The Impact of Regulatory Changes on Derivatives Markets

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Certificate

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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List of Abbreviations

ALC - Australian Liquidity Centre

AMEX - American Stock Exchange

ASIC - Australian Securities and Investment Commission

ASX - Australian Securities Exchange

ATS - Alternative Trading System

CBOE - Chicago Board Options Exchange

CFFEX - China Financial Futures Exchange

CFTC - Commodity Futures Trading Commission

CLOB - Central Limit Order Book

CSI - China Securities Index

CRS - Cost Recovery Scheme

ETF - Exchange-Traded Fund

FTT - Financial Transaction Tax

FTSE - Financial Times Stock Exchange

HFT - High Frequency Trading

KOSPI - Korea Composite Stock Price Index

IFM - Integrated Fee Model

IPO - Initial Public Offering

IIROC - Investment Industry Regulatory Organization of Canada

LIFFE - London International Financial Futures and Options Exchange

MiFID - Markets in Financial Instruments Directive

NASDAQ – Nasdaq Stock Market

NBBO - National Best Bid and Offer

NYSE - New York Stock Exchange

OTC - Over-the-Counter

SEC - Securities and Exchange Commission

SGX - Singapore Stock Exchange

SIMEX - Singapore International Monetary Exchange

SPDR - Standard and Poor's Depository Receipt

SSE - Shanghai Securities Exchange

STT - Securities Transaction Tax

SZSE - Shenzhen Securities Exchange

TAIFEX - Taiwan Futures Exchange

TRTH – Thompson Reuters Tick History

TSX - Toronto Stock Exchange

UK – United Kingdom

UMIR - Universal Market Integrity Rules

US - United States

Preface

Some of the work presented in this dissertation is published as joint work and has been submitted to refereed journals.

Chapter 3 constitutes one working paper

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Synopsis

This dissertation investigates the impact of regulatory changes on derivatives markets. The importance of these issues is underscored by the increasing prevalence of derivative securities worldwide. As both the benefits and detriments that derivatives bring to capital markets can be significant, it is essential to understand the microstructure of derivatives markets. Each essay addresses a research question with scarce or conflicting prior research findings to provide empirical evidence which can assist policy-makers to develop a comprehensive understanding of the potential impact of regulations on derivatives markets.

The first issue examined in this dissertation is the impact of short sales restrictions on futures pricing efficiency in China. In 2015, the regulator imposed new restrictions in China's equities market, which prohibited investors who borrow shares for short-selling from covering their positions within a trading day. This dissertation finds evidence that the short sales restrictions exert a significant effect on index futures mispricing. Futures under-pricing occurs more frequently across a range of transaction cost levels, while futures over-pricing occurs less frequently. In addition, results indicate that the relative size of futures mispricing is significantly greater at various transaction cost levels under the new short sales rule.

The second issue examined in this thesis relates to the effects of message traffic regulatory restrictions on the relative pricing efficiency between index futures contracts and the Exchange-Traded Funds (ETFs) that track the index. This study is conducted based on regulatory changes in four jurisdictions, namely Australia, Canada, Italy, and France. Results reveal that the message traffic restrictions impose a significant impact on the return correlations between index futures and ETFs. However, the direction of the changes vary across markets. The return correlations in Australia and Canada increase after the transition, while in Italy they decrease under the new regulation. Further, the return correlation between the two instruments in France remains unchanged during the sample period.

The third issue investigated in this thesis is the impact of dark trading regulations on options market liquidity. This dissertation aims to bridge the gap between the literature of dark trading and options market liquidity. This research documents that the restrictive dark trading regulation imposes a mixed impact on the options market liquidity. For call options, the bid-ask spread and market depth increase after the transition. The effective spread also increases, which indicates that call options traders experience higher execution costs under the new rules. Similarly, for put options, the bid-ask spread and market depth increase after the regulatory change. However, the effective spread for put options is less affected by the dark trading regulations. Results also reveal that the realised spread and price impact do not show a substantial change during the sample period for both call and put options.

Chapter 1 - Introduction

After the 2008 Global Financial Crisis, market regulation and market supervision have urgently been called for by investors, industry professionals, and academia. Financial regulators are charged with the role of improving market quality. They oversee the operations of capital markets to ensure a sound level of integrity, efficiency, and fairness. In the past decade, however, rapid technological improvement has revolutionised the way modern securities trading is conducted. High frequency trading and dark trading are two symbolic trading innovations, whose market share has increased substantially in many exchanges around the world. In the Australian equities market, for instance, high frequency trading accounts for approximately 27% of total market turnover and 47% of total message count in recent years. In addition, dark trading activity remains at 25 to 30% of total turnover during the first half of the 2010s (ASIC, 2015).

