; subscript *A*, the best ask quote for minute *i*, and subscript *B*, the best bid quote for minute *i*; *M* is the midpoint of best bid and ask; *Q* signifies the quantity of orders at the best bid or ask prices for interval *i*, and *n* is the number of minutes during the trading session.

Following Chordia et al. (2001), effective bid-ask spread is defined as the difference between the execution price and the mid-point of the prevailing best bid-ask price. Effective spread, proxies the total price impact as it measures the ability of market participants to trade immediately and the associated market impact or transaction cost. The effective spread is calculated based on the transaction and quotation data. The benefit of using effective spread as a liquidity measure is that it takes into account orders that walk down, or up the limit order book.

The effective spread/total price impact of a trade is measured as follows:

$$Effective\ Spread = 100 * \mathrm{D} * Ln\ (\mathrm{VWAP}/\ MQBefore) \qquad (4.4)$$

where $MQBefore$ is the prevailing mid-quote at the time of the trade, and VWAP is the volume weighted trade price. To account for instances where large orders are executed against multiple standing limit orders at different price levels, consecutive trades with the same direction and occurring within the same millisecond are packaged together. If a quote update is observed within the same millisecond, then a new trade package is initialized. The size of the order is given by the sum of all transaction records in the package; while the price is determined as the volume weighted average price of packaged trades. Consistent with Berkman, Brailsford and Frino (2005), prices were also sampled in calendar time, rather than transaction time as in Holthausen, Leftwich and Mayers (1990). D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. Consistent with the extant literature, Lee and Ready's (1991) method was applied to partition transactions into buyer or seller initiated trades.

4.3 Research Design

This section outlines the regression analysis used to examine the two hypotheses tested in this chapter. Following Brockman, Chung and Perignon (2009), the following time-series regressions in (4.5) are estimated for each index future market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \qquad (4.5)$$

where $\Delta Liquidity_{I,t}$ is the daily percentage change in liquidity for index future *I*. Four metrics of liquidity, $QS_{I,t}, RS_{I,t}, DD_{I,t}$ and $effective\ spread$ are adopted, where $QS_{I,t}$ is the average daily quoted bid-ask spread for index future I on day *t*; similarly, $RS_{I,t}$ is average daily relative spread for I on day t, and $DD_{I,t}$ is the average daily depth for I on day *t*. $\Delta Volatility_{I,t}$ is the daily proportional change in return volatility which is measured by the squared return. $\Delta Liquidity_{G,t}$ is the contemporaneous daily percentage change in global market liquidity and is computed as an equally weighted average across all index futures' liquidity movements except for those associated with index future *I*. [17] The $\Delta Liquidity_{G,t-1}$ and the $\Delta Liquidity_{G,t+1}$ are the lag and lead terms of $\Delta Liquidity_{G,t}$ respectively. These two variables are included to capture the non-contemporaneous adjustments in liquidity. $Return_{G,t}$ represents the global return on day *t* and is computed by equally averaging across all index futures' daily returns. Similarly, its lagged ($Return_{G,t-1}$)

[17] $\Delta Liquidity_{G,t}$ is calculated in a different way in Brockman, Chung and Perignon (2009). They calculated the global liquidity term for day *t* and day *t-1* respectively by averaging across all firms' liquidity measure in the global database and then computed the proportional change across these two successive trading days. While in our model, $\Delta Liquidity_{G,t}$ is computed as an equally weighted average across all index futures' liquidity proportional change on day t. Theoretically, this calculation difference will not affect the results too much and our calculations do not require currency exchange.

and lead ($Return_{G,t+1}$) terms are also included in the model in order to isolate the impacts of global market price swings on index future-specific liquidity variations.

In this chapter, the primary variable of interest is β_1 as it represents the correlation between the movements of individual index futures' liquidity and the movements of the global liquidity. This research design enables examinations of the first hypothesis ($H4_1$), which states that the global commonality in liquidity exists for index futures markets, i.e. the liquidity in an individual market moves simultaneously with the global wide liquidity. Liquidity is measured by quoted bid-ask spreads, relative spreads, effective spreads and market depth. A positive and significant β_1 would indicate that the liquidity of the individual index futures market co-moves with the global wide liquidity.

$$H4_{1Null}: The\ movements\ of\ liquidity\ in\ the\ individual\ index\ future's\ market$$

$$are\ not\ correlated\ with\ the\ global\ wide\ liquidity, i.e.\ \beta_1 = 0$$

$$H4_{1Alt}: The\ movements\ of\ liquidity\ in\ the\ individual\ index\ future's\ market$$

$$are\ correlated\ with\ the\ global\ wide\ liquidity, i.e.\ \beta_1 \neq 0$$

Further, the second hypothesis ($H4_2$) suggests that the regional liquidity commonality prevails within each GMT time zone for index futures markets— liquidity in an individual market co-moves with the regional liquidity as defined by time zone. The quoted bid-ask spread and the relative spread liquidity measures are adopted to test this hypothesis. International markets are divided into three different regions depending on GMT time zones. Markets located in the same or similar GMT time zones are grouped into one geographical region and the following time-series regression is conducted for each index future over a 5-year period:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{R,t} + \beta_2 \Delta Liquidity_{R,t-1} + \beta_3 \Delta Liquidity_{R,t+1} + \gamma_1 Return_{R,t} + \gamma_2 Return_{R,t-1} + \gamma_3 Return_{R,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.6)$$

where $\Delta Liquidity_{I,t}$ is the daily percentage change in liquidity for index future *I*. $\Delta Volatility_{I,t}$ controls for the index future-specific volatility. $\Delta Liquidity_{R,t}$ is the contemporaneous daily percentage change in regional market liquidity and is computed as an equally weighted average across all index futures within the region except for the one associated with index future *I*. The $\Delta Liquidity_{R,t-1}$and the $\Delta Liquidity_{R,t+1}$ are the lag and the lead terms of $\Delta Liquidity_{R,t}$ respectively. $Return_{R,t}$ represents the regional return on day *t* and is computed by equally averaging daily returns across all index futures within the region. Similarly, its lag ($Return_{R,t-1}$) and lead ($Return_{R,t+1}$) terms are also included in the model in order to isolate the impacts of regional market price swings on index future-specific liquidity variations. The primary variable of interest is β_1 which measures the correlation between the movements of individual index futures' liquidity and the movements of the regional liquidity. A positive and significant β_1 would indicate that the liquidity of the individual index futures market co-moves with the regional liquidity.

$$H4_{2Null}: The\ movements\ of\ liquidity\ in\ the\ individual\ index\ future's\ market\ are\ not\ correlated\ with\ the\ reginal\ liquidity, i.e. \beta_1 = 0$$

$$H4_{2Alt}: The\ movements\ of\ liquidity\ in\ the\ individual\ index\ future's\ market\ are\ correlated\ with\ the\ regional\ liquidity, i.e. \beta_1 \neq 0$$

4.4 Empirical Results

4.4.1 Descriptive statistics

In this section, descriptive statistics are presented for index futures employed in this study. The statistics are based upon data in the 10-year period from October 2002 to September 2012. Table 4-1 includes nine index futures markets across four regions defined by MSCI, and the benchmark stock index for each corresponding exchange. An index normally represents a capitalization-weighted measure of a group of stocks with the highest market caps listed on that exchange. The markets include Australia, Canada, Germany, Hong Kong, Hungary, Japan, Norway, the U.K. and the U.S., and the corresponding stock indexes are SPI 200, S&P TSX 60, DAX, Hang Seng, BUX, Nikkei 225, OBX, FTSE 100 and S&P 500. Daily return percentage is the percentage daily returns measured by the proportional change in daily close prices. The average daily returns ranges from 0.0121 for the Nikkei 225 index future (Japan) to 0.0918 for the OBX index futures (Norway), with an average of 0.0405 across all nine markets. The variable, "Quoted Spread/Tick Size", is the daily quoted spread divided by the minimum tick size for the index futures contract. To compare liquidity across index futures markets, tick size is integrated into the quoted spread measure to avoid the currency differences on spreads. The average value of Quoted Spread/Tick Size ranges from 1.0021 for Nikkei 225 index futures (Japan) to 43.168 for BUX index futures (Hungary), with an average of 43.168 for all nine countries,[18] indicating that Japan has the most liquid index future while Hungary has the least liquid index futures contract. The average daily relative spread ranges from 0.0140 for DAX index futures (Germany) to 0.1911 for OBX index futures (Norway),

[18] By comparing the mean and median of quoted spread for each index future, it was observed that the quoted spread measure is highly skewed. In addition, some of the extremely active index futures, such as S&P 500 and Nikkei 225, have a large portion of quotes that are close to or equal to their minimum tick size and result in a number of observations with zero daily quoted spread change. Since the depth data only covers the recent two years, primary liquidity measures are the relative spread and the effective spread.

with an average of 0.0595 for all 9 countries. The average daily effective spread ranges from 0.0103 for FTSE 100 index futures (the U.K.) to 0.0703 for OBX index futures (Norway), with an average of 0.0266 for all nine countries. The variable, “Volatility%”, presents the return volatility in percentage. The average volatility ranges from 0.0129 for SPI 200 index futures (Australia) to 0.0423 for OBX index futures (Norway), with an average value of 0.0244.

Table 4-D

TABLE 4-1

Descriptive Statistics of Index Futures Markets

Table 4-1 reports the average daily return, average daily quoted spread divided by local tick size, average daily relative spread and average return volatility over the period October 2002 – September 2012 for nine index futures in four regions. The first three columns present the name of the market, the name of the major exchange that the index constituent stocks are traded on, and the market classification defined by MSCI. The forth column gives the benchmark stock index for the corresponding exchange listed in column one. Daily Return% is the daily percentage return, where the return is measured by the proportional change on the daily close prices. Quoted Spread/Tick Size is the daily quoted spread divided by the minimum tick size of the index future and the term measures how liquid the index futures market is. The third last column provides the relative bid-ask spread in percentage and the second last column reports the effective bid-ask spread in percentage. The last column presents the return volatility in percentage.

Market	Exchange	Region	Index	Daily Return %	Quoted Spread/ Tick Size	Relative Spread %	Effective Spread %	Volatility %
Australia	Australian S. Ex.	Pacific	SPI 200	0.0219	1.2022	0.0277	0.0138	0.0129
Canada	Toronto S. Ex.	Americas	S&P TSX 60	0.0364	2.1447	0.0366	0.0143	0.0168
Germany	Frankfurt S. Ex.	Europe (D)	DAX	0.0495	1.4537	0.0140	0.0116	0.0270
Hong Kong	Hong Kong Ex.	Pacific	Hang Seng	0.0478	3.0983	0.0156	0.0121	0.0282
Hungary	Budapest S. Ex.	Europe (E)	BUX	0.0489	43.168	0.1215	0.0491	0.0275
Japan	Osaka Securities	Pacific	Nikkei 225	0.0121	1.0021	0.0913	0.0464	0.0261
Norway	Oslo Stock Ex.	Europe (D)	OBX	0.0918	9.5632	0.1911	0.0703	0.0423
U.K.	London S. Ex.	Europe (D)	FTSE 100	0.0262	1.6039	0.0159	0.0103	0.0205
U.S.	NYSE	Americas	S&P 500	0.0296	1.0112	0.0217	0.0116	0.0180
Average across All Index Futures				0.0405	7.1386	0.0595	0.0266	0.0244

4.4.2 Evidence of Global Commonality in Index Futures Markets

The time-series regression in (4.5) was estimated for each index future over a 10-year period,[19] coefficient estimates are summarized in Table 4-2. The primary variable of interest in the regression is the contemporaneous coefficient of global liquidity, β_1. The lag and lead coefficient estimates of global liquidity, and the sum of contemporaneous, lag and lead coefficients of global liquidity, along with the adjusted R-square, are also reported in Table 4-2. Results from three liquidity measures: quoted bid-ask spread (Panel A), relative bid-ask spread (Panel B), effective bid-ask spread (Panel C) and depth (Panel D), are presented in Table 4-2.

The regression results indicate strong evidence for liquidity commonality across global index futures markets for all three liquidity measures. The quoted spread results, reported in Table 4-2 Panel A, present that 5 of the 9 index futures have a positive contemporaneous coefficient and all these coefficients are significant at the 1% level. Australia, HK, Japan and Norway have positive but insignificant coefficients. For β_2, the lag term of global liquidity, only the U.K. reveals weak significance. Meanwhile, none of the index futures are significant for β_3. As reported in Table 4-2 Panel A, Germany DAX has the largest adjusted R-square value, at 0.1062, while the U.K. and Canada have the second and third largest values at 0.0494 and 0.0254, respectively.

Turning to the relative spread results as reported in Table 4-2 Panel B, 6 out of 9 index futures show positive and significant β_1 at the 5% level, which further confirms the existence of co-movements in liquidity among global index futures markets. Only two Asian index futures,

[19] Both the quoted bid-ask spread and the relative bid-ask spared have a 10-year sample period while the depth results are only based on two years' data due to a shorter availability of depth data.

HK Hang Seng index future and Japan Nikkei 225 index future, and one European index future, Oslo OBX, report positive but not significant coeffiecnet on β_1. Turning to coefficent β_2, only Japan demonstrates strong significance, but with a negative coefficient. Results suggest liquidity of Japan's index future moves away from global liquidity with a one-day lag.

Results for effective spread reported in Table 4-2 Panel C demonstrate that 56% of the index futures have a positive contemporaneous coefficient, and all these coefficients are significant at the 1% level. The coefficients for HK, Hungary, Japan and the U.K. are positive, but not statistically significant at traditional levels. None of the index futures report statistically significant coefficient on lagged global liquidity variable β_2,. The lead term of global liquidity, β_3, shows positive and strong significance for Australia, U.K. and U.S. This result suggests that index future's liquidity in Australia, U.K. and U.S. leads the liquidity movements in other futures markets by one day.

Depth data is only available in the recent two years for the U.S. market; hence depth analysis is based on two years' data only. Although the number of observations is dramatically reduced, the depth analysis corroborates aforementioned results. With the exception of HK and Norway, most index futures' depth, co-move with global market depth. Germany, the U.S. and the U.K. report the largest, second largest and third largest adjusted R-square value in depth's results. Turing to estimates of β_2, only Hungary report positive and strong statistical significance. Further, none of the index futures report significance for β_3, the lead term of global liquidity. All the markets have the adjusted R-square values over 1%, implying an improved goodness-of-fit relative to other liquidity measures.

TABLE 4-2

Global Commonality with Equally Weighted Global Liquidity

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.5)$$

The dependent variable is the proportional change in the liquidity of index future *I*. Four liquidity variables, quoted bid-ask spread (Panel A of Table 4-2), relative bid-ask spread (Panel B of Table 4-2), effective bid-ask spread (Panel C of Table 4-2) and depth (Panel D of Table 4-2), are adopted to conduct the regressions. The independent variables are the global return, the proportional change in global liquidity, as well as their lag and lead term. The proportional change in the return volatility of index future I is also included as a control variable. In each time-series regression, the global liquidity is the average liquidity across all index futures except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. $\beta_1,\ \beta_2\ and\ \beta_3$ represent contemporaneous, lagged, and lead coefficient estimates respectively. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results for the 10 index futures are presented in this table. The quoted bid-ask spread, relative bid-ask spared and effective bid-ask spread results have a 10 year sample period while the depth result is only based on data in the recent two years when the market depth is available for all nine index futures.

Index Futures	β_1	β_2	β_3	$\beta_1+\beta_2+\beta_3$	Adj. R^2
Panel A. Quoted Spread (over 10 years)					
Australia	0.0704	-0.0230	0.0626	0.1100	0.0110
Canada	0.3146***	0.1070	0.0624	0.4839	0.0254
Germany	0.2442***	0.0375	0.0455	0.3272	0.1062
HK-China	0.1657	-0.1396	0.1355	0.1616	0.0031
Hungary	0.4617***	0.2778	0.0721	0.8115	0.0105
Japan	0.0035	0.0013	0.0047	0.0094	-0.0026
Norway	0.2485	-0.1769	-0.1778	-0.1062	0.0005
U.K.	0.2474***	0.0792*	0.0684	0.3950	0.0494

U.S.	0.0200***	-0.0008	0.0019	0.0211	0.0246
Panel B. Relative Spread (over 10 years)					
Australia	0.0937**	-0.0431	0.0519	0.1025	0.0383
Canada	0.3296***	0.0834	0.0656	0.4787	0.0449
Germany	0.2622***	0.0333	0.0159	0.3114	0.2370
HK-China	0.1876	-0.1469	0.1519	0.1926	-0.0010
Hungary	0.4968***	0.2796	0.0526	0.8291	0.0219
Japan	0.0040	-0.0244***	-0.0125	-0.0329	0.3476
Norway	0.2897	-0.2138	-0.2093	-0.1334	0.0081
U.K.	0.2640***	0.0684	0.0454	0.3778	0.1042
U.S.	0.0353***	-0.0028	-0.0029	0.0296	0.5107
Panel C. Effective Spread (over 10 years)					
Australia	0.0460***	-0.0070	0.0500***	0.0890	0.0327
Canada	0.1234**	0.0062	-0.0071	0.1225	0.0158
Germany	0.2063***	0.0193	0.0101	0.2357	0.0490
HK-China	0.0419	0.0589	-0.0412	0.0596	0.0110
Hungary	0.0786	0.0899	-0.0090	0.1596	0.0136
Japan	0.0164	-0.0057	-0.0052	0.0055	0.0702
Norway	0.3449**	0.0523	0.1152	0.5124	0.0039
U.K.	0.1144	0.0746	0.2387***	0.4278	0.0035
U.S.	0.0932***	0.0165	0.0622***	0.1718	0.1365
Panel D. Depth (over 2 years)					
Australia	0.2871***	0.1261	-0.0088	0.4044	0.0370
Canada	0.2716**	-0.1557	0.0097	0.1256	0.0522
Germany	0.4686***	0.1402	0.0692	0.6780	0.2616
HK-China	0.5016	0.4221	0.2030	1.1268	0.0706
Hungary	0.4893**	0.5954***	-0.0391	1.0456	0.0294
Japan	0.1924*	0.1261	-0.0653	0.2532	0.0539
Norway	0.2734	0.0419	0.7405	1.0558	0.0154
U.K.	0.5564***	0.0976	0.0119	0.6658	0.1781
U.S.	0.3129**	-0.0933	0.0294	0.2490	0.1981

4.4.3 The Evolution of Global Commonality

Previous results reveal a strong global commonality among all liquidity measures. In the last 10 years, global financial markets have been transformed due to the introduction and growth of algorithmic trading and HFT. Furthermore, the connectivity between financial markets has also been stronger through time as the pace of globalization continues to increase. These initiatives are likely to have increased the commonality in liquidity across international borders. In this section, analysis is conducted on how global co-movements in liquidity vary through time. The 10-year time-series data is divided into five equal periods, and liquidity commonality is tested for each period. By comparing results obtained from different periods, the evolution of commonality is observed. Regression analysis is carried out separately for each period and both the contemporaneous coefficient estimates β_1 and the adjusted R-square are averaged across all index futures for the sample period. The sum of the contemporaneous, lead, and lagged coefficient estimates ($SUM_G = \beta_1 + \beta_2 + \beta_3$) are also averaged across all index futures. To assess how pervasive the commonality is in each test period, the number of significant index futures at the 5% and the 10% levels are computed respectively.

Results on the quoted spread measure, reported in Table 4-3 Panel A, indicate a clear trend of increasing commonality based on the number of significant index futures at the 5% significance level. This number increases dramatically from one in the first period to four in the last period, suggesting the strength of commonality in recent years is much stronger than that observed in early 2000. There appears to be a drop in Period 4 (July 2008 – June 2010) based on the quoted spread measure, but the drop is not significant for the relative spread and the effective spread measures. The adjusted R-square also reveals an upward trend. The value increases from 0.0076 in Period 1 to 0.0799 in Period 4 and then drops somewhat to 0.0649 in Period 5.