Such technological advancement may have unintended consequences for market quality. A large amount of empirical evidence relating to these two trading innovations demonstrates both beneficial and detrimental effects on the equities market. Regulations over high frequency trading and dark trading have been implemented in some jurisdictions. The efficiency and effectiveness of those regulations are discussed in depth in the existing literature. However, there is limited research examining the effects of these rules and policies on derivatives markets, such as futures and options.

Derivatives markets are an integral part of the global financial system as they can be easily utilised by investors to transfer risk, without actual transfer of ownership of assets. The total notional outstanding amount of over-the-counter (OTC) derivatives worldwide reached US$482.9 trillion at the end of 2016 (BIS, 2017). Given the increasing prevalence of derivatives securities, and their influence on underlying asset markets, it is pivotal for policy-makers to develop a comprehensive understanding of the potential impact of these regulations on both equities *and* derivatives markets.

Market liquidity and pricing efficiency are two main issues in the market microstructure literature. An efficient financial market contains both informed and uninformed traders. Informed traders acquire costly information and they trade on their views towards securities' intrinsic values. Their trading activity is generally considered to increase the pricing efficiency of the market. In addition, uninformed traders inject liquidity to the market and improve trade execution. Consequently, investigating the effects of regulatory changes on the behaviour and welfare of different types of traders is a key to measuring the impact of those policies and rules on market efficiency.

Among the literature, there is little consensus on the impact of regulatory changes on market quality. This dissertation examines three contemporary market regulation changes and their effects on derivatives markets. The first essay (Chapter 3) examines the impact of short-selling restrictions on the pricing efficiency of index futures contracts in China. The second essay (Chapter 4) evaluates the message traffic regulatory restrictions and their effects on the relative pricing efficiency between index futures contracts and index Exchange-Traded Funds (ETFs) in four jurisdictions, namely Australia, Canada, Italy, and France. The third essay (Chapter 5) investigates the relationship between dark trading regulations and options market liquidity in Canada.

1.1 The Impact of Short Sales Restrictions on Index Futures Pricing: Evidence from China

Short-selling restrictions are a common regulatory practice adopted to curb excess market volatility, especially during periods of market crashes. The first essay, presented as Chapter 3 of this dissertation, investigates the pricing of stock index futures in relation to short-selling restrictions in China. The literature suggests that theoretically, futures prices and the corresponding underlying prices are determined such that arbitrage opportunities do not exist. The relative pricing relationship is maintained by arbitrageurs who can capture profits from misalignment between futures and the underlying prices (e.g., MacKinlay & Ramaswamy, 1988). However, various obstacles to arbitrage trading strategies could lead to persistent futures mispricing. Existing studies demonstrate significant misalignment between the stock index futures price and the corresponding underlying index level in numerous markets (e.g., Cornell & French, 1983; Harris, 1989; Brennan & Schwartz, 1990; Chung, 1991; Yadav & Pope, 1994; Chu & Hsieh, 2002; Draper & Fung, 2003; Richie, Daigler, & Gleason, 2008; Cummings & Frino, 2011).

Chapter 3 extends the understanding of the relationship between short-selling restrictions and futures pricing on which there is disagreement in the literature. Numerous existing papers provide evidence that short-selling restrictions are a significant factor for stock index futures mispricing. Fung and Draper (1999) find that the removal of short-selling restrictions reduces the frequency and magnitude of index futures mispricing in Hong Kong. Kempf (1998) and Fung and Jiang (1999) reach qualitatively similar conclusions. On the contrary, if the owners of the underlying assets act on futures under-pricing (or the over-pricing of the underlying assets) quickly, short sale restrictions may not have a significant impact on futures pricing, especially futures under-pricing. By directly examining S&P 500 arbitrage trades during a period in 1989, Neal (1996) presents evidence that futures pricing is not significantly affected by short sale restrictions. Hence, the relationship between short sale restrictions and futures pricing is an empirical question.

A recent regulatory change in China provides a natural experimental environment in which to examine the relationship between short-selling restrictions and index futures pricing. On 4 August 2015, Chinese regulators imposed new restrictions on short-selling in China's equities market. After the rule change, investors who borrow shares for short-selling are not allowed to cover their positions within a trading day. This means that it is not possible for arbitrageurs to realise profits in the presence of futures mispricing within a trading day, which will likely discourage short-term arbitrageurs' activities. If short-term arbitrageurs are highly influential on futures pricing, market participants are likely to observe futures under-pricing more frequently under the new short sale rule. This essay uses a data set of the futures price and index values at one-minute time intervals. The market futures price is compared with its theoretical value, according to the "cost-of-carry" model. The frequency and magnitude of futures mispricing are measured against different levels of pre-assumed transaction costs ranging from 0 to 1.5%.

Results reveal that futures under-pricing occurs more frequently at the transaction cost levels, ranging from 0 to 1.5%, while futures over-pricing occurs less frequently under the transaction cost levels from 0 to 0.75% under the new short sale rule. This essay also finds evidence that the relative size of futures mispricing is significantly greater at the transaction cost levels from 0 to 0.25% after the regulatory change. One possible explanation is that under the new short sale rule, short-term arbitrageurs, who intend to realise profits within a trading day, are discouraged from trading in the presence of futures under-pricing (or over-pricing of the underlying assets), implying that futures under-pricing is more frequently observed after the regulatory change.

1.2 Message Traffic Restrictions and Relative Pricing Efficiency: Evidence from Index Futures Contracts and Exchange-Traded Funds

The contemporary growth in algorithmic trading has attracted the attention of market regulators, who have introduced various forms of message traffic regulatory restrictions in some countries. Prior literature reports that high order submission generally improves market quality, and these studies document that an increasing level of algorithmic trading, typically high frequency trading, is associated with improved market liquidity, faster price discovery, and lower market volatility (e.g., Brogaard, 2010; Hendershott, Jones, & Menkveld, 2011; Hasbrouck & Saar, 2013; Brogaard, Hendershott, & Riordan, 2014). In contrast, some studies focus on the negative externalities generated by high frequency trading. Jarnecic and Snape (2014) and Boehmer, Fong, and Wu (2015) find that high frequency trading increases short-term price volatility. Jarnecic and Snape (2014) also argue that a higher level of high frequency trading activity is associated with shorter order duration and thinner market depth. Kirilenko, Kyle, Samadi, and Tuzun (2017) suggest that high frequency traders increase price volatility by withdrawing from supplying liquidity, and even competing for liquidity, as they manage their inventory positions. It is argued that high frequency trading contributed to the extreme market stress during the "Flash Crash" in May 2010. Further, Biais, Foucault, and Moinas (2015) report that a high level of high frequency trading increases adverse selection costs of slower traders.

This generates an uneven playing field among market participants. Overall, the literature documents both positive and negative effects of high frequency trading on market quality.

Two popular adopted types of regulations related to high frequency trading are the market regulatory cost recovery based on message counts (e.g., Australia and Canada), and high frequency trading tax incorporated within a financial transaction tax (e.g., France and Italy). Specifically, Australian and Canadian regulators allocate their market regulatory costs to equity market participants based on their trade and message count. Those regulations raise the trading costs of certain groups of traders, especially high frequency trading firms. In addition, the design of modern financial transaction taxes incorporates a message traffic tax component, which levies based on the value of orders submitted, modified, or cancelled by traders. This tax component specifically targets high frequency traders who have high order-to-trade ratios and frequent changes in trading direction. For instance, the French financial transaction tax (implemented in 2012) and the Italian financial transaction tax (implemented in 2013) impose an additional high frequency trading tax on order amendments and cancellations which occur within a short time frame.

The availability of arbitrage opportunities reflects the pricing efficiency of related markets. Index arbitrageurs frequently implement their trading strategies, using index futures contracts and ETFs. Richie, Daigler, and Gleason (2008) identify the existence of mispricing between S&P 500 futures and its corresponding SPDR ETF. Further, Budish, Cramton, and Shim (2015) examine the return correlation between index futures and ETFs on the S&P 500 index. They find that the price of index futures and index ETFs is highly consistent in an efficient market, but the return correlation breaks down in high-frequency time intervals. In such situations, the price of two instruments does not move simultaneously, thereby generating profitable mechanical arbitrage opportunities for high speed traders. Message traffic restrictions, which increase the transaction costs of those traders, result in some arbitrage trading strategies becoming unprofitable. It then takes a longer time for markets to respond to mispricing. Hence, after the implementation of message traffic restrictions, the return correlation between index futures contracts and index ETFs is predicted to be lower.