Turning to the relative spread measure, stronger results are reported in Table 4-3 Panel B, the increase in the degree of commonality is more pronounced. It is noticeable that the number of significant index futures, at both the 5% and the 10% significance levels, has been continuously increasing from Period 1 to Period 5[20]. The number of significant index futures is five times larger in recent years than that observed in Period 1, indicating the global commonality has become much stronger and more pervasive than before. An increasing adjusted R-square across periods, reported in the last column of Table 4-3 Panel B, supports the previous finding on the evolution of liquidity commonality. The adjusted R-square increases from 0.0621 in Period 2 to 0.2494 in Period 5, suggesting the variations in $\Delta Liquidity_{I,t}$ for an individual index future can be better explained by the variations in global liquidity changes in recent 2 years compared to early 2000. This finding corroborates Karolyi, Lee and Dijk (2012), who show that the adjusted R-square is increasing through time when testing liquidity commonality in equity markets. The observed increase in adjusted R-square could be attributed to the more correlated liquidity movements between the individual index futures market and the global index futures market.[21]

Similar results are reported in Table 4.3 Panel C for the effective spread measure. Looking at the number of index futures with positive coefficients at the 5% significance level, an upward trend is noticed in the degree of liquidity commonality. This number increases significantly

[20] Fisher exact test is computed on the proportions which exhibit commonality in liquidity and produces a significant increase from Period 1 to Period 5.
[21] The increase in the adjusted R-square might result from the improved predictive power of either liquidity variables or non-liquidity variables in regression (4.5). To distinguish between these two possibilities, the following regression models are tested: the first one contains global liquidity variables only, and the second one includes all other variables. The results show an increased adjusted R-square for the first regression but not for the second one, which further confirms the finding that movements in individual index future's liquidity become more correlated with that associated with global wide liquidity.

from zero in the first period to five in the last period, suggesting the degree of commonality in recent years is much stronger than that observed in early 2000. Turning to the results at the 10% significance level, the number of index futures with positive coefficients grows from two in the first period to seven in the last period, indicating a substantial increase in the degree of liquidity commonality. The adjusted R-square also reports an upward trend. The value increases from 0.0241 in Period 1 to 0.1086 in Period 4 and then drops to 0.0742 in Period 5.

Overall, the findings in Table 4-3 represent the first empirical evidence of variations in global liquidity commonality for index futures markets. Global commonality has become much stronger and more pervasive in recent years, compared to early 2000, and the primary liquidity measure, relative spread, reveals a continuous increase in the degree of global commonality.

TABLE 4-3

Global Commonality in Different Periods

To observe how the global commonality varies through time, the 10-year period is divided into five equal sub-periods and the time-series regression is run separately for each index future in each period. The contemporaneous coefficient estimates β_1 and the adjusted R-square are averaged across nine index futures, and their averages are reported in the second and last columns respectively. The sum of the contemporaneous, lag, and lead coefficient estimates ($SUM_G = \beta_1 + \beta_2 + \beta_3$) are also averaged across index futures and its results are reported in the third column. The numbers of index futures, for which β_1/ β_2/ β_3 is positive and significant at 5% and 10% levels, are also presented in the forth and the fifth columns of the table respectively. The results from the quoted spread, the relative spread and the effective spread measures are reported in Panel A, Panel B and Panel C respectively.

Time Periods	Avg. Coeff.	Avg. SUM_G Coeff.	No. of index futures with >0 Coeff. Signif. 5% level	No. of index futures with >0 Coeff. Signif. 10% level	Avg. Adj. R^2
Panel A. Quoted Spread					
Period 1 (2002.10 – 2004.06)	0.2405	0.3058	1	3	0.0076
Period 2 (2004.07 – 2006.06)	-0.0124	-0.1381	2	2	0.0158
Period 3 (2006.07 – 2008.06)	0.2822	0.4954	3	3	0.0282
Period 4 (2008.07 – 2010.06)	0.0543	0.1840	2	2	0.0799
Period 5 (2010.07 – 2012.09)	0.3712	0.3223	4	5	0.0649
Period 1-5 (2002.10 – 2012.09)	0.1973	0.2459	5	6	0.0253
Panel B. Relative Spread					
Period 1 (2002.10 – 2004.06)	0.2422	0.3147	1	2	0.1100
Period 2 (2004.07 – 2006.06)	0.0098	-0.1009	2	2	0.0621
Period 3 (2006.07 – 2008.06)	0.3216	0.6059	3	3	0.1377

Period 4 (2008.07 – 2010.06)	0.1078	0.1125	3	3	0.2309
Period 5 (2010.07 – 2012.09)	0.3957	0.3011	6	6	0.2494
Period 1-5 (2002.10 – 2012.09)	0.2181	0.2395	6	6	0.1457
Panel C. Effective Spread					
Period 1 (2002.10 – 2004.06)	0.1063	0.0410	0	2	0.0241
Period 2 (2004.07 – 2006.06)	0.0136	0.0712	3	3	0.0176
Period 3 (2006.07 – 2008.06)	0.1140	0.2415	3	4	0.0492
Period 4 (2008.07 – 2010.06)	0.1842	0.2704	3	3	0.1086
Period 5 (2010.07 – 2012.09)	0.1566	0.3293	5	7	0.0742
Period 1-5 (2002.10 – 2012.09)	0.1183	0.1982	6	6	0.0373

After confirming an upward trend in the degree of global commonality in liquidity, this dissertation then examines the impact of the Global Financial Crisis (GFC) on global commonality in liquidity by creating three sub-periods as pre-GFC, GFC and post-GFC, and comparing the degree of global commonality between the three sub-periods. GFC represents a global market downturn during which the whole financial markets are affected and tied together. It is likely that the global financial markets are more connected during the GFC. Furthermore, it is also important to understand whether the GFC has strengthened or weakened the global commonality in liquidity.

By comparing results from three GFC periods, the quoted spread measure demonstrates an increase in the degree of commonality, with the strongest commonality occurring in the post-GFC period and the weakest in the pre-GFC (see Table 4-4 Panel A). These results support the previous conclusion that the degree of commonality is increasing through time.

Similar results are found from the relative spread measure as presented in Table 4-4 Panel B, the number of significant index futures at the 5% and the 10% significance level provide evidence for increasing liquidity commonality. Consistent with previous results in Table 4-3, an increasing adjusted R-square is also found across three GFC periods, which further confirms the finding on the evolution of commonality.

Turning to the effective spread, results reported in Table 4-4 Panel C, the GFC period tends to provide the strongest liquidity commonality, while the post-GFC period shows the second strongest liquidity commonality; the reverse is true for quoted spread and relative spread measures.

TABLE 4-4

The Impact of GFC on Global Commonality in Liquidity

The 10-year period is divided into three periods, pre-GFC, GFC and post-GFC, to assess the impacts of the Global Financial Crisis (GFC) on the global commonality in liquidity. The time-series regression is run separately for each index future in each period. The contemporaneous coefficient estimates β_1 and the adjusted R-squares are averaged across nine index futures, and their averages are reported in the second and last columns, respectively. The sum of the contemporaneous, lagged and lead coefficient estimates ($SUM_G = \beta_1 + \beta_2 + \beta_3$) are also averaged across index futures and the results are reported in the third column. The percentage of index futures, for which β_1/ β_2/ β_3 is positive and significant at 5% and 10% levels, are presented in the forth and the fifth columns of the table, respectively. The results from the quoted spread, the relative spread and the effective spread measures are reported in Panel A, Panel B and Panel C, respectively.

Time Periods	Avg. Coeff.	Avg. SUM_G Coeff.	No. of index futures with >0 Coeff. Signif. 5% level	No. of index futures with >0 Coeff. Signif. 10% level	Avg. Adj. R^2
Panel A. Quoted Spread					
Pre-GFC (2004.07 – 2007.07)	0.0909	0.0632	3	3	0.0182
GFC (2007.08 – 2009.07)	0.1311	0.5748	3	4	0.0712
Post-GFC (2009.08 – 2012.06)	0.3098	0.3036	4	5	0.0670
Panel B. Relative Spread					
Pre-GFC (2004.07 – 2007.07)	0.1113	0.0943	3	3	0.0688
GFC (2007.08 – 2009.07)	0.1848	0.4960	4	5	0.2208
Post-GFC (2009.08 – 2012.06)	0.3373	0.2776	6	6	0.2374
Panel C. Effective Spread					
Pre-GFC (2004.07 – 2007.07)	-0.0254	0.0636	2	3	0.0176
GFC (2007.08 – 2009.07)	0.2750	0.4066	5	6	0.0742
Post-GFC (2009.08 – 2012.06)	0.1451	0.3144	4	5	0.0449

4.4.4 Evidence of Regional Commonality in Liquidity

Previous results reveal a strong global commonality among all liquidity measures. This section extends previous findings and examines the liquidity commonality within geographical regions defined by GMT time zones. As addressed in Section 4.2.1, the sample period is reduced to May 2006 -- September 2012, with the aim of including six additional index futures markets. These additional markets have poor data quality for the period prior to 2006 and therefore are only included in the regional commonality analysis, but not in the global commonality analysis which covered a 10-year sample period. The final sample in this section consists of 15 index futures markets.

Markets located in the same or similar GMT time zones are grouped into one geographical region and the commonality in liquidity test is conducted for each region. Regional commonality in liquidity has a number of unique characteristics that may lead to differences relative to the global liquidity commonality. First, the day trading hours of an index futures market overlap with the other markets within the same time zone and the associated seasonality in liquidity may influence the extent of commonality in liquidity. Since markets with similar time zones tend to respond to news simultaneously, the expected regional liquidity commonality may be stronger relative to the global liquidity commonality. Second, markets with similar time zone have closer geographic distances and normally experience stronger linkages in trades and economy relative to the markets with different time zones. For regions with greater free trades agreements and tighter political and economic bonds, a stronger liquidity commonality is expected.

Table 4-5 reports descriptive statistics for the 15 sample markets examined in the analysis of regional liquidity commonality. The statistics are based upon data in the recent six-year period from May 2006 to September 2012. The table reports “Market”, “Exchange”, “Region” defined by MSCI, “Index” name, “Time Zone” defined by the standard Greenwich Mean Time Zone and “Daily Return%”.

Table 4-5 includes 15 index futures markets and covers six regions defined by MSCI which are: (1) Developed Markets: Europe and Middle East, (2) Emerging Markets: Europe, Middle East and Africa, (3) Developed Markets: Americas, (4) Emerging Markets: Americas, (5) Developed Markets: Pacific, and (6) Emerging Markets: Asia. This study includes the following index futures markets: Australia, Canada, Germany, Hong Kong, Hungary, Japan, Norway, the U.K., the U.S., Brazil, France, India, Italy, Singapore and Taiwan, and the corresponding stock indexes are SPI 200, S&P TSX 60, DAX, Hang Seng, BUX, Nikkei 225, OBX, FTSE 100, S&P 500, BOVESPA, CAC 40, Nifty 50, FTSE MIB, MSCI-Singapore and MSCI-Taiwan. The GMT time zone covers areas from GMT-5 to GMT+11 with the U.S. and Canada being the west longitude boundary and Australia being the east longitude boundary. The time zone information is used to divide markets into three regions -- Asia & Pacific, Europe and North & South America. The average daily returns for index futures contracts ranges from -0.0079 for FTSE MIB index future (Italy) to 0.1180 for Nifty 50 index futures (India), with an average of 0.0447 for all 15 markets.

TABLE 4-5

Descriptive Statistics of Index Futures Time Zones

Table 4-5 reports the average daily return over the period May 2006 – September 2012 for 15 index futures in six regions. The first three columns present the name of the market, the name of the major exchange that the index constituent stocks are traded on, and the market classification defined by MSCI[22]. The research covers six MSCI markets which are: (1) Developed Markets: Europe and Middle East, (2) Emerging Markets: Europe, Middle East and Africa, (3) Developed Markets: Americas, (4) Emerging Markets: Americas, (5) Developed Markets: Pacific, and (6) Emerging Markets: Asia. The forth column gives the benchmark stock index for the corresponding exchange listed in column two. The index normally represents a capitalization-weighted measure of a group of stocks with the highest market caps listed on that exchange. Time Zone shows the standard Greenwich Mean Time zone for each market based on the date of January 1, 2017[23]. Daily Return% is the daily percentage return, where the return is measured by the proportional change on the daily close prices.

Market	Exchange	Region	Index	Time Zone	Daily Return%
Australia	Australian S. Ex.	Pacific (D)	SPI 200	GMT + 11:00	0.0057
Canada	Toronto S. Ex.	America (D)	S&P TSX 60	GMT – 05:00	0.0139
Germany	Frankfurt S. Ex.	Europe (D)	DAX	GMT + 01:00	0.0167
Hong Kong	Hong Kong Ex.	Pacific (D)	Hang Seng	GMT + 08:00	0.0611
Hungary	Budapest S. Ex.	Europe (E)	BUX	GMT + 01:00	0.0064
Japan	Osaka Securities	Pacific (D)	Nikkei 225	GMT + 09:00	-0.0130
Norway	Oslo Stock Ex.	Europe (D)	OBX	GMT + 01:00	0.0398
U.K.	London S. Ex.	Europe (D)	FTSE 100	GMT + 00:00	0.0013
U.S.	NYSE	America (D)	S&P 500	GMT - 05:00	0.0176
Brazil	BM&F Bovespa	America (E)	BOVESPA	GMT - 02:00	0.0467
France	Euronext Paris	Europe (D)	CAC 40	GMT + 01:00	-0.0155
India	National S. Ex. of India	Asia (E)	Nifty 50	GMT + 05:30	0.0820
Italy	Borsa Italiana	Europe (D)	FTSE MIB	GMT + 01:00	-0.0400
Singapore	Singapore Ex.	Pacific (D)	MSCI-Singapore	GMT + 08:00	0.0436
Taiwan	Taiwan S. Ex.	Asia (E)	MSCI-Taiwan	GMT + 08:00	0.0177
Average across All Index Futures		All	All		0.0189

22 https://www.msci.com/market-classification

23 https://greenwichmeantime.com/time-zone/

This section extends previous findings by examining liquidity commonality within each time-zone region. The time-series regression in *(4.6)* is estimated on the relative spread measure[24] for each of the 15 markets over a six-year period and results are reported in Table 4-6. The primary variable of interest in the regression is the contemporaneous coefficient of global liquidity, β_1. The lag and lead coefficient estimates of regional liquidity, and the sum of contemporaneous, lag and lead coefficients of regional liquidity, along with the adjusted R-square, are also reported. Table 4-6 presents results from three time-zone regions, which are Asia and Pacific (Panel A) covering Australia, Hong Kong, India, Japan, Singapore and Taiwan, Europe (Panel B) covering Hungary, Germany, Italy, the U.K., Norway and France, and North & South America (Panel C) covering Brazil, Canada and the U.S.. For Asia and Pacific, only Australia and Taiwan exhibit strong commonality in liquidity. The adjusted R-square ranges from 0.0014 for Hang Seng in Hong Kong to 0.4376 for Nikkei 225 in Japan. Three out of six markets (Hong Kong, India and Singapore) have less than 1% adjusted R-square values. On the other hand, the European region demonstrates much stronger commonality in liquidity. All index futures markets present positive and highly significant contemporaneous coefficients. Germany has the largest adjusted R-square at 0.2154, while Italy and France present the second and the third largest adjusted R-square, respectively. Hungary and Norway have the smallest adjusted R-squares, but both values are still greater than 1%. Turning to the North and South America regions, all three markets exhibit strong commonality in liquidity and the adjusted R-square for the U.S. is 36.29%, which is the highest in the region.

[24] The analysis on the quoted spread measure is also conducted and results are reported in Appendix TABLE A-B-4.

TABLE 4-6

Time Zone Commonality with Equally Weighted Liquidity

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{R,t} + \beta_2 \Delta Liquidity_{R,t-1} + \beta_3 \Delta Liquidity_{R,t+1} + \gamma_1 Return_{R,t} + \gamma_2 Return_{R,t-1} + \gamma_3 Return_{R,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.6)$$

The dependent variable is the proportional change in the relative spread of index future *I*. The independent variables are the global return, the proportional change in regional liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the regional liquidity is the average liquidity across all index futures in the region except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. β_1, β_2 *and* β_3 represent contemporaneous, lagged, and lead coefficient estimates respectively. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results on relative spreads for 15 index futures in three regions are presented in this table. The regression is conducted on three different time zones, Asia & Pacific (Panel A), Europe (Panel B) and North & South America (Panel C).

Index Futures	β_1	β_2	β_3	$\beta_1+\beta_2+\beta_3$	Adj. R^2
Panel A. Asia & Pacific					
Australia	0.0439**	0.0185	-0.0207	0.0417	0.0642
Hong Kong	-0.0251	0.0296	0.1150	0.1195	0.0014
India	-0.0080	0.3126*	0.1757	0.4803	0.0045
Japan	0.0046	0.0047	0.0030	0.0123	0.4376
Singapore	0.0214	0.0072	0.0520	0.0806	0.0100
Taiwan	0.0538***	0.0348**	-0.0089	0.0797	0.1198
Panel B. Europe					
Hungary	0.3110***	0.1275**	0.1004*	0.5389	0.0208
Germany	0.2022***	0.0177	0.0347**	0.2546	0.2154
Italy	0.2505***	0.0547**	0.0718***	0.3770	0.1290
U.K.	0.1955***	0.0130	0.0518**	0.2603	0.0740
Norway	0.5523***	0.1820**	0.0873	0.8216	0.0205
France	0.2219***	0.0490**	0.0598***	0.3306	0.0972
Panel C. North & South America					
Brazil	0.2080***	0.0757	0.0379	0.3217	0.0371
Canada	0.1590***	0.0423	0.0412	0.2425	0.0305
U.S.	0.0192***	-0.0035	-0.0009	0.0147	0.3629

4.4.5 Robustness Tests

Previous results reveal a strong global commonality among all liquidity measures and the commonality becomes stronger and more pervasive in recent years. In this section, two analyses have been undertaken to access the robustness of the global commonality in liquidity with nine index futures markets (1) control for expiry effects and (2) principal components weighting.

As discussed earlier, it is likely that index futures markets have different liquidity commonality relative to equity markets due to the maturity cycle in futures markets and the associated seasonality in liquidity. It is important to investigate the impacts of expiration on the co-movements in liquidity for two reasons. First, the expiration effects of futures may have contributed to additional commonality in liquidity. Second, they may have also caused the insignificant commonality results for Australia, Hong Kong, Japan and Norway due to their different expiry dates from the main expiry, "Quarterly Third Friday", of the remaining index futures. To test whether the seasonality effects associated with futures data impact commonality in liquidity, a new expiration dummy variable is incorporated in equation *(4.5)*. The new regression model is as follows:

$$\begin{aligned}\Delta Liquidity_{I,t} = \alpha &+ \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} \\ &+ \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} \\ &+ \beta_8 D_{Expiry} + \varepsilon_{I,t} \qquad (4.7)\end{aligned}$$

The dummy variable, D_{Expiry}, equals to one on days when index future contracts expire or within 3 days to expiration and zero otherwise.

Table 4-7 reports the regression results with expiration dummy variables. The contemporaneous coefficient β_1, the expiry coefficient β_8 and the adjusted R-square are averaged across nine index futures, and their averages are reported in Table 4-7. The sum of the contemporaneous, lagged and lead coefficient estimates (SUMG = β_1 + β_2 +β_3) are also averaged across index futures and the average is reported. Table 4-7 also presents the number of index futures for which β_1 is positive and significant at the 5% level and the number of index futures that have a positive and significant expiry coefficient. Regression results for the nine index futures on the bid-ask spread measures are based on a 10-year sample period, while the result on dollar depth is based on the recent two-year data.

Summarized regression coefficients are presented in Table 4-7. Liquidity commonality remains strong after controlling for the expiration effects, evidenced by six out of nine markets revealing a positive and significant contemporaneous coefficient. Furthermore, the average expiry coefficient is much smaller than the contemporaneous coefficient for each liquidity measure, suggesting that the expiry effects are not as substantial as the commonality effects. Turning to the expiry effects, as measured by β_8, Norway is the only country that provides significant results at the 5% level for the quoted spread, the relative spread and the depth measures. For the effective spread measure, despite the fact that four markets reveal significant expiry effects, six out of nine markets are still presenting significant commonality effects. Therefore, the expiration effects of futures data do not have a significant impact on the global liquidity commonality.[25]

[25] In this study, the associated expiry effects with the index future *I* is considered. However, due to the differences in expiry dates among the remaining 8 index futures, the expiry issues related to the global index futures portfolio are not examined, where the global portfolio is calculated as the average of the remaining index futures' liquidity measure.