However, some research finds that the frequency and duration of arbitrage opportunities increases when high frequency trading increases in the market (Frino, Mollica, Webb, & Zhang, 2016; Kozhan & Tham, 2012). Frino, Mollica, Webb, and Zhang (2016) suggest that a higher level of high frequency trading activity can increase the execution risks of arbitrage trading, which drives index futures mispricing. In this situation, the relative pricing efficiency will improve with message traffic restrictions. Therefore, it is an empirical question whether the overall impact of message traffic restrictions on the relative pricing efficiency between index futures and ETF markets is significant or not.

Chapter 4 incorporates the implementation of four message traffic regulations, which are the Cost Recovery Scheme in Australia (2012), the Integrated Fee Model in Canada (2012), the Financial Transaction Tax in France (2012), and the Financial Transaction Tax in Italy (2013). These transitions provide an opportunity to investigate the market impact of high frequency trading regulations. This essay utilises an order-level data set and creates daily return correlations based on the paired securities' prices every one second.

Results reveal that the message traffic restrictions impose a significant impact on the return correlation between index futures contracts and index ETFs, after controlling for the effects of futures market volatility and trading volume. However, the direction of changes varies across markets. Specifically, the return correlations in Australia and Canada increase after the transition, while a decrease in correlation is observed in Italy. Further, the return correlation between those two instruments in France does not experience a significant change. This is because the French high frequency trading tax, implemented in the underlying equities market, excludes transactions in financial derivatives and exchange-traded products.

1.3 Dark Trading Regulation and Option Market Liquidity: Evidence from Canada

Dark trading allows traders to submit their orders without pre-trade transparency. Therefore market participants' trading interests can be hidden before trades are executed. Modern technology enables dark orders to be matched continuously and automatically, contributing to its rapid growth. The proliferation of dark trading in contemporary capital markets can be attributed to its advantages, such as reduced information leakage and lower market impact costs. The emergence of dark trading has attracted considerable attention, among both investors and regulators. Regulatory authorities in many jurisdictions have made public consultations on the effect of dark trading on equity market efficiency. Prior literature widely evaluates this issue from both theoretical and empirical perspectives (e.g., Hendershott & Mendelson, 2000; Degryse, Van Achter, & Wuyts, 2009; Ye, 2012; Zhu, 2014; Comerton-Forde & Putnins, 2015; Foley & Putnins, 2016; Comerton-Forde, Malinova, & Park, 2016). However, there is only limited research that examines the impact of dark trading on the options market liquidity.

The potential effect of dark trading on the options market liquidity is ambiguous. The possible implications are two-fold. On the one hand, options market makers are predicted to face higher hedging costs with an increasing level of dark trading, which will result in wider bid-ask spreads in options markets. Zhu (2014) suggests that dark trading leads to the segregation of market participants. Unlike traditional exchanges, dark venues have no designated market makers who can absorb excess order flow, and thus traders face increased execution risks. Informed traders are more likely to trade in the same direction, clustering on the heavy side of the market. Consequently, informed traders face larger execution risks relative to uninformed traders in the dark. This feature forces the segregation of traders, with a larger proportion of informed traders remaining in the lit market. A high density of informed traders will result in larger adverse selection risk and higher bid-ask spreads in lit markets (Zhu, 2014).

Further, options market makers have to trade excessively in the underlying stock market to hedge their inventory exposures. The trading costs from their hedging activities must be compensated from the bid-ask spread posted in options markets (Huh, Lin, & Mello, 2015). Hence, it has been suggested that the liquidity of the underlying equity market is positively related to that in options markets (Cho & Engle, 1999; Petrella, 2006). Therefore, the bid-ask spread in options market is expected to widen with a higher level of dark trading.

On the other hand, dark trading can decrease the aggregate amount of information produced about securities' fundamental values. As a result, the adverse selection risk in the options market reduces, leading to lower bid-ask spreads. As discussed, a larger proportion of uninformed traders tend to migrate to dark trading venues (Zhu, 2014). The profitability of acquiring information decreases, which reduces the incentives for market participants to obtain costly information (Comerton-Forde & Putnins, 2015). Thus, less information is produced in aggregate and fewer traders choose to become informed, and options market makers will face lower adverse selection risks. Consequently, with a high level of dark trading, the bid-ask spread in the options market is predicted to reduce, according to the information-based models of market microstructure literature (Bartram, Fehle, & Shrider, 2008; Ahn, Kang, & Ryu, 2008).