Table 4-7

TABLE 4-7

Global Commonality with Expiration Dummy Variable

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \beta_8 D_{Expiry} + \varepsilon_{I,t} \quad (4.7)$$

The dependent variable is the proportional change in the liquidity of index future *I*. Four liquidity measures, quoted spread, relative spread, effective spread and dollar depth, are adopted to conduct the regressions. The independent variables are the global return, the proportional change in global liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the global liquidity is the average liquidity across all index futures except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. $\beta_1, \beta_2\ and\ \beta_3$ represent contemporaneous, lagged, and lead coefficient estimates respectively. The dummy variable, D_{Expiry}, is equals to one on days when index future contracts expire or within three days to expiration, and zero otherwise. The contemporaneous coefficient β_1, the expiry coefficient β_8 and the adjusted R-square are averaged across nine index futures, and their averages are reported in the second, the fifth and the last columns respectively. The sum of the contemporaneous, lagged and lead coefficient estimates ($SUM_G = \beta_1 + \beta_2 + \beta_3$) are also averaged across index futures and the average is reported in the fourth column. We also present the number of index futures for which β_1 is positive and significant at 5% and the number of index futures that have a positive and significant expiry coefficient. Regression results for the nine index futures on bid-ask spread measure are based on a 10-year sample period while the result on dollar depth is based on the recent two-year data.

Liquidity Measures	Avg. β_1 Coeff.	No. of markets with >0 significant β_1 Coeff.	Avg. SUM_G Coeff.	Avg. β_8 Coeff.	No. of markets with >0 significant β_8 Coeff.	Avg. Adj. R^2
Quoted Spread	0.1754	5	0.2170	0.0089	1	0.0256
Relative Spread	0.1942	6	0.2122	0.0081	1	0.1480
Effective Spread	0.1313	6	0.1835	0.0009	4	0.0435
Dollar Depth	0.3602	6	0.5164	0.0180	1	0.1003

The weighting methodology for global market liquidity may lead to a difference in both the degree and the significance of global liquidity commonality. There are various ways the same portfolio of index futures can be weighted in the global liquidity term. In order to test the robustness of previous results, an alternative weighting style is assessed for the global liquidity term. Instead of equally weighted across all index futures, Korajczyk and Sadka (2008) and Hasbrouck and Seppi (2001) introduce a new method, Principle Component Analysis (PCA), to construct the global liquidity term. In this section, the previous regression model in (4.5) is slightly modified by using a different global liquidity portfolio with PCA weightings, rather than equal weightings. For each index future, the cross-sectional average is computed across all index futures' liquidity except the one in question on a daily basis. Then the mean and the standard deviation of the daily data are calculated. Flowing standardizing each of the daily observations by the mean and the standard deviation, the first principle component is extracted across index futures markets. Then the new global liquidity term is constructed using the loadings of the first principle component as the weights of the global liquidity portfolio. A larger PCA loading for a specific market normally represents a more important role in explaining global liquidity variations. Last, the above process is repeated for the calculation of the global return term. The new global terms provide higher weights for the markets that have greater PCA loadings.

As reported in Table 4-8, commonality estimates determined by PCA weighted global portfolios reveal greater and more significant global liquidity commonality. The numbers of markets with positive β_1 coefficients are five, eight, four and five for the quoted spread, the relative spread, the effective spread and the dollar depth measures, respectively, at the 5% significance level. The summary statistics at the 10% significance level provide more pervasive commonality. Furthermore, Table 4-8 reports larger adjusted R-squares compared to previous results reported in Table 4-2, indicating that the global liquidity, constructed from the first principle component, is able to achieve better performance in explaining individual market's liquidity. Hence, the commonality in liquidity is more evident under the PCA weighting structure.

TABLE 4-8

Global Commonality with Global Portfolio Extracted from PCA

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t+1} + \beta_3 \Delta Liquidity_{G,t-1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t+1} + \gamma_3 Return_{G,t-1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.5)$$

The dependent variable is the proportional change in the liquidity of index future *I*. The four liquidity measures are adopted to conduct the regressions. The independent variables are the global return, the proportional change in global liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the global liquidity is represented by the first principal component across all index futures liquidity except for the one in question. The contemporaneous coefficient β_1 and the adjusted R-square are averaged across nine index futures, and their averages are reported in the second and the last column respectively. The sum of the contemporaneous, lagged and lead coefficient estimates ($SUM_G = \beta_1 + \beta_2 + \beta_3$) is also averaged across index futures and the average is reported in the fifth column. The number of index futures is presented for which β_1 is positive and significant at 5% and 10% levels. Regression results for the nine index futures on bid-ask spread measures are based on a 10-year sample period, while the result on dollar depth is based on the recent two-year data.

Liquidity Measures	Avg. β_1 Coeff.	No. of markets with >0 β_1 significant @ 5%	No. of markets with >0 β_1 significant @ 10%	Avg. SUM_G Coeff.	Avg. Adj. R^2
Quoted Spread	0.2814	5	6	0.3813	0.0319
Relative Spread	0.4622	8	8	0.5424	0.1676
Effective Spread	0.1888	4	5	0.2171	0.0273
Dollar Depth	0.4031	5	6	0.6630	0.1079

4.5 Conclusion

This study examines whether individual stock index futures market's liquidity co-moves with global market liquidity. The empirical results reveal strong evidence of global liquidity commonality for index futures markets over a 10-year period. These results are robust to the inclusion of expiration dummy variables and the adoption of different weighting structure for global market liquidity. After confirming the existence of global liquidity commonality for index futures markets, the analysis sought to determine whether the commonality in liquidity had changed through time. The results demonstrate that commonality in liquidity is higher and more pervasive in recent years than that observed in early 2000 for both the quoted spread and the relative spread measures. Further, this study investigates regional liquidity commonality defined by time zones. Regions with greater free trades agreements and tighter political and economic bonds may experience higher levels of liquidity commonality. Results show that regional commonality is not evident in the Asia and Pacific region. However, it is very pervasive and strong in the Europe and the North and South America regions, and the commonality effects, within these two regions, are more widespread than the global commonality.

Chapter 5. The Impact of HFT on Market Liquidity around Macroeconomic Announcements: Evidence from Australian Futures Market

5.1 Introduction

Using the introduction of co-location facilities by the ASX as an exogenous event, this chapter examines the impact of HFT on the price effects associated with trades in the Australian futures market around scheduled macroeconomic announcements. The general findings of the existing literature, discussed in Section 2.4, state that news announcement period represents a very different informational environment relative to normal trading sessions (Ederington & Lee, 1993, 1995: Frino & Hill, 2001; Cai et al., 2001; Andersen & Bollerslev, 1998), and further that HFT improves price efficiency during new information releases in foreign exchange and equity markets (Jiang et al., 2015; Chaboud et al., 2014; Chordia et al. 2016; Brogaard et al., 2014; Frino et al., 2016). However, the impact of co-location on the amount of HFT around macro news in futures markets remains unresolved in the literature. Furthermore, the causal effect of a change in HFT on market liquidity is not tested for futures markets. This chapter addresses these gaps in the literature, and specifically focuses on the futures market and days with information releases.

The outline of this chapter is as follows. Section 5.2 provides an overview of the most actively traded futures contracts in Australia and identifies major Australian macroeconomic announcements. In section 5.3, the research design is outlined. Section 5.4 presents the descriptive statistics on price adjustments and trading activity around news releases. Section 5.5 describes the 2SLS regression results on the causality between HFT and market liquidity, and Section 5.6 presents concluding remarks.

5.2 Institutional Detail

This analysis investigates the three most actively traded interest rate futures contracts in Australia: the 10-year Government Bond, the 3-year Government Bond, and the 90-day Bank Accepted Bills (BABs)[26].

The minimum tick for the BABs (0.01%) and the 10-year Government Bond (0.005%) remains constant during the sample period considered. In relation to the 3-year Government Bond, ASX mandates a minimum tick of 0.01%, except for trading days between the eighth of the expiry month and the settlement date. During the period close to expiration, the minimum tick is reduced to 0.005% for the 3-year Government Bond. The variable minimum tick rule applies to all available contract months, irrespective of expiry. To avoid any confounding

[26] The index future contract, SPI 200, is not included for the co-location analysis due to the coincident introduction of a cost recovery charge on cash market equity message traffic that raised the costs and lowered the benefits of stock index arbitrage.

effects of this regime change, this analysis excludes trading days that are close to expiration and have a minimum tick of 0.005% for the 3-year Government Bond.

5.3 Data

5.3.1 Futures Data

All trading data on interest rate futures are sourced from Thomson Reuters Tick History (TRTH) database. The data obtained from TRTH are transaction & quotation data including: (1) the best bid price, (2) the best ask price, (3) the best bid size, (4) the best ask size, (5) trade price, and (6) volume of trade; and end of day data including: (1) open interest, and (2) trading volume for each contract on each trading day. To select the most active futures contract, the data sample only includes contracts with the highest trading volume for each day. The following filters have been applied to remove outliers in the dataset: days on which less than 10 contracts transacted, and observations with bid-ask spreads smaller than the minimum tick are excluded.

5.3.2 Macroeconomic Announcements Data

This analysis examines HFT behaviour and market quality around macroeconomic announcements over a two-year sample period centred around the introduction of co-location on February 20, 2012. All pre-scheduled macro-economic news announcements are collected from the Australian Bureau of Statistics (ABS). As the normal day trading hours for interest rate futures are from 9:50 a.m. to 4:30 p.m., with a focus on 11:30 am announcements, this analysis is not affected by the pre-market opening and closing phases.

Consistent with Jiang et al. (2015), a 30-minute window is considered around announcement time extending from 15 minutes pre- to 15 minutes post- the release time of 11:30 am. For the case that multiple news releases occur at the same announcement time on the same day, this analysis only selects the one with the highest impact factor[27] across all those that are released simultaneously. There are, in total, 276 macroeconomic releases selected over a two-year sample period.

The first step in the sample selection process is to identify "major" macroeconomic announcements. Following Frino and Hill (2001), this analysis selects the types of announcements with a significant impact on market volatility for all three interest rate futures as "major" announcements[28]. Following McInish and Wood, volatility is calculated as the standard deviation of the quote midpoint during each one-minute interval as follows:

$$QTESD_t = \sqrt{\frac{\sum_{i=1}^{n}(Q_i - \bar{Q})^2 t_i}{\sum_{i=1}^{n} t_i}} \qquad (5.1)$$

Q_i is the last quote midpoint observed on or before *i*; $\bar{Q}$ is the average quote price during interval *t*; t_i is the amount of time Q_i is alive during interval *t*.

[27] The impact factor is a number defined by Bloomberg and attached to each type of macroeconomic announcements. It measures how sensitive the market is to each type of announcements.

[28] The approach adopted to determine the major announcements is different between Chapter 3 and Chapter 5. Chapter 5 is focused on collecting the types of macro releases that are important to the interest rate futures market and hence the dummy variable approach is more suitable. While on the other hand, Chapter 3 aims to select all announcement days that have pronounced price movements, and hence comparing the pre- and the post-announcement returns is a more suitable approach.

The following regression, similar to the methodology used by Fleming and Remolona (1997), is estimated to determine "major" announcements:

$$QTESD_t = a_{0j} + \sum_{k=1}^{K} a_k D_{kt} + e_t \qquad (5.2)$$

where $QTESD_{jt}$ is the price volatility during the one-minute interval following announcements on day t. D_{kt} is a dummy variable that is equal to 1 if announcement k is made on day t and 0 otherwise. A positive and significant a_{kj} coefficient would indicate announcement type k has a significant impact on market volatility. On the other hand, a zero/insignificant a_{kj} coefficient indicates announcement k has little influence on market volatility.

The regression model is estimated on 276 announcement days for each interest rate futures. Regression coefficient estimates are reported in Table 5-1. The table reports the type of macro announcements, the a_{kj}coefficients on the BABs, the 3-year Government Bond and the 10-year Government Bond respectively, and the frequency of announcement releases. As reported in Table 5-1, 9 of 20 sources of news releases reveal significant a_{kj} coefficients for the BABs, at either 5% or the 1% statistical level. The average impact of significant announcements is 0.0066. Turning to the 3-year Government Bond, results are consistent with the BABs, except announcements of BoP Current Account Balance are not eventful. The average a_{kj} coefficient of significant announcements is 0.0081 for the 3-year Government Bond. In terms of the 10-year Government Bond, further to the 9 news announcements identified for BABs, the release of the NAB Business Confidence index is eventful, 10% significance level. The average impact of significant announcements is 0.0034 for the 10-year Government Bond, which is much larger compared to 0.0001, the average impact of news that are not significant. This analysis selects announcements that are significant at the 5% level for all three interest rate futures as the “major” releases. On this basis, the selected eight types of announcements are: Private Capital Expenditure, Consumer Price Index, Gross Domestic Product, Producer Price Index, Retail Sales, Building Approvals, Trade Balance and Unemployment Rate, and spans over 94 days.

Overall, the selected announcements reported in Table 5-1 are similar to those identified in extant literature.

TABLE 5-1

The Impact of Macro Announcements on Interest Rate Futures

This table presents regression analysis of the impact of macro-economic announcements on the volatility of three interest rate futures contracts. The following regression model is estimated:

$$QTESD_{jt} = a_{0j} + \sum_{k=1}^{K} a_{kj} D_{kt} + e_{jt} \tag{5.2}$$

where $QTESD_{jt}$ is the volatility proxy for each announcement day; D_{kt} is the dummy variable that equals 1 if announcement k is released on day t and zero otherwise. The a_{kj} coefficients are reported for the 90-day BABs, the 3-year government bond and the 10-year government bond in the second, third and fourth columns respectively. * indicates a_{kj} significant at 10%, ** indicates a_{kj} significant at 5% and *** indicates a_{kj} significant at the 1% level. The announcement type is reported in the first column while the frequency of releases is reported in the last.

Announcement	***BABs***	***3-Y Bond***	***10-Y Bond***	***Frequency***
Job vacancies	-0.0005	-0.0004	-0.0001	Quarterly
House Price Index	0.0016	-0.0006	0.0005	Quarterly
Dwelling Starts	0.0006	0.0003	0.0001	Quarterly
Average Weekly Wages	-0.0014	-0.0006	-0.0002	Quarterly
BoP Current Account Balance	0.0025**	0.0012	0.0010**	Quarterly
Private Capital Expenditure	0.0032***	0.0044***	0.0024***	Quarterly
Consumer Price Index	0.0161***	0.0189***	0.0078***	Quarterly
Company Operating Profit	-0.0004	-0.0003	0.0008	Quarterly
Gross Domestic Product	0.0067***	0.0092***	0.0053***	Quarterly
Import price index	-0.0007	-0.0009	-0.0003	Quarterly
Producer Price Index	0.0050***	0.0051***	0.0032***	Quarterly
Retail Sales	0.0083***	0.0054***	0.0039***	Monthly
ANZ Job Advertisements	0.0002	0.0000	0.0000	Monthly
NAB Business Confidence	0.0006	0.0006	0.0005*	Monthly
Private Sector Credit	0.0001	0.0009	0.0004	Monthly
Home Loans	0.0005	0.0006	0.0007***	Monthly
Building Approvals	0.0034***	0.0047***	0.0030***	Monthly
Trade Balance	0.0012**	0.0013**	0.0010***	Monthly
Unemployment Rate	0.0134***	0.0157***	0.0086***	Monthly
New Motor Vehicle Sales	-0.0005	-0.0009	-0.0003	Monthly

5.4 Research Design

This section presents the research design used to test the hypotheses developed in this chapter. First, HFT proxies and market quality metrics are defined. The section then describes the 2 Stage Least Square (2SLS) regression model employed to evaluate the causality between the intensity of HFT and market quality around macro-economic announcements, with the introduction of co-location facilities as the instrumental variable.

5.4.1 High Frequency Trading Proxies

The SEC document lists several characteristics commonly attributed to HFT including:

> *(1) the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders; (2) the use of co-location services and individual data feeds offered by exchanges and others to minimize network and other types of latencies; (3) very short time-frames for establishing and liquidating positions; (4) the numerous orders that are cancelled shortly after submission; and (5) ending the trading day as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night)*[29].

During the sample period February 20, 2011 – February 20, 2013, the Australian futures market experienced significant improvements in the speed of trading and dramatic growth in HFT, stimulated by the introduction of co-location facilities on February 20, 2012. As HFTs

[29] See Page 4 https://www.sec.gov/marketstructure/research/hft_lit_review_march_2014.pdf

cannot be explicitly identified in the Australian futures data which remains an anonymous market, this analysis employs three proxies to measure HFT, consistent with Hendershott, Jones and Menkveld (2011). The HFT proxies are then used to quantify the change in the extent of HFT in the Australian interest rate futures market.

5.4.1.1 Message Traffic

Message traffic includes new order submissions, modifications and cancellations. This analysis sources the market depth data from TRTH to aggregate such information. In this analysis, message traffic is defined as the sum of changes in the order book for each minute interval. The larger the message traffic is; the more active the high frequency traders are.

$$Message\ Traffic_{it} = \ The\ Number\ of\ Records\ on\ Market\ Depth_{it} \quad (5.3)$$

5.4.1.2 Order-to-Trade Ratio

As documented in Hasbrouck and Saar (2010), high frequency activity is normally associated with rapid order submissions, cancellations and modifications. For a market with active HFT, orders could be transacted and amended at a higher frequency; meanwhile, the resting time of orders on the book could also be significantly reduced. Order-to-trade ratio measures the rate of converting order-book updates to actual transactions. A higher order-to-trade ratio suggests a greater presence of HFT. The following formula calculates the order-to-trade ratio for each index future *i* at each minute interval *t*:

$$OrdertoTrade_{it} = \frac{Message\ Traffic_{it}}{Total\ Number\ of\ Transactions_{it}} \qquad (5.4)$$

5.4.1.3 Algo_Trade

Computer algorithms are able to process large amounts of information and respond faster than humans. For the same size of trading volume, algorithms can trade more frequently at a higher speed and smaller value per trade. Consistent with Hendershott et al. (2011), this analysis normalizes message traffic by trading volume and computes Algo_Trade for each interest rate future *i* at each minute interval *t*. Specifically, Algo_Trade is the negative of the dollar trading volume associated with each order-book update at each test interval. The new HFT proxy, Algo_Trade, is calculated as follows:

$$Algo\_Trade_{it} = \frac{-Dollar\ Turnover_{it}/100}{Message\ Traffic_{it}} \qquad (5.5)$$

where $Message\ Traffic_{it}$ measures the number of order-book updates at each minute interval *t* for each interest rate future *i*; and $Dollar\ Turnover_{it}$ is the Australian dollar trading volume at each minute interval *t* for each interest rate future *i*. As HFT increases in the market, Algo_Trade also increases given the dollar trading volume remains relatively stable.

This section defines the market quality metrics used in this chapter. To measure liquidity, this analysis uses time weighted quoted spread (TWQS), time weighted relative spread (TWRS), time weighted dollar depth (TWDD), and effective spread at each minute interval from 15 minutes before to 15 minutes after announcements. Further trading volume, volatility and the number of trades for the pre- and the post- announcement periods are also measured. Volatility is proxied by the difference between the highest and the lowest price for each future contract at each minute interval (Parkinson, 1980), where price is defined as the midpoint of the best bid and ask for each quote update. Midpoints of the best quotes, rather than trade prices, are adopted for the calculation of volatility as they mitigate complications associated with the "bid-ask bounce".

$$Volatility_{it} = \ln(\frac{High_{it}}{Low_{it}}) \tag{5.6}$$

5.4.2 Liquidity Variables

5.4.2.1 Quoted Bid-Ask Spread

The quoted bid-ask spread is computed for every quote as[30]

$$Quoted\_BAS = Best\_Askprice - Best\_Bidprice \tag{5.7}$$

Suppose that at interval (T_0, T), there are N quote updates, occurring at times t_i, i= 1, 2, …, N, where $t_0 = T_0$ and $t_{n+1} = T$. BAS_0 is based on the quote that is outstanding at time T_0, which is the quote outstanding at the beginning of each minute interval. For each minute interval, the time weighted spread is computed as:

$$TWQS = \sum_{n=0}^{N} \left(\frac{Quoted\_BAS_i(t_{i+1} - t_i)}{T - T_0}\right) \tag{5.8}$$

[30] Unlike liquidity measures employed in Chapter 4 where analysis is conducted at the daily level, Chapter 5 requires intraday liquidity proxies to capture liquidity variations at the minute level. Therefore, liquidity variables are calculated based on all quote updates in the order book and then consolidated at minute intervals.

5.4.2.2 Relative Bid-Ask Spread

The relative bid-ask spread is defined as

$$Relative\_BAS = \frac{Best\_Askprice\ -\ Best\_Bidprice}{(Best\_Askprice\ +\ Best\_Bidprice)/2} \tag{5.9}$$

Similarly, the time weighted relative bid-ask spread for each minute interval is defined as follows:

$$TWRS = \sum_{n=0}^{N} \left(\frac{Relative\_BAS_i(t_{i+1} - t_i)}{T - T_0} \right) \tag{5.10}$$

5.4.2.3 Dollar Depth

The level 1 dollar depth is computed for every quote as:

$$\begin{aligned} &Dollar\_Depth \\ &= (\text{Best\_AskSize} * Best\_Askprice\ + \text{Best\_BidSize} * Best\_Bidprice)/2 \end{aligned} \tag{5.11}$$

Similarly, the time weighted dollar depth for each minute interval is defined as:

$$TWDD = \sum_{n=0}^{N} \left(\frac{Dollar\_Depth_i(t_{i+1} - t_i)}{T - T_0} \right) \tag{5.12}$$

5.4.2.4 Effective Spread

Consistent with Chapter 4, Section 4.2.2, the effective spread of a trade is measured as:

$$Effective\ Spread = 100 * \mathrm{D} * Ln\ (\mathrm{VWAP}/\ MQBefore) \qquad (5.13)$$

where $MQBefore$ is the prevailing mid-quote at the time of the trade, and VWAP is the volume weighted trade price. To account for instances where large orders are executed against multiple standing limit orders at different price levels, consecutive trades with the same direction and occurring within the same millisecond are packaged together. If a quote update is observed within the same millisecond, then a new trade package is initialized. The size of the order is given by the sum of all transaction records in the package; while the price is determined as the volume weighted average price of packaged trades. Consistent with Berkman, Brailsford and Frino (2005), prices were also sampled in calendar time, rather than transaction time as in Holthausen, Leftwich and Mayers (1990). D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. Consistent with the extant literature, Lee and Ready's (1991) method was applied to partition transactions into buyer or seller initiated trades.

5.4.3 Two-Stage Least Squares Regression

Chapter 4 adopts an ordinary least squares (OLS) model which assumes that errors in the dependent variable are not correlated with independent variables. However, the relationships tested in Chapter 5 are bidirectional between dependent and independent variables, i.e. HFT proxies and liquidity variables could be endogenously determined. In such case, an OLS model no longer provides optimal estimates, and a two-stage least-squares (2SLS) regression is required to establish the causality between dependent and independent variables. The first stage regression uses an instrumental variable, the introduction of co-location, to compute estimated values of HFT activity. The co-location service reduces the response time between HFT and the exchange. It thus enables HFT to react faster to information releases, but it does not have any other direct impact on market liquidity, which fulfils the conditions of being an instrument variable. The second stage then uses those predicted HFT values to estimate a linear regression model of the market liquidity variables (dependent variables). Given that the predicted HFT activity is resulted from co-location facilities that are uncorrelated with the errors, the results of the 2SLS are optimal.

This section outlines the 2SLS regression analysis used to examine the two hypotheses tested in this chapter. The first hypothesis states that the introduction of co-location facilities by an exchange leads to significantly greater trading activity by high frequency traders. On February 20, 2012, the Australian Securities Exchange (ASX) allowed market participants to co-locate their computer servers in the same room as the exchange server where the trading system operates. This analysis focuses on HFT around macro news releases and defines the 15-minute interval prior to the announcement as the pre-announcement period and the 15-minute interval following the announcement as the post-announcement period. Following Hendershott, Jones and Menkveld (2011), the first stage regression in (5.14) is estimated for each interest rate future contract *i* during the pre and the post announcement periods on each announcement day:

$$HFT_{it} = \alpha_i + \beta * colo_{it} + \delta_1 * volatility_{it} + \delta_2 * |surprise|_{it} + \delta_3 * bad\_news_{it} + \delta_4 * post\_news_{it} + \sum_t \rho_t * interval_t + \varepsilon_{it} \qquad (5.14)$$

where α_i measures the fixed effect for each interest rate future i; HFT_{it} refers to high frequency trading proxies (Message_Traffic, Order-to-Trade and Algo_Trade); $colo_{it}$ is a dummy variable that takes the value of 1 for the period after the introduction of co-location on February 20, 2012 and 0 for the period prior to the co-location; $volatility_{it}$ measures price movements at each minute interval; $post\_news_{it}$ is a dummy variable that equals to 1 if the interval is in the post announcement period, i.e. the 15 minutes following announcements, and 0 if it's in the pre announcement period, i.e. the 15 minutes prior to announcements; $interval_t$ is a series of dummy variables that measure the fixed effects associated with each minute interval t. For intervals far away from the announcement time of 11.30 am, no abnormal trading activity is observed (see Appendix A-C-1, 2 & 3). The study focuses on isolating the immediate effects associated with news releases; therefore, interval dummy variables are only included for intervals that are within 5 minutes to the release time. The dummy variable takes the value of 1 if the interval equals to t and 0 otherwise, where $t \in [-5,5]$. Following Chordia et al (2015) and Balduzzi et al (2001), this analysis computes post-announcement returns as the percentage mid-quote change from the release time to the 5-minute following announcements. $|surprise|_d$ is defined as the absolute post-announcement returns on each news day; bad_news_{it} is a dummy variable that takes the value of 1 if the post-announcement return is negative and 0 otherwise.

The primary variable of interest is β as it captures the impact of co-location facilities on HFT. A positive and significant β indicates the introduction of co-location has significantly lifted the level of HFT activity in the interest rate futures market around macro-economic announcements. This research design enables examinations of the first hypothesis ($H5_1$), which tests whether technological upgrades at ASX leads to an increase in HFT surrounding information releases.

$$H5_{1Null}: Colocation\ reduces\ HFT\ in\ the\ market, i, e, \beta < 0;\ or\ colocation\ has\ no\ impcat\ on\ HFT, i.e. \beta = 0$$

$$H5_{1Alt}: Colocation\ increases\ HFT\ in\ the\ market, i, e, \beta > 0$$

The second objective of this chapter is to understand the impact of an elevated level of HFT on market liquidity and other market quality metrics surrounding information releases. Following Hendershott, Jones and Menkveld (2011), the second stage regression in (5.15) examines the causal relation between HFT and market quality by employing an exogenous instrument, the co-location dummy variable. A good instrument needs to fulfil two conditions: firstly, the instrument is not correlated to market quality metrics, and secondly, the instrument is highly correlated with HFT proxies. The introduction of co-location facilities satisfies these two conditions and provides a natural experiment to evaluate the amount of market liquidity affected by the heightened level of HFT due to a latency reduction.

$$MQ_{it} = \alpha_i + \beta * \widehat{HFT_{it}} + \delta_1 * volatility_{it} + \delta_2 * |surprise|_{it} + \delta_3 * bad\_news_{it} + \delta_4 * post\_news_{it} + \sum_t \rho_t * interval_t + \varepsilon_{it} \quad (5.15)$$

where MQ_{it}refers to both liquidity and non-liquidity market quality measures computed for each interest rate future *i* at each minute interval *t*; liquidity is proxied by quoted spread, relative spread, level 1 dollar depth and effective spread and other market quality measures including volume and trade frequency; $\widehat{HFT_{it}}$ is the predicted message traffic from (5.14) for each interest rate future *i* at each minute interval *t*; all other independent variables are the same as those defined in (5.14). Consistent with the extant literature that examines market liquidity around news releases, this analysis controls for volatility, announcement surprise, announcement classification, the pre- and the post- announcements and seasonal patterns associated with minute intervals that are within 5 minutes to the release time. As documented in Chaboud, Wright and Chernenko (2008), scheduled macroeconomic announcements are associated with spikes in trading volumes that tend to occur even though the announcements are in line with market expectations. Therefore, this analysis includes all major announcements days in the sample, rather than just the days with announcement shocks.

The principal objective is a significant β as it captures the impact of increased level of HFT on market quality around information releases. A positive and significant β for dollar depth indicates that the increased level of HFT improves market depth at the first level. Meanwhile, a negative and significant β for bid-ask spread measures indicates that the elevated level of HFT improves market liquidity by reducing bid-ask spreads. This research design enables examinations of the second hypothesis ($H5_2$), which examines the impact of HFTs on market liquidity surrounding macro news releases.

$$H5_{2Null}: HFT\ has\ no\ impact\ on\ market\ liquidity, i.e. \beta = 0; or\ HFT\ reduces\ market\ liquidity, i.e. \beta < 0\ for\ depth\ measure\ and\ \beta > 0\ for\ spread\ measures$$

$$H5_{2Alt}: HFT\ improves\ market\ liquidity, i.e. \beta > 0\ for\ depth\ measure\ and\ \beta < 0\ for\ spread\ measures$$

5.5 Empirical Results

5.5.1 Descriptive Statistics

In this section, descriptive statistics are presented for the three interest rate futures contracts. The statistics are based upon data in the two-year period from February 20, 2011 to February

19, 2013, coinciding with a 24-month event window centred on the introduction of co-location facilities in the Australian futures market. This analysis primarily focuses on time intervals surrounding macro-economic announcements; therefore all statistics are calculated based on the 30-minute interval surrounding announcements, with a 15-minute pre- and a 15-minute post- event window. The analysis splits the sample into two periods by the co-location date as the pre- and the post- co-location periods, and computes summary statistics for each future contract for each co-location period. Several market quality metrics are computed and compared between the pre and the post co-location periods. Table 5-2 reports the average trading volume, number of trades, volatility, natural log of level 1 dollar depth, quoted bid-ask spread, relative bid-ask spread and effective bid-ask spread for each minute interval in the pre and the post co-location periods. The table also reports the mean difference between the two co-location groups, as well as the t-statistics for the null hypothesis that the mean values between the two groups are the same.

Table 5-2 reports volume and number of trades increased significantly for 10-year Government Bonds following the introduction of co-location, and no change is observed in 3-year Government Bonds. A significant reduction in trade volume is observed following co-location for BABs. Volatility remains unchanged for all three futures contracts. Turning to liquidity measures, dollar depth improves significantly, across all three futures contracts, following the introduction of co-location. Consistent results are presented for all spread measures, as evidenced by a significant reduction on the relative spread and the effective spread for all three futures contracts, and a significant reduction on the quoted spread for two futures contracts (the 10-year Government Bond and the BABs).

In summary, descriptive statistics reported in Table 5-2 provide preliminary evidence that liquidity improves following the introduction of co-location for interest rate futures contracts on news announcement dates.

TABLE 5-2

Descriptive Statistics of Index Futures Liquidity and Trading Intensity

This table documents summary statistics of liquidity variables and other market quality metrics over the period 12 months before and 12 months after the implementation of co-location on the ASX. This table reports the average trading volume, number of trades, volatility, natural log of level 1 dollar depth, quoted bid-ask spread, relative bid-ask spread and effective bid-ask spread for each minute interval for the pre and post co-location periods. The mean difference between the pre and post groups is computed and reported in the "Difference" column. T-Statistics are reported next to the "Difference" for the null hypothesis that the values between the pre and post groups are the same. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level. Panel A presents statistics for the 10-year Government Bond, Panel B presents results for the 3-year Government Bond and Panel C presents results for the 90-Day Bank Accepted Bills.

	Volume	No. of Trades	Volatility	Dollar Depth L1 (LN)	Quoted Spread	Relative Spread	Effective Spread
Panel A. 10-year Government Bond							
Pre	87.7834	5.4302	0.0037	9.3596	0.0053	0.0028	0.0027
Post	107.400	6.7825	0.0036	9.5345	0.0052	0.0027	0.0026
Difference	19.5998	1.3523	-0.0001	0.1749	-0.0001	-0.0001	-0.0001
t-stat	3.79***	4.78***	-0.73	6.59***	-4.88***	-7.46***	-5.81***
Panel B. 3-year Government Bond							
Pre	597.4	6.4929	0.0048	11.6231	0.0101	0.0053	0.0052
Post	652.5	7.2752	0.0047	11.8458	0.0101	0.0052	0.0051
Difference	55.0285	0.7823	-0.0001	0.2227	-0.0000	-0.0001	-0.0001
t-stat	1.11	1.56	-0.18	8.18***	-1.62	-7.37***	-7.16***
Panel C. 90-day Bank Accepted Bill							
Pre	148.0	1.5828	0.0036	11.0585	0.0110	0.0057	0.0056
Post	114.0	1.5600	0.0031	11.1495	0.0103	0.0053	0.0053
Difference	-34.007	-0.0228	-0.0005	0.0910	-0.0007	-0.0004	-0.0003
t-stat	-2.64***	0.17	1.44	2.59***	-6.03***	-7.23***	-3.29***

5.5.2 The Impact of Co-location on High Frequency Trading

This section assesses the causal impact of co-location on HFT. Specifically, this section estimates equation (5.14) for each HFT proxy to evaluate hypothesis $H5_1$. Table 5-3 reports coefficient estimates for message traffic (Panel A), order-to-trade ratio (Panel B) and normalized message traffic by trading volume (Panel C).

As reported in Table 5-3, the introduction of co-location stimulates HFT activity for all three futures contracts, as evidenced by a positive and significant coefficient on the co-location dummy variable. This finding is consistent across all three HFT proxies. Message traffic, as reported in Table 5-3 Panel A, presents the largest adjusted R^2 among all proxies, and therefore is adopted for the second stage regression[31]. For intervals far away from the announcement time of 11.30 am, no abnormal trading activity is observed (see Appendix A-C-1, 2 & 3). One of the primary focuses of this study is to evaluate changes in HFT and market quality surrounding news releases; therefore, dummy variables are included for intervals that are within 5 minutes to 11.30 am. Results on interval coefficients are reported for the message traffic proxy in Table 5-3 Panel A. HFT activity surges starting from two minutes before releases (T-2) and remain elevated for eight minutes. Turning to announcement surprise, HFT is positively correlated with the degree of a surprise, i.e. the higher the announcement surprise, the greater the presence of HFT; however, this may attribute to the higher trading volume associated with the announcement surprise. The negative coefficients on $|surprise|_{it}$ as reported in Table 5-3 Panel B confirms the proposed inference.

[31] The second stage regressions provide qualitatively similar results when the other two HFT proxies are used, but results are less significant compared to the message traffic proxy.

Table 5-N

TABLE 5-3

The Impact of Co-Location on High Frequency Trading

This table reports regression results on the impact of co-location on HFT for news release days. This analysis only focuses on the 30-minute window around macro news releases and defines the 15-minute interval prior to the announcement as the pre-announcement period and the 15-minute interval following the announcement as the post-announcement period. The following regression model is estimated for the pre and post announcement periods:

$$HFT_{it} = \alpha_i + \beta * colo_{it} + \delta_1 * volatility_{it} + \delta_2 * |surprise|_{it} + \delta_3 * bad\_news_{it} + \delta_4 * post\_news_{it} + \sum_t \rho_t * interval_t + \varepsilon_{it} \quad (5.14)$$

HFT_{it} is the high frequency trading proxies, which are Message_Traffic (Panel A), Order-to-Trade (Panel B) and Algo_Trade (Panel C); $colo_{it}$ is a dummy variable that takes the value of 1 for the period after the introduction of co-location on February 20, 2012 and 0 otherwise; $volatility_{it}$ measures the price movements within each minute interval; $|surprise|_d$ is defined as the absolute post announcement return for each news release day; bad_news_{it} is a dummy variable that takes the value of 1 for bad announcements and 0 otherwise; $post\_news_{it}$ is a dummy variable that equals to 1 if the interval is in the post announcement period, i.e. the 15 minutes following announcements, and 0 otherwise; $interval_t$is a series of dummy variables that measure the fixed effects associated with each minute interval *t*. The study focuses on isolating the immediate effects associated with news releases; therefore, interval dummy variables are only included for intervals that are within 5 minutes to the release time. The dummy variable takes the value of 1 if the interval equals to t and 0 otherwise, where $t \in [-5,5]$.[32] The event window extends 1 year pre to 1 year post the co-location date. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level. The regression is conducted on 10-year government bonds, 3-year government bonds and 90-day Bank Accepted Bills.

	10-year Government Bonds	3-year Government Bonds	90-day Bank Accepted Bills
Panel A. Ln(Message_Traffic)			
Co-location	0.5628***	0.6603***	0.3604***
Volatility	86.0048***	37.878***	42.143***
|Surprise|	0.0667	0.2927**	-0.1211
Bad_News	-0.0267	-0.1799***	0.0340
Post_News	0.4590***	0.4016***	0.3047*
Interval -5	0.1112	0.0730	0.2769*

[32] The interval effects are similar among different HFT measures with the Message Traffic measure provides the most significant results, and hence the interval effects are only reported for Panel A.

Interval -4	-0.0539	0.0484	0.3092*
Interval -3	0.0824	0.1488	0.3007*
Interval -2	0.5231***	0.6114***	0.6487***
Interval -1	0.1501	0.5643***	0.6918***
Interval 0	-0.2211*	0.6112***	1.0993***
Interval 1	0.6628***	1.2021***	1.0251***
Interval 2	0.3437***	0.8227***	0.5356***
Interval 3	0.6991***	0.9223***	0.7547***
Interval 4	0.5150***	0.8591***	0.5250***
Interval 5	0.3800***	0.6343***	0.3934**
Adjusted-R^2	0.4556	0.4903	0.2836
<u>Panel B. Order-to-Trade Ratio</u>			
Co-location	4.9547***	7.2711***	3.6621***
Volatility	-233.03***	-202.66***	-59.740**
|Surprise|	-3.9137*	-2.6163	-4.0279*
Bad_News	-0.1000	0.5004	0.6188
Post_News	1.8351	4.1168	1.4549
Adjusted-R^2	0.0474	0.1231	0.0532
<u>Panel C. Algo_Trade</u>			
Co-location	0.0058***	0.0349***	0.0304***
Volatility	-0.4927***	-2.1740***	-1.5351***
|Surprise|	-0.0002	0.0304*	-0.0287
Bad_News	-0.0011	-0.0142***	0.0149*
Post_News	0.0036	-0.0046	0.0239
Adjusted-R^2	0.0259	0.0600	0.0124

5.5.3 The Impact of High Frequency Trading on Market Liquidity

After identifying a strong positive correlation between HFT and co-location, this section examines the impact of a heightened level HFT on market liquidity for both the pre- and the post- announcement periods[33]. Further this section determines the directional causality between HFT and market liquidity using co-location as an instrumental variable.

Table 5-4 presents coefficient estimates of equation (5.15) and reveals a positive correlation between HFT and dollar depth, and a negative correlation between HFT and measures of bid-ask spreads. Table 5-4 Panel A reports that dollar depth is positively correlated with HFT for all three futures contracts. The correlation is strongly significant for the 10-year and the 3-year Government Bonds. Announcement |Surprise| is also negatively correlated with market depth, which indicates that the higher the surprise is, the thinner the market depth is. Turning to the characteristics of news, market depth increases when negative news is announced in the market. Mixed results are found on the post news dummy variable[34]. Table 5-4 Panel A identifies a significant reduction in market depth when examining minute intervals surrounding information releases. This finding suggests that market participants reduce positions in the order book when scheduled information approaches to prevent unintentional executions in the case of an announcement shock. The market depth remains relatively low for intervals post 11.31 a.m.

Table 5-4 Panel B summarises regression results on the relative spread. A significant reduction on the relative spread is observed following a heighted level of HFT for all three

[33] The impact of HFT on market quality, measured by trading volumes and the number of trades, are present in Appendix C.