In late 2012, the Canadian market regulator imposed a new dark trading regulation, namely "Minimum Price Improvement". This requires dark orders to provide a minimum price improvement over the National Best Bid and Offer (NBBO). Dark trading, as a proportion of total market turnover, reduced substantially after this event. This regulatory change provides a natural experiment to examine the impact of dark trading on the options market liquidity. Chapter 5 utilises an order-level data set for options contracts and performs an event study utilising regression analysis techniques.

This essay extends the understanding of dark trading and bridges the gap between the literature of options market efficiency and dark trading. The multivariate analysis, in this essay, suggests that the restrictive dark trading regulation imposes a mixed impact on the options market liquidity. For call options, the percentage bid-ask spreads and quoted depth increase after the transition. The effective spread also increases after the event, which illustrates that traders of call options face larger execution costs with a lower level of dark trading. Similarly, for put options, the percentage bid-ask spread and quoted depth increase after the regulatory change. However, the effective spread is less affected by the new regulation. In addition, the realised spread and price impact do not exhibit significant changes during the sample period, for both call and put options. These results are robust for different time interval assumptions.

1.4 Summary

The three essays of this dissertation examine the impact of various regulatory changes on the derivatives markets. The issues explicitly analysed focuses on the impact of the behaviours of different types of traders, and then potential changes in market quality. Such research is motivated by a number of factors, including the lack of consensus in the extant literature regarding the impact of the analysed regulatory changes. This thesis is therefore concerned with the promotion of derivatives markets that are both fair and efficient.

The remainder of this dissertation is organised as follows. Following this introduction, Chapter 2 describes the prior literature related to each of the above issues and develops several testable hypotheses. Chapters 3, 4, and 5 investigate the three issues discussed in this chapter. Each chapter includes sections that describe the data, sample, research design, empirical results, robustness tests, and conclusions reached. Overall conclusions and future areas for research are presented in Chapter 6.

Chapter 2 - Literature Review

This dissertation consists of three empirical studies of the impact of regulatory changes on the efficiency of derivatives markets. This chapter reviews the literature related to those three essays examined in this dissertation and highlights the areas of existing literature upon which this dissertation builds. In turn, based on the literature reviewed, a number of testable hypotheses are developed.

This chapter is structured as follows. Section 2.1 reviews the literature that examines the impact of short sale restrictions on market quality. Section 2.2 sheds light on the pricing mechanism of index futures contracts and some market factors that drive futures mispricing. Section 2.3 summarises prior studies which analyse the market effects of a financial transaction tax. Section 2.4 provides a literature review related to algorithmic trading and high frequency trading. Section 2.5 focuses on the literature that examines the impact of dark trading on equities market efficiency. The literature that investigates the options market liquidity is explored in Section 2.6. Section 2.7 uses the reviewed literature to develop testable hypotheses that are tested subsequently in this dissertation. Section 2.8 summarises and concludes this chapter.

2.1 Short Sale Regulations and Market Quality

Miller (1977) is the first to develop a model to examine the market impact of short sale restrictions. He argues that short-sale constraints can inflate market prices because pessimists are prohibited from acting on their views. Jarrow (1980) extends Miller's model and points out that universal short sale constraints lead to over-pricing of the entire market. Further, Diamond and Verrecchia (1987) argue that short sellers are rational informed traders who can push mispriced stocks back to their intrinsic values, thus enhancing market pricing efficiency. Empirical studies prove that trading by short sellers can help correct overvaluation in the market (e.g., Boehmer, Jones, & Zhang, 2008; Diether, Lee, & Werner, 2009a; Boehmer & Wu, 2013).

Prior research on short-sales is conducted based on various types of proxies. The change in short interest (short interest ratio, SIR) is one popular proxy adopted. It is computed as the number of shares that are short as a proportion of total number of shares outstanding (e.g., Figlewski, 1981; Senchack & Starks, 1993; Desai, Ramesh, Thiagarajan, & Balachandran, 2002; Asquith, Pathak, & Ritter, 2005). The cost of security lending/rebate rates is another proxy widely utilised (e.g, Jones & Lamont, 2002; D'Avolio, 2002; Cohen, Diether, & Malloy, 2007). In addition, the introduction of an exchange traded option on the stock offers a low-cost way for traders to implement their negative views (Boehme, Danielson, & Sorescu, 2006).

2.1.1 Impact on Stock Price

Previous studies find negative abnormal returns following the relaxation of short sale constraints, which is consistent with the hypothesis that non-shortable stocks are overpriced. Senchack and Starks (1993) test Diamond and Verrecchia's (1987) hypothesis and find that stocks with unexpected increases in short interest are accompanied with negative abnormal returns. Results show that the magnitude of negative abnormal returns is positively related to the degree of unexpected short interest and is lower for firms with exchange options.