[34] Please note that regressions (5.14 & 5.15) are conducted on minute intervals from T-15 to T+15 and interval dummies are only included for minutes from T-5 to T+5. Therefore, an adoption of a post news dummy variable for the whole event window (T-15 to T+15) will not cause multicollinearity in the regressions.

futures contracts. Table 5-4 Panel B reveals similar results with Table 5-4 Panel A for coefficient on volatility, announcement surprise and characteristics of news. Turning to results for interval coefficients, the relative spread reports a liquidity shortage starting from 4-minutes prior to information releases. However, this order book movement is less significant than that observed for market depth; meanwhile, the relative spread tends to reduce following the withdrawal of market depth.

Results on the quoted spread and the effective spread are similar with those reported on the relative spread, but with a lower degree of significance. Therefore, the interval coefficients are not presented for the other two spread measures in Table 5-4. In aggregate, results reported in Table 5-4 confirm that the increased level of HFT, resulted from co-location, causes an improvement in liquidity as measured by both bid–ask spreads and depth, for the period around macroeconomic announcements. Focusing on intervals immediately surrounding news releases, liquidity reduces during the period from T-5 to T_0 and from T+1 to T+5.

Table 5-O

TABLE 5-4

The Impact of High Frequency Trading on Market Liquidity

This table reports results on the two-stage-least-squares (2SLS) regression analysis which examines the impact of HFT on market liquidity on news release days. The first stage regression model (5.14) is documented in Table 5-2 and the second stage regression is estimated as follows:

$$MQ_{it} = \alpha_i + \beta * \widehat{HFT}_{it} + \delta_1 * volatility_{it} + \delta_2 * |surprise|_{it} + \delta_3 * bad\_news_{it} + \delta_4 * post\_news_{it} + \sum_t \rho_t * interval_t + \varepsilon_{it} \tag{5.15}$$

where MQ_{it} refers to liquidity measures computed for each interest rate future i on each minute interval t; liquidity is proxied by level 1 dollar depth (Panel A), relative spread (Panel B), quoted spread (Panel C), and effective spread (Panel D); $\widehat{HFT}_{it}$ is the predicted message traffic from (5.14) for each interest rate future i on each minute interval t; $volatility_{it}$ measures the price movements within each minute interval; $|surprise|_d$ is defined as the absolute post announcement return for each news release day; bad_news_{it} is a dummy variable that takes the value of 1 if it's a bad announcement and 0 otherwise; $post\_news_{it}$ is a dummy variable that equals to 1 if the interval is in the post announcement period, i.e. the 15 minutes following announcements, and 0 otherwise; $interval_t$is a series of dummy variables that measure the fixed effects associated with each minute interval t. The study focuses on isolating the immediate effects associated with news releases; therefore, dummy variables are only included for intervals that are within 5 minutes to the release time. The dummy variable takes the value of 1 if the interval equals to t and 0 otherwise, where $t \in [-5,5]$[35]. The event window extends 1 year pre to 1 year post the co-location date. T-Statistics are in parentheses for the null hypothesis that the values between Pre and Post are the same. * indicates significant at 10%, ** indicates significant at 5% and *** indicates significant at 1% level. The last three columns present statistics for the 10-year Government Bond, the 3-year Government Bond and the 90-Day Bank Accepted Bill respectively.

	10-year Government Bonds	3-year Government Bonds	90-day Bank Accepted Bills
Panel A. Log (Dollar Depth)			
Log_MSG	0.2536***	0.2741***	0.0032
Volatility	-65.430***	-27.490	-25.651***
|Surprise|	-0.9325***	-1.6192	-1.2659***
Bad_News	0.1745***	0.1758	0.0700**
Post_News	-0.1773*	0.0521	0.0839

[35] The interval effects are similar among different spread measures, and hence the interval results are only reported for the depth and the relative spread measures. For intervals far away from the announcement time of 11.30 am, no abnormal trading activity is observed (see Appendix A-C-1, 2 & 3), therefore the regression (5.15) only includes interval dummies that are within 5 minutes to 11.30 am.

Interval -5	-0.3682***	-0.4194***	-0.1101
Interval -4	-0.4062***	-0.4724***	-0.1740
Interval -3	-0.4689***	-0.6713***	-0.2488**
Interval -2	-0.7065***	-1.0228***	-0.3770***
Interval -1	-0.9125***	-1.3752***	-0.6357***
Interval 0	0.0107	-0.2905*	0.0100
Interval 1	-0.4757***	-0.5877***	-0.2721*
Interval 2	-0.2826***	-0.4591***	-0.2644**
Interval 3	-0.2983***	-0.4419***	-0.1562
Interval 4	-0.1526	-0.3849***	-0.1339
Interval 5	-0.1532	-0.3339**	-0.1121
Adjusted-R^2	0.2349	0.3166	0.1547
__Panel B. Relative Spread__			
Log_MSG	-0.0002***	-0.0002***	-0.0007***
Volatility	0.0418***	0.0184***	0.0758***
|Surprise|	0.0002***	0.0002***	0.0017***
Bad_News	-0.0001***	-0.0000**	-0.0001**
Post_News	0.0001	0.0000	0.4980
Interval -5	0.0001*	0.0000	0.0002
Interval -4	0.0001**	0.0000	0.0005*
Interval -3	0.0002***	0.0001	0.0004*
Interval -2	0.0004***	0.0001**	0.0006**
Interval -1	0.0006***	0.0007***	0.0014***
Interval 0	-0.0000	-0.0000	0.0010***
Interval 1	0.0002***	0.0001**	0.0009***
Interval 2	0.0001	0.0001*	0.0009***
Interval 3	0.0001**	0.0001**	0.0005*
Interval 4	0.0001*	0.0001*	0.0002

Interval 5	0.0001	0.0001	0.0003
Adjusted-R^2	0.2003	0.1670	0.1535
<u>Panel C. Quoted Spread</u>			
Log_MSG	-0.0002^{***}	-0.0001	-0.0010^{***}
Volatility	0.0692^{***}	0.0239^{***}	0.1299^{***}
|Surprise|	0.0003^{***}	0.0003^{***}	0.0033^{***}
Bad_News	-0.0001^{***}	-0.0000	-0.0002^{**}
Post_News	0.0001	-0.0001	0.0002
Adjusted-R^2	0.2057	0.1774	0.1661
<u>Panel D. Effective Spread</u>			
Log_MSG	-0.0001^{***}	-0.0002^{***}	-0.0003
Volatility	0.0224^{***}	0.0128^{***}	0.0318^{***}
|Surprise|	0.0000	0.0001	0.0008^{***}
Bad_News	-0.0001^{***}	0.0000	-0.0001
Post_News	0.0001	0.0001	-0.0000
Adjusted-R^2	0.1358	0.1057	0.1378

5.6 Conclusion

On February 20, 2012, ASX introduced co-location facilities to Australian futures markets. A previous study conducted by Frino, Mollica and Webb (2014) provides the first Australian evidence on the impact of co-location on HFT activity and market liquidity. This study extends their work by examining the impact of co-location on HFT around scheduled macroeconomic announcements. Announcement periods represent a sensitive and different informational environment relative to the normal times, and it is important to determine the impact of co-location on trading activity around scheduled news releases. Furthermore, this analysis examines the causality effect between HFT and market liquidity around announcement time by employing co-location as an exogenous event to HFT.

Results based on the first hypothesis $H5_1$ demonstrate that HFT activity increases following the introduction of co-location across all three interest rate futures contracts. Furthermore, results based on the second hypothesis $H5_2$ reports that the heighted level of HFT, exhibited in the post co-location period, results in a significant improvement in market liquidity around macro news releases, as evidenced by an increase in the level 1 dollar depth and a reduction in the relative spread, the quoted spread and the effective spread.

CHAPTER 6. Conclusion

This dissertation presents three examinations relating to the price effects of trades in futures markets. Specifically, this dissertation considers the permanent price impacts of block trades across different market conditions, the impact of global market liquidity on price effects of trades in individual markets, and the impact of HFTs on price effects of trades around information releases.

The literature review in Chapter 2 highlights several important topics that are underrepresented in existing studies. First, Chapter 2 indicates that the extant literature identifies an asymmetric relationship between the price impacts of block purchases and sales (Chan & Lakonishok, 1993, 1997; Keim & Madhavan, 1995, 1997; Saar, 2001; Bozcuk & Lasfer, 2005; Chiyachantana et al., 2004), and also states that bull and bear market settings have boosted a number of asymmetric responses in the microstructure literature (Chiyachantana et al., 2004; Chiang, Lin & Yu, 2009; Pradkhan, 2015). However, it remains unclear in the literature whether the asymmetric relationship also exists between the permanent price impacts of block purchases and sales. Second, Chapter 2 identifies evidence of liquidity commonality in the U.S. stock market (Chordia, Roll & Subrahmanyam, 2000), the FX market (Mancini, Ranaldo & Wrampelmeyer, 2013) and non-U.S. stock exchanges (Brockman & Chung, 2002; Fabre & Frino, 2004). Despite the importance of futures markets and their superior liquidity, literature concerning the liquidity spill-over and its impact on price effects of trading in futures markets is limited. Third, Chapter 2 identifies that announcement periods represent a very different informational environment relative to normal times (Ederington & Lee, 1993, 1995; Frino & Hill, 2001; Cai, Cheung & Wong, 2001; Andersen & Bollerslev, 1998) and documents the debate in the extant literature over the pros and cons of the development of HFTs. Given the unique informational characteristics of announcement times and the tremendous development in HFTs over the last decade, it is crucial to fill the gap in the literature on the impact of HFTs on market liquidity around macroeconomic releases.

Chapter 3 extends the analysis of Chiyachantana et al. (2004) by empirically examining the information or permanent price effects of large or block trades in bull and bear markets, using a sample of transactions executed in the E-mini S&P 500 index futures contracts and the SPDR EFT shares. Furthermore, Chapter 3 develops and tests a theoretical model based on Easley and O'Hara (1987) and Saar (2001), which produces the somewhat counter-intuitive prediction that the information effect of block purchases relative to block sales is greater in bear markets relative to bull markets. By incorporating market sentiment and its interaction with contrarian information, Chapter 3 builds on the workhorse models of the permanent price impact that have ignored such factors. Empirical results are consistent with the theoretical predictions, specifically that the permanent price effect of block buys is greater than sales during bearish periods and the permanent price effect of block sells is greater than buys during bullish periods. These results improve the understanding of the impact of investment constraints and market sentiments on the price formation process.

A previous study, conducted by Brockman, Chung, and Perignon (2009), examines global commonality in liquidity in equity markets. Considering the differences in market participants and speed of trading between index futures and equities, Chapter 4 extends previous literature by examining the global commonality in liquidity across nine stock index futures markets in five different MSCI regions over a 10-year period from October 2002 to September 2012. Further, Chapter 4 examines whether liquidity commonality varies over the 10-year period to identify if commonality in liquidity has become more pronounced. Empirical results reveal strong evidence of global commonality in liquidity for index futures markets, and such liquidity commonality is higher in significance and more pervasive in recent years than that observed in early 2000. These results are robust to the inclusion of expiration effects, alternative weighting structures for global market liquidity and different measures of liquidity, such as effective spread, quoted spread, relative spread and market depth. In addition, this study investigates the regional liquidity commonality divided by time zones. Regions with greater free trades agreements and tighter political and economic bonds may experience higher levels of liquidity commonality. Results show that the regional commonality is not evident in the Asia and Pacific region. But, it is very pervasive and strong in the European and the North and South American regions, and the effects, in these two regions, are even more widespread than the observed global commonality. As liquidity commonality is considered as a common risk factor shared by every country in global markets, the results reported in Chapter 4 improve the understanding of such systematic liquidity risk across international borders for index futures markets.

Chapter 5 uses the introduction of co-location in the Australian market as an exogenous event to isolate the effect of latency on liquidity, and also to identify the causal effect of a change in HFT on liquidity. Chapter 5 compares futures market responses to macro-economic releases between the pre- and the post- co-location periods. Results demonstrate that HFT activity increases dramatically for intervals surrounding news releases after the introduction of co-location. Furthermore, results suggest that the increased HFT, resulting from co-location facilities, improves market liquidity around macro news releases for various liquidity measures, including price effects of trades, relative spreads, quoted spreads and different levels of market depth.

Appendices

Appendix A. Proof of Model on Asymmetry in the Permanent Price Impact of Block Purchases and Sales

Lemma 1. *If* $\pi > 1 - \pi$, *then the separating equilibrium for the ask side of the market implies a separating equilibrium for the bid side of the market. If* $\pi < 1 - \pi$, *the reverse is true.*

Proof

By conditions (2) and (3) it follows that if the separating equilibrium exists on the bid side of market then:

$$\frac{Q_L}{Q_S} \geq 1 + f_{\underline{\theta}}(\pi),$$

and if it exists on the ask side of market then:

$$\frac{Q_L}{Q_S} \geq 1 + f_{\overline{\theta}}(\pi).$$

In order to prove the lemma, it has to be shown that $f_{\underline{\theta}}(\pi) > f_{\overline{\theta}}(\pi)$, if and only if $\pi \in (\frac{1}{2}, 1]$. Signals are perfect then $f_{\underline{\theta}}(\pi) - f_{\overline{\theta}}(\pi) = \frac{(1-\pi)\mu}{\gamma} - \frac{\pi\mu}{\gamma} = \frac{(1-2\pi)\mu}{\gamma}$, that is positive if and only if $\pi > \frac{1}{2}$.

Lemma 2. *If* $\pi > 1-\pi$, *and a pooling equilibrium exists in both sides of the market, then the probability of observing a large information based sell order is greater than the probability of observing a large information based buy order. If* $\pi < 1-\pi$, *the reverse is true.*

Proof

For any $\theta \in \{\underline{\theta}, \overline{\theta}\}$, $\sigma_L \in [0,1]$, and $\pi \in [0,1]$ we define the following functions:

- $\alpha_\theta(\sigma_L) = \frac{\gamma + \mu\sigma_L \Pr(\theta|\underline{V})}{\gamma + \mu\sigma_L \Pr(\theta|\overline{V})}$

- $\Pi_\theta(\pi, \sigma_L) = E[\tilde{V}|\theta] - \frac{\pi}{\pi + \alpha_\theta(\sigma_L)(1-\pi),}$

- $\mathrm{G}_\theta(\pi, \sigma_L) = \Pi_\theta(\pi, \sigma_L)Q_L - \Pi_\theta(\pi, 1-\sigma_L)Q_S$.

By combining (5) and (6) it is found that in a pooling equilibrium the strategies of informed traders are $\sigma_{\underline{\theta}} = \{1-\sigma_{\underline{\theta},L}, \sigma_{\underline{\theta},L}\}$, and $\sigma_{\overline{\theta}} = \{1-\sigma_{\overline{\theta},L}, \sigma_{\overline{\theta},L}\}$, such that $\mathrm{G}_{\underline{\theta}}(\pi, \sigma_{\underline{\theta},L}) = \mathrm{G}_{\overline{\theta}}(\pi, \sigma_{\overline{\theta},L}) = 0$. Observe that *i)* $\frac{\partial \mathrm{G}_\theta(\pi,\sigma_L)}{\partial \sigma_L} < 0$ for all θ, and *ii)* $\mathrm{G}_{\underline{\theta}}(\pi, \sigma_L) = \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L)$. Hence, $\sigma_{\underline{\theta},L} > \sigma_{\overline{\theta},L}$ if $\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L) < \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L)$ for all σ_L, and $\sigma_{\underline{\theta},L} < \sigma_{\overline{\theta},L}$ if $\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L) > \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L)$ for all σ_L. In the following we will show that $\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L) < \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L)$ for all σ_L if and only if $\pi > 1/2$ and $\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L) > \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L)$ for all σ_L if and only if $\pi < 1/2$.

Let define $H(\pi, \sigma_L) = \frac{\Pi_{\overline{\theta}}(\pi, 1-\sigma_L)}{\Pi_{\overline{\theta}}(\pi, \sigma_L)}$ and notice that:

$$\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L) < \mathrm{G}_{\overline{\theta}}(1-\pi, \sigma_L) \Leftrightarrow$$

$$\Pi_{\overline{\theta}}(\pi,\sigma_L)\left(\frac{Q_L}{Q_S}-H(\pi,\sigma_L)\right)<\Pi_{\overline{\theta}}(1-\pi,\sigma_L)\left(\frac{Q_L}{Q_S}-H(1-\pi,\sigma_L)\right). \qquad (7)$$

Moreover, $\Pi_{\overline{\theta}}(\pi,\sigma_L)<\Pi_{\overline{\theta}}(1-\pi,\sigma_L)$ for any σ_L if and only if $\pi>1/2$. Indeed, simple algebraic calculus shows that:

$$\Pi_{\overline{\theta}}(\pi,\sigma_L)<\Pi_{\overline{\theta}}(1-\pi,\sigma_L)\Leftrightarrow(2\pi-1)\left(1-\alpha_{\overline{\theta}}(\sigma_L)\alpha_{\overline{\theta}}(1)\right)>0\Leftrightarrow\pi>1/2, \quad (8)$$

since both $\alpha_{\overline{\theta}}(\sigma_L)$ and $\alpha_{\overline{\theta}}(1)$ are lower than 1. Second, some algebraic manipulation gives:

$$H(\pi,\sigma_L)=\frac{\left(\alpha_{\overline{\theta}}(1-\sigma_L)-\alpha_{\overline{\theta}}(1)\right)\left(\pi+(1-\pi)\alpha_{\overline{\theta}}(\sigma_L)\right)}{\left(\alpha_{\overline{\theta}}(\sigma_L)-\alpha_{\overline{\theta}}(1)\right)\left(\pi+(1-\pi)\alpha_{\overline{\theta}}(1-\sigma_L)\right)},$$

and since

$$\frac{\partial H(\pi,\sigma_L)}{\partial\pi}=\frac{\sigma_L\alpha_{\overline{\theta}}(1)\left(\alpha_{\overline{\theta}}(\sigma_L)-\alpha_{\overline{\theta}}(1-\sigma_L)\right)}{\left(\alpha_{\overline{\theta}}(\sigma_L)-\alpha_{\overline{\theta}}(1)\right)\left(\pi+(1-\pi)\alpha_{\overline{\theta}}(1-\sigma_L)\right)^2}>0,$$

because $\alpha_{\overline{\theta}}(\sigma_L)>\alpha_{\overline{\theta}}(1)$ for any σ_L, we can conclude that $H(\pi,\sigma_L)>H(1-\pi,\sigma_L)$ if and only if $\pi>1/2$, and then:

$$\left(\frac{Q_L}{Q_S}-H(\pi,\sigma_L)\right)>\left(\frac{Q_L}{Q_S}-H(1-\pi,\sigma_L)\right)\quad\forall\pi<\frac{1}{2}$$

$$\left(\frac{Q_L}{Q_S}-H(\pi,\sigma_L)\right)<\left(\frac{Q_L}{Q_S}-H(1-\pi,\sigma_L)\right)\quad\forall\pi>\frac{1}{2}.$$

By combining this result with (7) and (8), we obtain that $\mathrm{G}_{\underline{\theta}}(\pi, \sigma_L) = \mathrm{G}_{\overline{\theta}}(1 - \pi, \sigma_L)$ is larger than $\mathrm{G}_{\overline{\theta}}(\pi, \sigma_L)$ if $\pi > 1/2$.

Proof of Proposition

Before going on with the proof, it can be remarked that in the separating equilibrium, $\lambda_S(\pi) = \lambda_B(\pi) = \frac{\gamma+\mu}{\gamma} \equiv \lambda > 1$, and in the pooling equilibrium $\lambda_S(\pi) = \frac{\gamma+\mu\sigma_{\underline{\theta},L}}{\gamma} > 1$, and $\lambda_B(\pi) = \frac{\gamma+\mu\sigma_{\overline{\theta},L}}{\gamma} > 1$, with $\sigma_{\underline{\theta},L}$ and $\sigma_{\overline{\theta},L}$ satisfying conditions (5) and (6), respectively.

Consider a bull market (i.e., assume $\pi > 1/2$). The price impact expression can be written as

$$J(\pi) = \frac{(1-\pi)\phi}{(\pi\lambda_S(\pi)+(1-\pi))(\pi\lambda_B(\pi)+(1-\pi))},$$

where $\phi = \pi(2\lambda_B(\pi) - \lambda_B(\pi)\lambda_S(\pi) - 1) - (1 - \pi)(2\lambda_S(\pi) - \lambda_B(\pi)\lambda_S(\pi) - 1)$, and $J(\pi) < 0$ if and only if $\phi < 0$.

First assume that a separating equilibrium exists on both sides of the market. By substituting $\lambda_B(\pi) = \lambda_S(\pi) = \lambda$ in ϕ and rearranging terms, it gives $\phi = (1 - 2\pi)(\lambda - 1)^2$, which is negative since we are assuming $\pi > 1/2$. Therefore, $J(\pi) < 0$ in a bull market.d e

Now assume that a separating equilibrium exists on the bid side of the market and a pooling equilibrium exists on the ask side (from Lemma 1 we know that the opposite is not possible in a bull market). Then, $\lambda_B(\pi) < \lambda$. Since

$$\frac{\partial J(\pi)}{\partial \lambda_B(\pi)} = \frac{\partial \Delta B(\pi)}{\partial \lambda_B(\pi)} = \frac{\pi(1-\pi)}{(\pi\lambda_B(\pi)+(1-\pi))^2} > 0,$$

it can be concluded that also in this case $J(\pi) < 0$.

Finally, assume that a pooling equilibrium exists on both sides of the market. From Lemma 2 we know that $\lambda_S(\pi) > \lambda_B(\pi)$ in a bull market. Moreover, when $\lambda_S(\pi) = \lambda_B(\pi), J(\pi) < 0$ if $\pi > 1/2$ and

$$\frac{\partial J(\pi)}{\partial \lambda_S(\pi)} = -\frac{\partial \Delta S(\pi)}{\partial \lambda_S(\pi)} = -\frac{\pi(1-\pi)}{\left(\pi+(1-\pi)\lambda_S(\pi)\right)^2} < 0,$$

then $J(\pi) < 0$ in a bull market where a pooling equilibrium exists on both sides of the market.

The proof for the case of a bear market is analogous and omitted.

Stealth trading states that medium-sized trades are associated with the greatest information effects and are the main forces that move the stock market. Some may argue that in current markets, traders do not trade in large quantities anymore but tend to split trades into small orders when occupying private information. However, this chapter, based on futures data, suggests this is not the case. Table A-A-1 reports the mean permanent and total price effects of orders executed on S&P 500 index futures and SPDR ETF for different trade size brackets. Transactions are categorized into five size groups with the first including the smallest 25% of trades by volume and the last one being the largest 1% of trades by volume. Panel A documents the mean permanent and total price impacts for each trade size group for index futures; Similarly, Panel B shows the mean permanent and total price impacts for ETF. For block traders, the total impact is the cost of taking liquidity from the order-book and it is also the cost of transacting in large quantities. The total price impact is measured as follows:

$$Total\,Price\ Impact \;\; = 100 * \mathrm{D} * Ln\ (\mathrm{P}/\ P_{prior}),$$

where P_{prior} is the equilibrium market price prior to the block transaction, and P is the order execution price. D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. The prevailing mid-quote price preceding the block is used as a proxy for P_{prior}. As trade size increases, both permanent and total price impacts increase for index futures and ETF. Based on results presented in Table A-A-1, block trades are the most informed ones, evidenced by the greater permanent and total price impacts relative to the medium and small trades. They are the ones that drive the market price, not the medium ones, which explains the motivation of this chapter for analyzing the impact of block trades.

TABLE A-A-1

Descriptive Statistics of Permanent and Total Price Impact by Trade Size Groups

This table reports the mean permanent and total price effects of orders executed on S&P 500 index futures and SPDR ETF for different trade size brackets. Transactions are categorized into five size groups with the first including the smallest 25% of trades by volume and the last one being the largest 1% of trades by volume.

Panel A documents the mean permanent and total price impacts for each trade size group for index futures; Similarly, Panel B shows the mean permanent and total price impacts for ETF. The permanent price impact of each trade is defined as follows: permanent price impact = 100*D*ln(MQAfter/MQBefore) and the total price impact of each trade is defined as follows: total price impact = 100*D*ln(TradePrice/MQBefore) where D is a binary variable that equals 1 for buyer initiated orders and -1 for seller initiated orders. MQBefore is the prevailing mid-quote at the time of the trade and MQAfter is the mid-quote five minutes after the trade. TradePrice is the order execution price.

Percentage (%)	Permanent Impact	Total Impact
Panel A. Index Future		
25	0.00359	0.00636
50	0.00487	0.00635
75	0.00527	0.00640
99	0.00575	0.00641
100	0.00901	0.00804
Panel B. ETF		
25	0.00240	0.00264
50	0.00291	0.00271
75	0.00309	0.00275
99	0.00363	0.00293
100	0.00563	0.00419

Appendix B. Robustness Tests for Commonality in Liquidity across International Borders

This appendix reports the results of robustness tests from Chapter 4.

Table A-B-1 extends the regression analysis on commonality in liquidity (Table 4-2) by including a new dummy variable to capture the expiration effects associated with futures contracts.

The relative spread results reported in Table A-B-1 are indistinguishable from previous results in Table 4-2, suggesting that the commonality remains strong after controlling for the expiration effects in futures data. Comparing results presented in Table A-B-1 and Table 4-2, the magnitude of the commonality term, as reflected in the β_1 coefficient, has a slight drop, but the significance of commonality coefficients remains similar for all index futures examined for the relative spread, the quoted spread and the depth measures. Turning to the β_8 coefficient of the expiry dummy, Norway is the only country that provides significant results at the 5% level for the quoted spread, the relative spread and the depth liquidity measures. With the effective spread measure, Hungary, Hong Kong and Japan provide insignificant results on the commonality test; meanwhile, Canada, the U.S., the U.K. and Norway reveal significant results on the expiry dummy variable. Despite the fact that four markets reveal significant expiry effects, six out of nine markets are still showing significant commonality effects and the significant markets are significant with previous results for the effective spread measure. Therefore, the expiration effects of futures do not have a significant impact on the global liquidity commonality.

TABLE A-B-1

Global Commonality with Expiration Dummy Variable

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \beta_8 D_{Expiry} + \varepsilon_{I,t} \quad (4.6)$$

The dependent variable is the proportional change in the liquidity of index future *I*. Four liquidity measures are adopted to conduct the regressions. The independent variables are the global return, the proportional change in global liquidity, as well as their lag and lead terms. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the global liquidity is the average liquidity across all index futures except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. β_1, β_2 and β_3 represent contemporaneous, lag, and lead coefficient estimates respectively. The dummy variable, D_{Expiry}, equals to one on days when index future contracts expire or within 3 days to expiration and zero otherwise. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results for the 10 index futures over a 10-year sample period are presented in this table.

Index Futures	β_1	β_2	β_3	β_8	Adj. R^2
Panel A. Quoted Spread with Expiration Dummy(over 10 years)					
Australia	0.0612	-0.0228	0.0549	0.0087	0.0122
Hungary	0.4057***	0.2454**	0.0661	0.0211	0.0107
Canada	0.2771***	0.0935	0.0564	0.0082	0.0247
U.S.	0.0178***	-0.0007	0.0017	0.0001	0.0236
Germany	0.2160***	0.0327	0.0408	0.0036	0.1057
Hong Kong	0.1472	-0.1243	0.1203	-0.0007	0.0021
U.K.	0.2192***	0.0699*	0.0611	0.0024	0.0485
Japan	0.0034	0.0013	0.0040	0.0010	-0.0019
Norway	0.2308	-0.1663	-0.1598	0.0356**	0.0045

Panel B. Relative Spread with Expiration Dummy(over 10 years)					
Australia	0.0822**	-0.0403	0.0457	0.0079	0.0389
Hungary	0.4384***	0.2474**	0.0487	0.0175	0.0217
Canada	0.2906***	0.0725	0.0594	0.0085	0.0443
U.S.	0.0315***	-0.0025	-0.0026	-0.0004	0.5102
Germany	0.2326***	0.0293	0.0143	0.0017	0.2363
Hong Kong	0.1666	-0.1308	0.1350	-0.0006	-0.0020
U.K.	0.2340***	0.0602	0.0408	0.0025	0.1034
Japan	0.0040	-0.0215***	-0.0113	0.0013	0.3675
Norway	0.2682	-0.1967	-0.1856	0.0347**	0.0119
Panel C. Effective Spread with Expiration Dummy(over 10 years)					
Australia	0.0479***	-0.0047	0.0504***	-0.0076	0.0330
Hungary	0.0813	0.0883	-0.0004	0.0195	0.0138
Canada	0.1441***	-0.0082	0.0363	0.1210***	0.0418
U.S.	0.0933***	0.0142	0.0646***	0.0124***	0.1393
Germany	0.2063***	0.0195	0.0100	-0.0009	0.0486
Hong Kong	0.0420	0.0592	-0.0410	-0.0029	0.0105
U.K.	0.2203***	0.1684**	0.2809***	-0.2038***	0.0268
Japan	0.0164	-0.0057	-0.0051	-0.0008	0.0698
Norway	0.3299**	0.0363	0.1025	0.0710***	0.0080
Panel D. Depth with Expiration Dummy(over 2 years)					
Australia	0.2876***	0.1265	-0.0084	-0.0018	0.0345
Hungary	0.4774**	0.5890***	-0.0344	0.0388	0.0280

Canada	0.2752**	-0.1528	0.0095	-0.0100	0.0499
U.S.	0.3140**	-0.0928	0.0293	-0.0033	0.1959
Germany	0.4702***	0.1412	0.0689	-0.0045	0.2597
Hong Kong	0.4949	0.4130	0.2083	-0.0207	0.0683
U.K.	0.5580***	0.0987	0.0115	-0.0048	0.1760
Japan	0.1819	0.1198	-0.0690	-0.0301	0.0536
Norway	0.1823	-0.0518	0.6298*	0.1985***	0.0370

Table A-B-2 replicates the regression analysis on commonality in liquidity (Table 4-2) using Principle Component Analysis (PCA) as the weights of the global futures portfolio, rather than the simple equal weighting.

New regression results with PCA weighted global portfolios reveal greater and more significant global liquidity commonality. In terms of whether the global liquidity coefficients are significant, Hong Kong is not significant for the quoted spread measure, the relative spread measure and the effective spread measure; meanwhile, Japan is not significant for quoted spread measure, the effective spread measure and the depth measure; and Norway is not significant for the depth measure. Furthermore, the new results provide larger adjusted R-squares compared to previous ones reported in Table 4-2 for most markets for all four liquidity measures, indicating that the global liquidity, constructed from the first principle component, is able to achieve better performance in explaining individual market's liquidity. Therefore, the commonality in liquidity is more evident under the new weighting structure.

TABLE A-B-2

Global Commonality with Global Liquidity Extracted from PCA

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t+1} + \beta_3 \Delta Liquidity_{G,t-1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t+1} + \gamma_3 Return_{G,t-1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.5)$$

The dependent variable is the proportional change in the liquidity of index future *I*. The relative spread measure is adopted to conduct the regressions. The independent variables are the global return, the proportional change in global liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the global liquidity is represented by the first principal component across all index futures liquidity except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. $\beta_1,\ \beta_2\ and\ \beta_3$ represent contemporaneous, lag, and lead coefficient estimates respectively. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results for the 10 index futures are presented in this table. The quoted bid-ask spread and relative bid-ask spared has a 10-year sample period while the depth results are only based on recent two years data due to the shorter period of depth data.

Markets	β_1	β_2	β_3	$\beta_1+\beta_2+\beta_3$	Adj. R^2
<u>Panel A. Quoted Spread (over 10 years)</u>					
Australia	0.0908^{*}	-0.0299	0.1100^{**}	0.1708	0.0137
Budapest	0.5108^{***}	0.2435^{*}	0.0505	0.8047	0.0114
Canada	0.4708^{***}	0.1215	0.2523^{**}	0.8445	0.0296
U.S.	0.0238	0.0018	0.0028	0.0284	0.0324
Germany	0.3089^{***}	0.0761^{***}	0.0258	0.4108	0.1336
Hong Kong	0.1623	-0.0744	0.0372	0.1252	0.0007
London	0.3157^{***}	0.1104^{**}	0.0430	0.4690	0.0645
Japan	0.0009	-0.0023	0.0006	-0.0008	-0.0044

Norway	0.6485***	-0.0390	-0.0303	0.5792	0.0059
Panel B. Relative Spread (over 10 years)					
Australia	0.1682***	-0.0805	0.1112	0.1989	0.0479
Hungary	0.4298***	0.2626**	0.0400	0.7324	0.0245
Canada	0.9118***	0.0458	0.3178**	1.2755	0.0589
U.S.	0.0702***	-0.0211***	0.0004	0.0495	0.5594
Germany	0.5889***	0.1092**	-0.0026	0.6956	0.2753
Hong Kong	0.3127	-0.0840	0.0724	0.3011	-0.0016
U.K.	0.7062***	0.2170***	0.0553	0.9785	0.1427
Japan	0.0288**	-0.0154	-0.0131	0.0004	0.3844
Norway	0.9436***	-0.1754	-0.1180	0.6501	0.0172
Panel C. Effective Spread (over 10 years)[36]					
Australia	0.0651	0.0689	0.0993*	0.2334	0.0142
Hungary	0.5134**	0.2819	0.1269	0.9222	0.0090
Canada	0.2009*	0.1386	0.0088	0.3482	0.0321
U.S.	0.0178***	0.0028	0.0051	0.0257	0.0204
Germany	0.2536***	0.0515	0.0747	0.3799	0.0803
Hong Kong	-0.0375	-0.2434	-0.1766	-0.4575	0.0035
U.K.	0.4186***	0.1299**	0.1125	0.6611	0.0841
Japan	0.0026	-0.0042	0.0088	0.0072	-0.0041
Norway	0.2648	-0.0958	-0.3356	-0.1666	0.0065

[36] When using the principle component as the weights to construct global liquidity, missing value in one market will result in a missing global liquidity. Therefore the regression results might be affected when the data quality for an individual market is poor.

Panel D. Dollar Depth (over 2 years)

Australia	0.2137*	0.1888*	0.0483	0.4508	0.0285
Hungary	0.7477***	0.7529***	0.2219	1.7225	0.0467
Canada	0.3466***	-0.1863	-0.0650	0.0953	0.0615
U.S.	0.3992**	-0.3050*	0.2400	0.3342	0.1955
Germany	0.4827***	0.1420**	-0.0619	0.5629	0.2541
Hong Kong	0.6868	0.1295	0.3686	1.1850	0.0739
U.K.	0.4563***	0.0426	-0.0140	0.4850	0.1400
Japan	0.1880	0.0860	-0.1593	0.1147	0.0653
Norway	0.1067	0.3238	0.5866*	1.0170	0.1052

The time-series regression in (4.5) is conducted for each one of the 15 markets over a six-year period. And results on the relative spread and the quoted spread measures are reported in Table A-B-3. The new regression, with 15 international markets, provides much stronger evidence for liquidity commonality, relative to the regression with nine markets. The relative spread results demonstrate that all index futures markets have a positive contemporaneous coefficient, and 14 out of 15 of these coefficients are significant at 10% level. Hong Kong is the only market that reveals an insignificant result. For the lag term of global liquidity, four markets (Australia, Hungary, Italy and France) present weak significance. For β_3, the lead term of global liquidity, three markets (Australia, Germany and Canada) manifest positive and significant results at 1% level. Japan shows negative and significant β_3 at 1% level, but the magnitude of the lead coefficient is smaller than the contemporaneous coefficient. Turning to the quoted spread results, the reported adjusted R-square is much lower compared to the relative spread measure. Comparing results on the significance of contemporaneous coefficients, Japan is the only difference between the two liquidity measures with insignificant result for the quoted spread and significant result for the relative spread.

Table A-B-4 replicates the regression analysis on commonality in liquidity (Table 4-6) with a different liquidity measure, the quoted spread. The quoted spread results are indistinguishable from previous results for the relative spread on the β_1 coefficients. The only noticeable difference is that the adjusted R-squares are generally larger for the relative spread than for the quoted spread.

Table S **TABLE A-B-3**

Global Commonality with Equally Weighted Liquidity – 15 Markets

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.5)$$

The dependent variable is the proportional change in the relative spread (Panel A) and the quoted spread (Panel B) of index future *I*. The independent variables are the global return, the proportional change in global liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the regional liquidity is the average liquidity across all index futures except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. $\beta_1, \beta_2\ and\ \beta_3$ represent contemporaneous, lagged, and lead coefficient estimates respectively. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results on the quoted bid-ask spread for 15 index futures are presented in this table.

Index Futures	β_1	β_2	β_3	$\beta_1+\beta_2+\beta_3$	Adj. R^2
Panel A. Relative Spread					
Australia	0.1339^{***}	0.0448^{*}	0.0707^{***}	0.2495	0.0369
Hong Kong	0.0783	0.1979	-0.1113	0.1649	0.0023
India	0.3570^{*}	-0.0264	0.0754	0.4060	0.0024
Japan	0.0163^{***}	-0.0087	-0.0143^{***}	-0.0067	0.4209
Singapore	0.2112^{***}	-0.0865	-0.0466	0.0782	0.0123
Taiwan	0.1218^{***}	0.0256	-0.0444	0.1030	0.0170
Hungary	0.3980^{***}	0.1782^{**}	0.1083	0.6844	0.0224
Germany	0.3013^{***}	0.0270	0.0578^{***}	0.3862	0.2168
Italy	0.2500^{***}	0.0638^{**}	0.0659^{**}	0.3797	0.1344

U.K.	0.2990***	0.0162	0.0497	0.3648	0.0854
Norway	0.5394***	0.1429	-0.0179	0.6643	0.0209
France	0.2705***	0.0531*	0.0725**	0.3960	0.0897
Brazil	0.5281***	-0.0059	0.1631**	0.6853	0.0603
Canada	0.4487***	0.0084	0.1681***	0.6251	0.0485
U.S.	0.0227***	-0.0060	0.0050	0.0217	0.4900
Panel B. Quoted Spread					
Australia	0.1066***	0.0514**	0.0686***	0.2266	0.0115
Hong Kong	0.0711	0.2022	-0.0585	0.2149	-0.0009
India	0.3656*	-0.0469	0.0940	0.4126	-0.0009
Japan	0.0037	-0.0001	-0.0019	0.0016	0.0114
Singapore	0.1965***	-0.0930	-0.0454	0.0582	0.0068
Taiwan	0.1034**	0.0187	-0.0186	0.1035	0.0012
Hungary	0.3588***	0.1907**	0.1035	0.6530	0.0117
Germany	0.3134***	0.0477**	0.0788***	0.4399	0.1242
Italy	0.2189***	0.0885***	0.0771**	0.3845	0.0653
U.K.	0.3264***	0.0420	0.0672**	0.4357	0.0580
Norway	0.5045***	0.1691	0.0064	0.6800	0.0119
France	0.2557***	0.0866***	0.0598**	0.4021	0.0423
Brazil	0.5007***	-0.0173	0.1289*	0.6123	0.0411
Canada	0.4472***	0.0057	0.1488**	0.6017	0.0339
U.S.	0.0174***	-0.0009	-0.0008	0.0158	0.0430

TABLE A-B-4

Time Zone Commonality with Equally Weighted Liquidity

The following regression is adopted to examine the global liquidity commonality for index futures market:

$$\Delta Liquidity_{I,t} = \alpha + \beta_1 \Delta Liquidity_{G,t} + \beta_2 \Delta Liquidity_{G,t-1} + \beta_3 \Delta Liquidity_{G,t+1} + \gamma_1 Return_{G,t} + \gamma_2 Return_{G,t-1} + \gamma_3 Return_{G,t+1} + \delta \Delta Volatility_{I,t} + \varepsilon_{I,t} \quad (4.5)$$

The dependent variable is the proportional change in the **quoted bid-ask spread** of index future *I*. The independent variables are the global return, the proportional change in global liquidity, as well as their lead and lag term. The proportional change in the return volatility of index future *I* is also included as a control variable. In each time-series regression, the regional liquidity is the average liquidity across all index futures except for the one in question. The symbol Δ represents a proportional change in the variable preceding it. β_1, β_2 and β_3 represent contemporaneous, lagged, and lead coefficient estimates respectively. A positive and significant β_1 would indicate the existence of commonality in liquidity for index futures. The symbol *, **, *** mean the coefficient estimates are significant at 10%, 5%, and 1% confidence levels respectively. Regression results on the quoted bid-ask spread for 15 index futures in three regions are presented in this table. The regression is conducted on three different time zones, Asia & Pacific (Panel A), Europe (Panel B) and North & South America (Panel C).

Index Futures	β_1	β_2	β_3	$\beta_1+\beta_2+\beta_3$	Adj. R^2
Panel A. Asia & Pacific					
Australia	0.0357***	0.0114	-0.0180	0.0799	0.0230
Hong Kong	-0.0307	0.0396	0.1003	0.0574	0.0032
India	-0.0132	0.3194**	0.1477	0.4539	0.0015
Japan	0.0003	-0.0015	-0.0012	-0.0024	0.0026
Singapore	0.0178	-0.0095	0.0572	0.0655	0.0026
Taiwan	0.0547***	0.0267**	-0.0071	0.0743	0.0210
Panel B. Europe					
Hungary	0.2750***	0.1423**	0.0978	0.5151	0.0106
Germany	0.2035***	0.0419***	0.0560***	0.3014	0.1222

Italy	0.2158***	0.0743***	0.0968***	0.3869	0.0692
U.K.	0.2034***	0.0342	0.0744***	0.3120	0.0454
Norway	0.5182***	0.2156**	0.1726*	0.9064	0.0138
France	0.2106***	0.0738***	0.0611***	0.3455	0.0534
Panel C. North & South America					
Brazil	0.1737***	0.0614	0.0433	0.2784	0.0225
Canada	0.1450***	0.0520	0.0380	0.2350	0.0161
U.S.	0.0096***	-0.0014	-0.0001	0.0080	0.0358

Appendix C. The Impact of High Frequency Trading on Market Quality around Macroeconomic Announcements

This appendix analyses the impact of HFT on market quality, measured by trading volumes and the number of trades; specifically, it compares trading activity between the pre- and the post- co-location periods during announcement times. The pre-colo (extending from February 2011 to February 2012) is defined as the one-year period prior to the introduction of co-location and the post-colo is defined as the one-year period (extending from February 2012 to February 2013) following the introduction of co-location. This appendix also visualises market responses to major announcements, which are those with a statistically significant impact on market volatility.

Table A-C-1 reports the results of regression analysis (5.15) with the dependent variable equals to the trading volume (Panel A) and the number of trades (Panel B). Comparing trading volumes across interest rate futures, this analysis finds mixed results. As HFT increases in the market, volume also increases for the 10-year and three-year government bond futures, but decreases for the 90-day bank bill contract. Volatility is positively correlated with trading volume for all three futures contracts. When examining time intervals surrounding the announcement time of 11:30 a.m., volume significantly declines in the minute immediately before announcements, and then increases dramatically following announcements. And this increase is more persistent and pronounced for the three-year government bond and the 90-day bank bill futures. In general, it takes at least two minutes for the volume to reach a new equilibrium level following news releases in the Australian interest rate futures market.

Similar to the previous literature, this analysis finds that trading frequency significantly increases immediately following the news release time and remains relatively higher than normal for roughly five minutes. Combined with results on the trading volume, the finding of this analysis is in line with Frino and Hill (2001) who conclude that the jump in volumes following announcements is mainly driven by increased trading frequency. In addition, trading frequency is positively correlated with HFT for all three futures contracts.

TABLE A-C-1

The Impact of High Frequency Trading on Market Quality

This table reports results from the two-stage-least-squares (2SLS) regression analysis, which examines the impact of HFT on market quality measures. The first stage regression model (5.14) is documented in Table 5-2 and the second stage regression is estimated as follows:

$$MQ_{it} = \alpha_i + \beta * \widehat{HFT}_{it} + \delta_1 * volatility_{it} + \delta_2 * |surprise|_{it} + \delta_3 * bad\_news_{it} + \delta_4 * post\_news_{it} + \sum_t \rho_t * interval_t + \varepsilon_{it} \quad (5.15)$$

where MQ_{it} refers to trading volume (Panel A) and number of trades (Panel B) for each interest rate future i on each minute interval t; $\widehat{HFT}_{it}$ is the predicted message traffic from (5.14) for each interest rate future i on each minute interval t; $volatility_{it}$ measures the price movements within each minute interval; $|surprise|_d$ is defined as the absolute post announcement return for each news release day; bad_news_{it} is a dummy variable that takes the value of 1 if it's a bad announcement and 0 otherwise; $post\_news_{it}$ is a dummy variable that equals to 1 if the interval is in the post announcement period and 0 otherwise; $interval_t$ measures the fixed effect associated with each minute interval and takes the value of 1 if the interval equals to t and 0 otherwise. The event window extends one year pre to one year post the co-location date. T-Statistics are in parentheses for the null hypothesis that the values between Pre and Post are the same.

	10-year Government Bonds	3-year Government Bonds	90-day Bank Accepted Bills
Panel A. Trading Volume			
Log_MSG	37.674***	89.354	-68.045**
Volatility	7968.6***	60695***	13561***
|Surprise|	-12.600	-318.11***	23.228
Bad_News	2.0981	33.268	20.210
Post_News	2.1768	103.89	38.894
Interval_-5	-8.2729	28.291	6.2599
Interval_-4	-8.1845	28.300	15.444
Interval_-3	-20.639	21.066	8.5618
Interval_-2	-22.444	-24.408	48.341

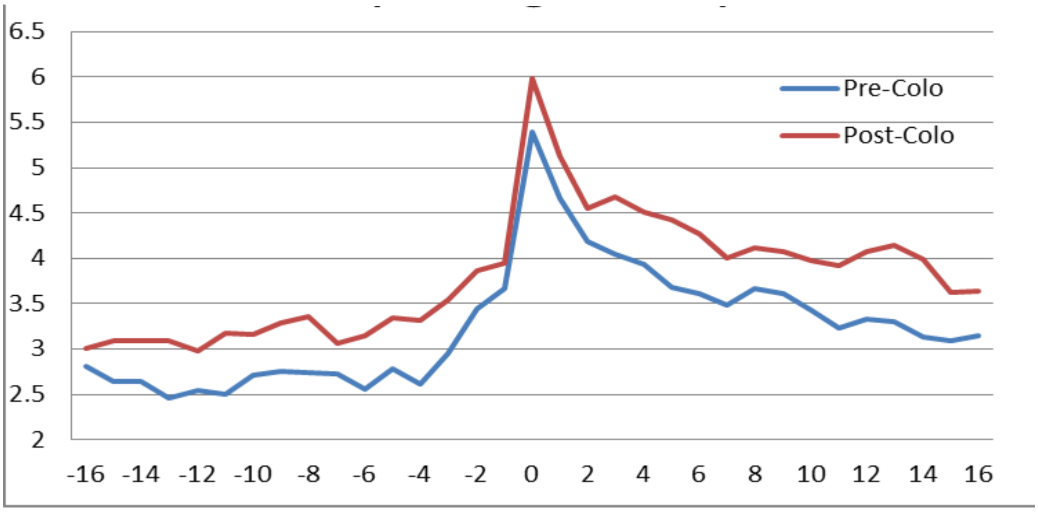
Interval_-1	-41.977***	-396.61***	-2.1420
Interval_ 0	92.699***	1771.7***	427.72***
Interval_ 1	62.550***	1300.3***	222.14***
Interval_ 2	29.071*	470.45***	122.87**
Interval_ 3	25.585	377.79***	145.60***
Interval_ 4	26.069	437.98***	183.76***
Interval_ 5	11.130	278.81**	88.571*
Adjusted_R^2	0.3984	0.5579	0.1805
Panel B. No. of Trades			
Log_MSG	2.6686***	1.4271***	0.1871
Volatility	483.01***	736.69***	180.14***
|Surprise|	0.9347	-1.3213	-0.1589
Bad_News	-0.1329	-0.2704	0.1718*
Post_News	-0.1943	0.5134	0.0539
Interval_-5	-0.4143	0.4516	-0.1598
Interval_-4	-0.9275	-0.0100	-0.0452
Interval_-3	-0.4667	-0.2620	0.0481
Interval_-2	-1.6528**	-0.3416	0.0352
Interval_-1	-1.8229***	-2.6690**	-0.4400
Interval_ 0	10.158***	18.917***	4.1863***
Interval_ 1	4.5092***	9.4867***	1.2743***
Interval_ 2	2.0284***	4.1404***	0.3716
Interval_ 3	1.7553**	2.7883**	0.9942**
Interval_ 4	1.9092***	3.7827***	0.7496*
Interval_ 5	1.0611	1.8092*	0.3021
Adjusted_R^2	0.6324	0.7291	0.4336

This analysis computes the average number of order book updates (message traffic) for each minute interval surrounding the announcement time. Figure A-C-1 displays the message traffic surrounding macro news releases from 16 minutes before to 16 minutes after the announcement time for the three-year government bond futures, and compares the HFT activity between pre- and post- co-location periods. As seen in the figure, the introduction of co-location has significantly increased the level of HFT for intervals before and after the announcement time. For both pre-colo and post-colo periods, HFT activity increases two minutes prior to the announcement time and peaks one-minute following the release time. After the initial surge, the message traffic gradually declines but stays relatively high for the next 16 minutes.

Figure A-C-1
High Frequency Trading: Message Traffic Proxy

Figure A-C-1 graphs the HFT behaviour surrounding macro news releases from 16 minutes before to 16 after the announcement time for the three-year government bond futures, where the blue line indicates the pre-colo period and the red line indicates the post-colo period. HFT is proxied by the natural logarithmic of message traffic for each minute interval. The event window extends one year pre to one year post the co-location date.

High Frequency Trading: Message Traffic Proxy



To examine how the market adjusts to new information and to determine whether the speed of adjustments differs between the two periods, the following figure looks at the patterns of price volatility, trading volume and trade frequency around scheduled information for both periods.

As shown in Figure A-C-2-1, price volatility starts to rise and then spikes up in the minute immediately following the news releases for both periods, reflecting the market's initial reaction to new information. The volatility in the pre-colo period is slightly higher than in the post-colo period at their peak values.

Figure A-C-2-2 reveals the intraday trading volume around 11:30 am on major announcement days for both pre-colo and post-colo periods. It is noticeable that the volume increases sharply in the minute immediately following the announcement and it is slightly more pronounced in the post-colo period than in the pre-colo period at their peak values. After the initial surge, the volume gradually declines but stays relatively high for the next 16 minutes.

The difference in trading intensity between the pre-colo and the post-colo periods is more evident in Figure A-C-2-3. The figure suggests that the post-colo market demonstrates a much higher trading frequency for the minute immediately following the news releases. This might be due to the rapid growth of HFT after the related technology upgrades.

Figure A-C-2
Trading Intensity: Volatility, Volume and Trade Frequency

Figure A-C-2 graphs the trading intensity measures surrounding macro news releases from 16 minutes before to 16 after the announcement time for the three-year government bond futures, where the blue line indicates the pre-colo period and the red line indicates the post-colo period. The event window extends one year pre to one year post the co-location date. Figure A-C-2-1 depicts the average volatility as measured by the log difference between the highest and the lowest mid-quote price for each minute interval. Figure A-C-2-2 depicts the average trading volume for each minute interval. Figure A-C-2-3 depicts the average trade frequency for each minute interval.

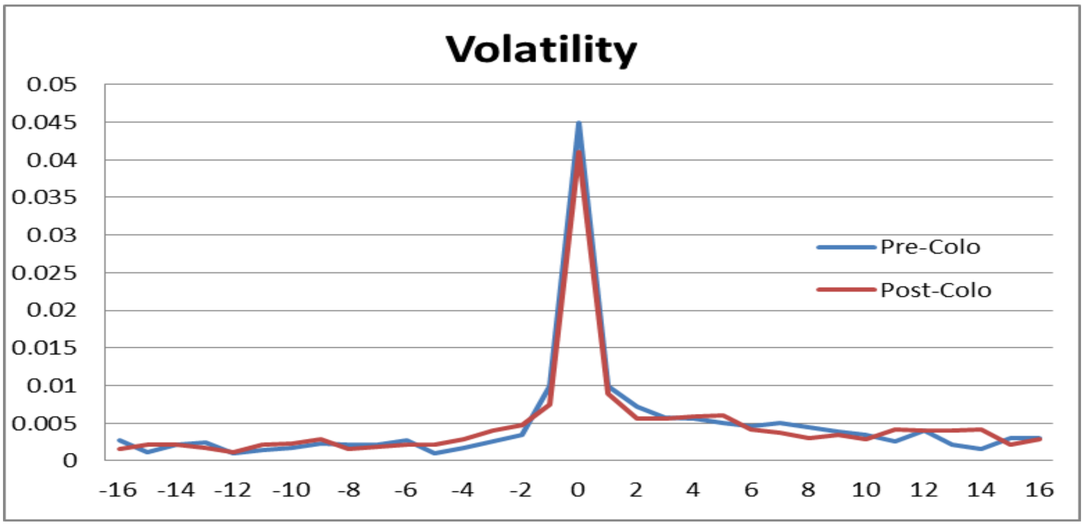


Figure A-C-2-1

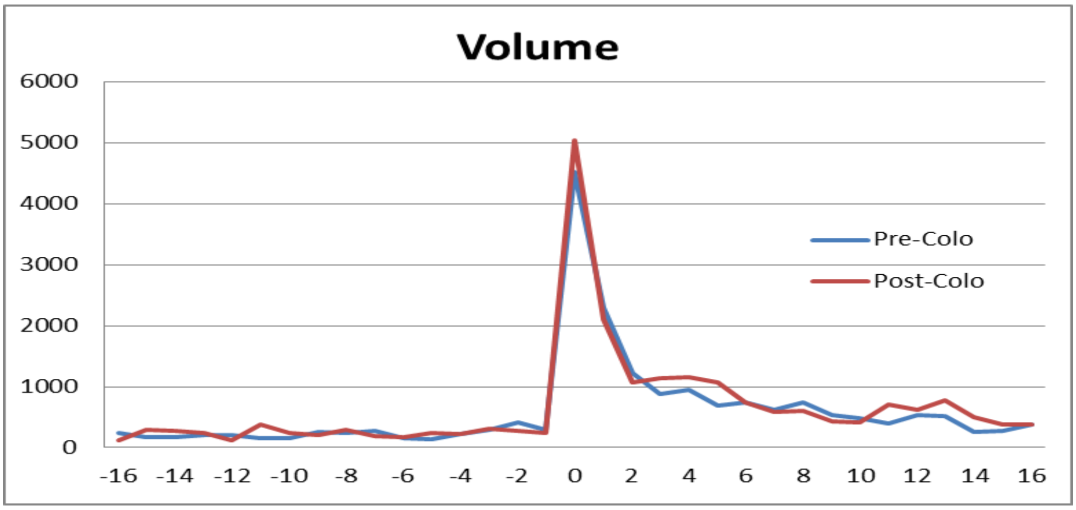


Figure A-C-2-2

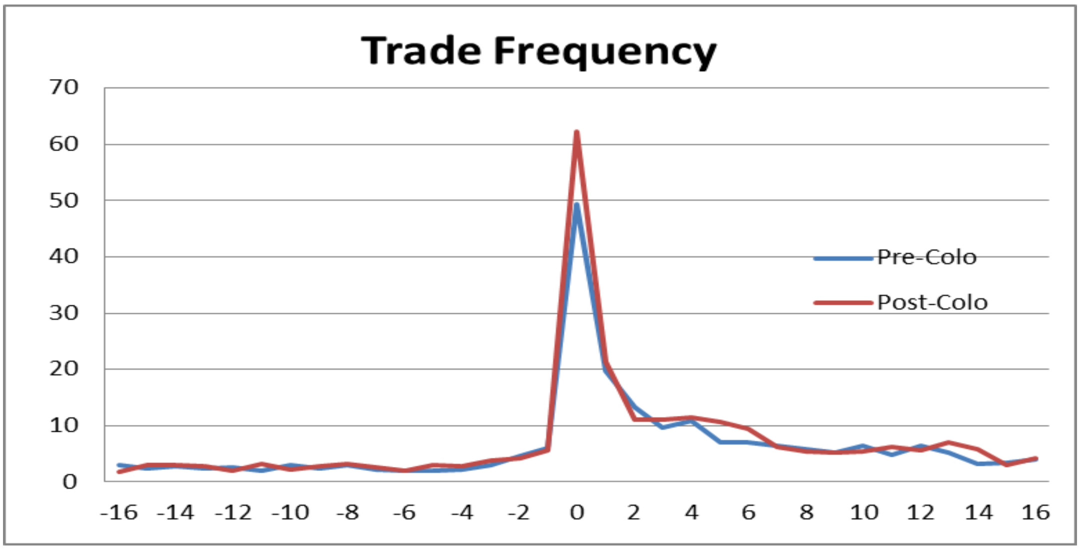


Figure A-C-2-3

Figure A-C-3 compares liquidity responses to public information arrivals between the pre-colo and the post-colo periods. Figure A-C-3-1 shows that the Level 1 dollar depth reduces before the announcement time, almost simultaneously for both periods, and reaches the bottom of the curve in the minute immediately prior to the release time. The patterns are similar between the two sample periods; however, the level of depth is higher in the post-colo period consistently throughout the announcement times. Consistent results are found for the relative spread and the effective spread and both have revealed a better liquidity for the post-colo period. Based on the quoted spread measure, liquidity is higher for the post-colo period at the exact announcement time and remains similar between the two periods for intervals preceding and following the release time.

Figure A-C-3

Liquidity: Dollar Depth, Relative Spread, Quoted Spread and Effective Spread

Figure A-C-3 graphs the market liquidity measures surrounding macro news releases from 16 minutes before to 16 after the announcement time for the three-year government bond futures, where the blue line indicates the pre-colo period and the red line indicates the post-colo period. The event window extends one year pre to one year post the co-location date. Figure A-C-3-1 depicts the average natural logarithm of Level 1 dollar depth for each minute interval. Figure A-C-3-2 depicts the average relative spread (Bid-Ask Spread %) for each minute interval. Figure A-C-3-3 depicts the average quoted spread (Bid-Ask Spread Ticks) for each minute interval. Figure A-C-3-4 depicts the average effective spread for each minute interval.

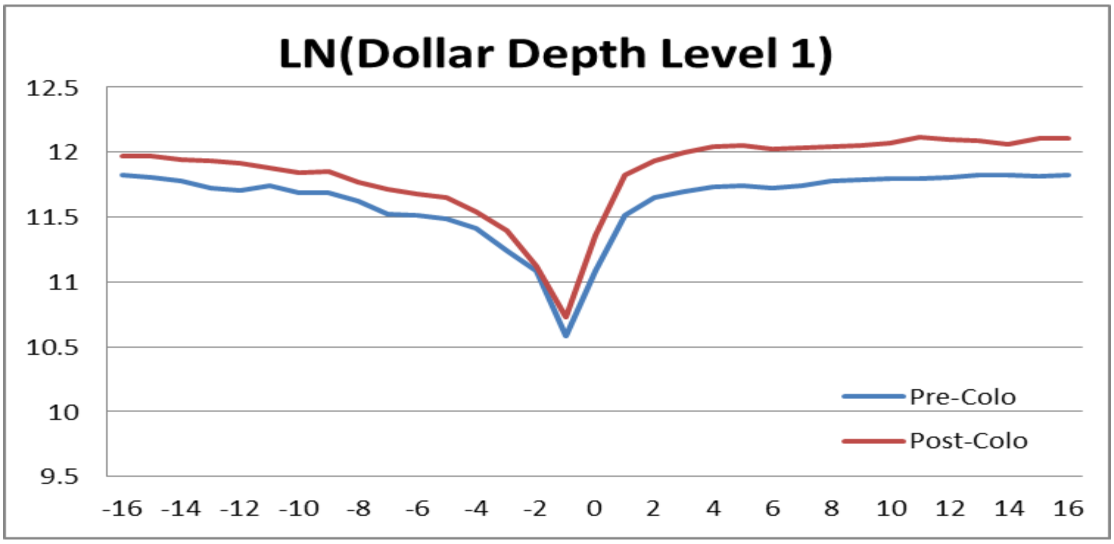


Figure A-C-3-1

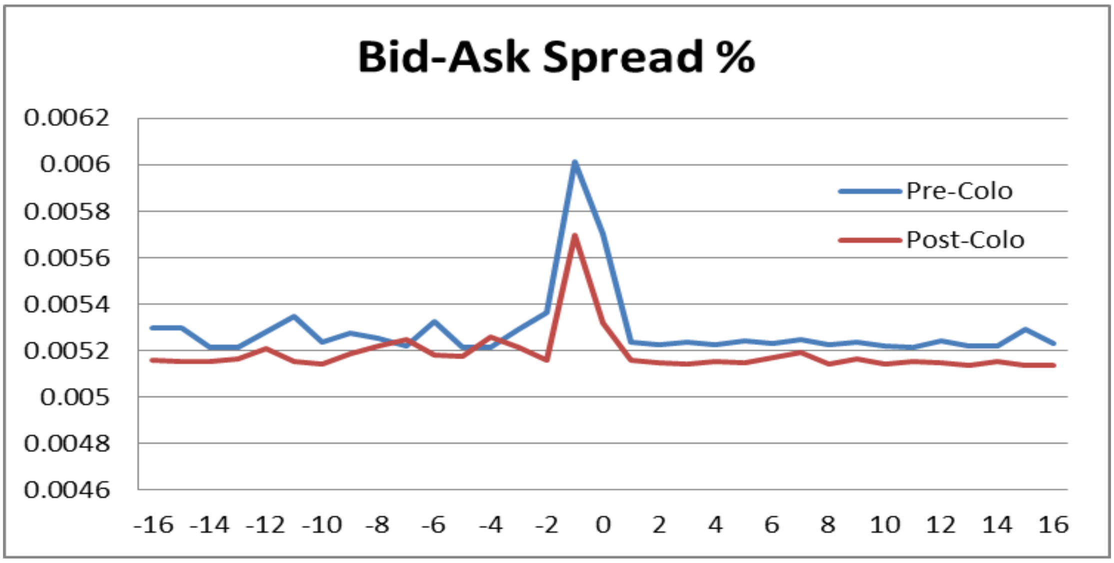


Figure A-C-3-2

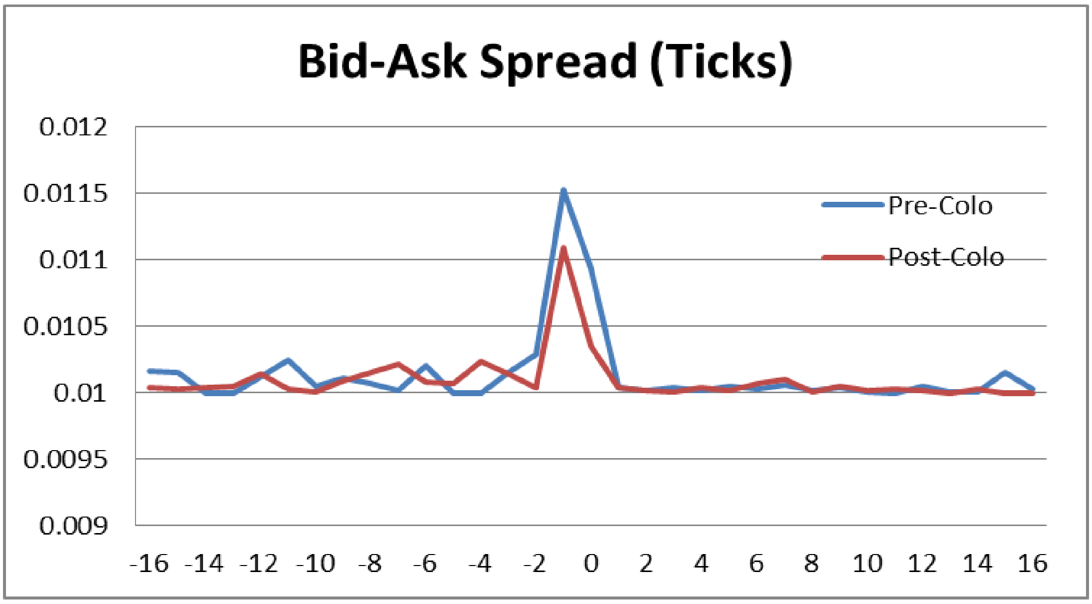


Figure A-C-3-3

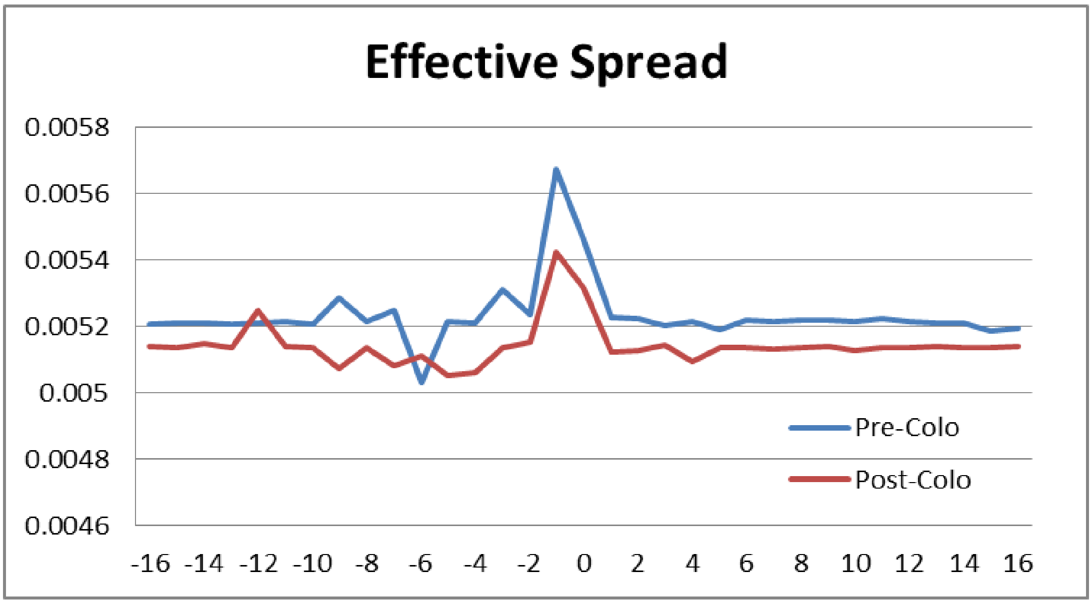


Figure A-C-3-4

References

A

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 375-410.

Ahn, H. J., Kang, J., & Ryu, D. (2010). Information effects of trade size and trade direction: Evidence from the KOSPI 200 index options market. *Asia‐Pacific Journal of Financial Studies, 39*(3), 301-339.

Aitken, M., Frino, A., & Sayers, S. (1994). The intra-day impact of block trades on the Australian Stock Exchange. *Asia-Pacific Journal of Management, 11*(2), 237-253.

Amihud, Y., & Mendelson, H. (1980). Dealership market: Market-making with inventory. *Journal of Financial Economics, 8*(1), 31-53.

B

Balduzzi, P., Elton, E. J., & Green, T. C. (2001). Economic news and bond prices: Evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis, 36*(04), 523-543.

Barclay, M. J., & Warner, J. B. (1993). Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics, 34*(3), 281-305.

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *Review of Financial Studies, 20*(6), 1783-1831.

Berkman, H., Brailsford, T., & Frino, A. (2005). A note on execution costs for stock index futures: Information versus liquidity effects. *Journal of Banking and Finance, 29*(3), 565-577.

Bernard, V. L., & Thomas, J. K. (1989). Post-earnings-announcement drift: delayed price response or risk premium?. Journal of Accounting research, 1-36.

Bessembinder, H., Maxwell, W., & Venkataraman, K. (2006). Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics, 82*(2), 251-288.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium fast trading. *Journal of Financial Economics, 116*(2), 292-313.

Biais, B., Hillion, P., & Spatt, C. (1995). An empirical analysis of the limit order book and the order flow in the Paris Bourse. *The Journal of Finance, 50*(5), 1655-1689.

Borio, C. (2000). III. Special feature: Market liquidity and stress: selected issues and policy implications. *BIS Quarterly Review*.

Boehmer, E., Fong, K. Y., & Wu, J. J. (2015). International evidence on algorithmic trading. *AFA 2013 San Diego Meetings Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2022034

Bozcuk, A., & Lasfer, M. A. (2005). The information content of institutional trades on the London Stock Exchange. *Journal of Financial and Quantitative Analysis, 40*(03), 621-644.

Brockman, P., & Chung, D. Y. (2002). Commonality in Liquidity: Evidence from an Order‐Driven Market Structure. *Journal of Financial Research, 25*(4), 521-539.

Brockman, P., Chung, D. Y., & Pérignon, C. (2009). Commonality in liquidity: A global perspective. *Journal of Financial and Quantitative Analysis*, *44*(04), 851-882.

Brogaard, J. (2010). *High frequency trading and its impact on market quality* (Northwestern University Kellogg School of Management Working Paper, 66).

Brogaard, J., Hagströmer, B., Nordén, L., & Riordan, R. (2015). Trading fast and slow: Co-location and liquidity. *Review of Financial Studies*, *28*(12), 3407-3443.

Brogaard, J., Hendershott, T., Hunt, S., & Ysusi, C. (2014). High frequency trading and the execution costs of institutional investors. *Financial Review, 49*(2), 345-369.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. *Review of Financial Studies, 27*(8), 2267-2306.

Budish, E., Cramton, P., & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics*, *130*(4), 1547-1621.

Burdett, K., & O'hara, M. (1987). Building blocks: An introduction to block trading. *Journal of Banking & Finance*, 11(2), 193-212.

C

Cao, M., & Wei, J. (2010). Option market liquidity: Commonality and other characteristics. *Journal of Financial Markets, 13*(1), 20-48.

Cartea, Á., & Penalva, J. (2012). Where is the value in high frequency trading? *The Quarterly Journal of Finance, 2*(03), 1250014.

Cetin, U., Jarrow, R., Protter, P., & Warachka, M. (2006). Pricing options in an extended Black Scholes economy with illiquidity: Theory and empirical evidence. *Review of Financial Studies, 19*(2), 493-529.

Chaboud, A. P., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. *The Journal of Finance, 69*(5), 2045-2084.

Chakravarty, S. (2001). Stealth-trading: Which traders' trades move stock prices? *Journal of Financial Economics, 61*(2), 289-307.

Chan, L. K., & Lakonishok, J. (1993). Institutional trades and intraday stock price behavior. *Journal of Financial Economics, 33*(2), 173-199.

Chan, L. K., & Lakonishok, J. (1995). The behavior of stock prices around institutional trades. *The Journal of Finance, 50*(4), 1147-1174.

Chan, L. K., & Lakonishok, J. (1997). Institutional equity trading costs: NYSE versus Nasdaq. *The Journal of Finance, 52*(2), 713-735.

Chen, Y. (2011). Derivatives use and risk taking: Evidence from the hedge fund industry. *Journal of Financial and Quantitative Analysis, 46*(04), 1073-1106.

Chiang, M. H., Lin, T. Y., & Yu, C. H. J. (2009). Liquidity provision of limit order trading in the futures market under bull and bear markets. *Journal of Business Finance and Accounting, 36*(7-8), 1007-1038.

Chiyachantana, C. N., Jain, P. K., Jiang, C., & Wood, R. A. (2004). International evidence on institutional trading behavior and price impact. *The Journal of Finance, 59*(2), 869-898.

Chordia, T., Green, T. C., & Kottimukkalur, B. (2015). Do high frequency traders need to be regulated? Evidence from algorithmic trading on macro news. Retrieved from http://www.bus.emory.edu/cgreen/docs/Chordia,Green,Kottimukkalur_WP2015.pdf

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics, 56*(1), 3-28.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The Journal of Finance*, *56*(2), 501-530.

Coughenour, J. F., & Saad, M. M. (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics, 73*(1), 37-69.

Cvitanic, J., & Kirilenko, A. A. (2010). High frequency traders and asset prices. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1569067

D

Dang, T. L., Moshirian, F., Wee, C. K. G., & Zhang, B. (2015). Cross-listings and liquidity commonality around the world. *Journal of Financial Markets*, *22*, 1-26.

Demsetz, H. (1968). The cost of transacting. *The Quarterly Journal of Economics, 82*(1), 33-53.

E

Easley, D., & O'Hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics, 19*(1), 69-90.

Edwards, A. K., Harris, L. E., & Piwowar, M. S. (2007). Corporate bond market transaction costs and transparency. *The Journal of Finance, 62*(3), 1421-1451.

Elder, J., Miao, H., & Ramchander, S. (2012). Impact of macroeconomic news on metal futures. *Journal of Banking and Finance, 36*(1), 51-65.

F

Fabre, J., & Frino, A. (2004). Commonality in liquidity: Evidence from the Australian stock exchange. *Accounting and Finance, 44*(3), 357-368.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1996). Trading costs and the relative rates of price discovery in stock, futures, and option markets. *Journal of Futures Markets, 16(4)*, 353-387.

Foucault, T., Hombert, J., & Roşu, I. (2016). News trading and speed. *The Journal of Finance, 71*(1), 335-382.

Foucault, T., Kozhan, R., & Tham, W. W. (2017). Toxic arbitrage. *The Review of Financial Studies*, 30(4), 1053-1094.

Frino, A., & McKenzie, M. D. (2002). The pricing of stock index futures spreads at contract expiration. *Journal of Futures Markets, 22*(5), 451-469.

Frino, A., Mollica, V., & Romano, M. G. (2013). Transaction fees and trading strategies in financial markets. *Studi Economici, 111,* 25-50.

Frino, A., Mollica, V., & Webb, R. I. (2014). The impact of co-location of securities exchanges' and traders' computer servers on market liquidity. *Journal of Futures Markets, 34*(1), 20-33.

Frino, A., & Oetomo, T. (2005). Slippage in futures markets: Evidence from the Sydney Futures Exchange. *Journal of Futures Markets, 25*(12), 1129-1146.

Frino, A., Prodromou, T., Wang, G. H., Westerholm, P. J., & Zheng, H. (2016). An empirical analysis of algorithmic trading around earnings announcements. *Pacific-Basin Finance Journal*, forthcoming.

Frino, A., & West, A. (2003). The impact of transaction costs on price discovery: Evidence from cross-listed stock index futures contracts. *Pacific-Basin Finance Journal, 11*(2), 139-151.

G

Gemmill, G. (1996). Transparency and liquidity: A study of block trades on the London Stock Exchange under different publication rules. *The Journal of Finance, 51*(5), 1765-1790.

Glosten, L. R., & Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics, 14*(1), 71-100.

Goldstein, M. A., Kumar, P., & Graves, F. C. (2014). Computerized and high frequency trading. *Financial Review, 49*(2), 177-202.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review, 70*(3), 393-408.

H

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics, 59*(3), 383-411.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance*, *66*(1), 1-33.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *The Journal of Finance, 66*(1), 1-33.

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis, 48*(4), 1001-1024.

Hoffmann, P. (2014). A dynamic limit order market with fast and slow traders. *Journal of Financial Economics, 113*(1), 156-169.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1987). The effect of large block transactions on security prices: A cross-sectional analysis. *Journal of Financial Economics, 19*(2), 237-267.

Holthausen, R. W., Leftwich, R. W., & Mayers, D. (1990). Large-block transactions, the speed of response, and temporary and permanent stock-price effects. *Journal of Financial Economics, 26*(1), 71-95.

Hu, G. (2009). Measures of implicit trading costs and buy–sell asymmetry. *Journal of Financial Markets*, 12(3), 418-437.

Huberman, G., & Halka, D. (2001). Systematic liquidity. *Journal of Financial Research, 24*(2), 161-178.

Huh, Y. (2011). Algorithmic trading and liquidity commonality (Working paper). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2337523

J

Jovanovic, B., & Menkveld, A. J. (2016). Middlemen in limit order markets (Working paper). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1624329

K

Karolyi, G. A., Lee, K. H., & Van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics, 105*(1), 82-112.

Keim, D. B., & Madhavan, A. (1995). Anatomy of the trading process empirical evidence on the behavior of institutional traders. *Journal of Financial Economics, 37*(3), 371-398.

Keim, D. B., & Madhavan, A. (1997). Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics, 46*(3), 265-292.

Kervel, V., & Menkveld, A. J. (2016). High-frequency trading around large institutional orders. *Western Finance Association (WFA) Conference, 2016*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2619686

Kirilenko, A. A., Kyle, A. S., Samadi, M., & Tuzun, T. (2016). The flash crash: High frequency trading in an electronic market. *Journal of Finance*, forthcoming. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id-1686004

Korajczyk, R. A., & Sadka, R. (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics, 87*(1), 45-72.

Koski, J. L., & Michaely, R. (2000). Prices, liquidity, and the information content of trades. *Review of Financial Studies, 13*(3), 659-696.

Kraus, A., & Stoll, H. R. (1972). Price impacts of block trading on the New York Stock Exchange. *The Journal of Finance, 27*(3), 569-588.

Kross, W., & Schroeder, D. A. (1984). An empirical investigation of the effect of quarterly earnings announcement timing on stock returns. Journal of Accounting Research, 153-176.

L

Lee, K. H. (2011). The world price of liquidity risk. *Journal of Financial Economics, 99*(1), 136-161.

Lee, C., & Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance, 46*(2), 733-746.

Levin, E. J., & Wright, R. E. (2002). Estimating the price elasticity of demand in the London stock market. *The European Journal of Finance, 8*(2), 222-237.

M

Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. *The Journal of Finance, 68*(5), 1805-1841.

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2013). Liquidity commonality in commodities. *Journal of Banking and Finance, 37*(1), 11-20.

Martinez, V. H., & Rosu, I. (2013). High frequency traders, news and volatility. *AFA 2013 San Diego Meetings Paper*.

McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. the Journal of Finance, 47(2), 753-764.

Milgrom, P., & Stokey, N. (1982). Information, trade and common knowledge. *Journal of Economic Theory, 26*(1), 17-27.

Moshirian, F., Qian, X., Wee, C. K. G., & Zhang, B. (2017). The determinants and pricing of liquidity commonality around the world. *Journal of Financial Markets, 33,* 22-41.

O

O'hara, M. (1995). Market microstructure theory (Vol. 108). Cambridge, MA: Blackwell.

O'Hara, M. (2003). Presidential address: Liquidity and price discovery. The Journal of Finance, 58(4), 1335-1354.

P

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *Review of Financial Studies, 19*(3), 871-908.

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642-685.

Pradkhan, E. (2015). Information content of trading activity in precious metals futures markets. *Journal of Futures Markets, 36*(5), 421-456.

R

Riordan, R., & Storkenmaier, A. (2012). Latency, liquidity and price discovery. *Journal of Financial Markets, 15*(4), 416-437.

Roll, R. (1988). The international crash of October 1987. *Financial Analysts Journal, 44*(5), 19-35.

Rosu, I. (2016). Fast and slow informed trading. *AFA 2013 San Diego Meetings Paper*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1859265

Ryu, D. (2013). Price impact asymmetry of futures trades: Trade direction and trade size. *Emerging Markets Review, 14,* 110-130.

S

Saar, G. (2001). Price impact asymmetry of block trades: An institutional trading explanation. *Review of Financial Studies, 14*(4), 1153-1181.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics, 80*(2), 309-349.

Schoenfeld, S.A. (2004). *Active index investing: Maximizing portfolio performance and minimizing risk through global index strategies*. Hoboken, NJ: John Wiley & Sons.

Scholes, M. S. (1972). The market for securities: Substitution versus price pressure and the effects of information on share prices. *The Journal of Business, 45*(2), 179-211.

Securities, U. S., & Exchange Commission. (2014). Equity market structure literature review Part II: High frequency trading. Staff of the Division of Trading and Markets.

Shleifer, A. (1986). Do demand curves for stocks slope down? *The Journal of Finance, 41*(3), 579-590.

Subrahmanyam, A. (1991). A theory of trading in stock index futures. *The Review of Financial Studies, 4(1),* 17-51.

X

Xu, C. (2014). Expiration-day effects of stock and index futures and options in Sweden: The return of the witches. *Journal of Futures Markets, 34*(9), 868-882.

Z

Zhong, M., Darrat, A. F., & Otero, R. (2004). Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. *Journal of Banking and Finance, 28*(12), 3037-3054.