Danielsen and Sorescu (2001) examine the abnormal stock returns after option listings in the 1980s. They find that the introduction of options is associated with negative abnormal returns in underlying stocks. Consistently, Ofek, and Richardson (2003) discover that short-sale constraints, in the form of stock option lockups, exert a significant and persistent negative effect on stock returns. Jones and Lamont (2002) report that stocks with a high cost to short sell have high valuations and low subsequent returns.

Desai, Ramesh, Thiagarajan, and Balachandran (2002) investigate the relationship between short interest and stock returns in the NASDAQ market from June 1988 to December 1994. They report that firms with significant short interest are more likely to have substantial negative abnormal returns. Therefore, a high level of short interest is a strong bearish signal.

Similarly, Asquith, Pathak, and Ritter (2005) compute short interest ratios for NYSE and AMEX stocks from 1980 to 2002, and for NASDAQ stocks from 1988 to 2002. They find that stocks with high short interest generally underperform the market. They identify short-sale constraints as a strong short interest (a proxy for demand) compared to a limited institutional ownership (a proxy for supply). The authors document that stocks which are short-sale constrained experience negative abnormal returns.

However, Chang, Cheng, and Yu (2007) do not find substantial changes in abnormal returns around the removal of short sale constraints. In addition, Diether, Lee, and Werner (2009a) do not discover changes in average returns around the suspension of short-sale price tests (removal of short sale restrictions). Further, Boulton and Braga-Alves (2010) document positive abnormal returns after the implementation of short sale restrictions.

Dechow, Hutton, Meulbroek, and Sloan (2001) provide some evidence that short sellers incorporate information to implement their trading strategies. Short sellers are found to prefer those stocks that have high market-to-fundamental ratios (e.g., Price-to-earnings ratio and price-to-book ratio). Those stocks are considered as examples of over-pricing and are predicted to have lower future returns. Christophe, Ferri, and Angel (2004) analyse the short-sales transactions prior to earnings announcements of NASDAQ stocks. They find that short sellers are primarily informed traders and short sales are more active in stocks with low book-to-market valuations.

Cohen, Diether, and Malloy (2007) study the impact of short sales on stock prices using proprietary data on stock lending fees and quantities over a four-year period. They conclude that shorting demand is an important factor for future stock returns. Stocks that are more expensive to short have lower subsequent returns. However, stock prices are less affected by supply shifts. The authors point out that the stock lending fee is not a sufficient determinant for stock overvaluation.

Chan, Kot, and Yang (2010) examine the impact of short-selling restrictions on stock prices, by comparing the price for stocks which are cross-listed in China mainland (A-shares: ineligible for short sale) and Hong Kong (H-shares: some stocks are eligible for short sale). In a bearish market, they find that the prices of shortable H-shares (stocks that allow short-selling) decrease more than those of non-shortable H-shares. In addition, the trading volume of shortable H-shares (as a proportion of A-shares) is larger than that of non-shortable H-shares. The results indicate that short-selling restrictions lead to stock relative over-pricing and reduces trading volume when the market falls.

2.1.2 Impact on Market Efficiency

Diamond and Verrecchia (1987) investigate the relationship between short sale restrictions and the speed of price adjustment to private information. They find that short sale constraints reduce the speed at which prices adjust to negative information. Consistent with Diamond and Verrecchia (1987), Reed (2007) shows that stocks which are difficult to short have larger price reactions to earnings announcements. When short selling is restricted, trading volume reduces and prices become less informative. In addition, Reed (2007) finds that the median duration of a position in the equity lending market is three days, and the mode of the distribution is only one day. This illustrates that short sellers appear to be short-term traders in the market. Similarly, Diether, Lee, and Werner (2009b) find that in 2005 the average days-to-cover ratio is approximately four days.

Ho (1996) reports that daily stock volatility increases when short-sale constraints are implemented. However, Chang, Cheng, and Yu (2007) find that when short-sale restrictions are lifted, stock return volatility increases. These findings are confirmed by Henry and McKenzie (2006) for a sample of stocks in Hong Kong. Diether, Lee, and Werner (2009a) investigate the effects of removing short-sale price-tests in the US. They find that the intraday volatility increases, while daily volatility is less affected after the restrictions are suspended. Lecce, Lepone, and Segara (2008) argue that naked short-sales deteriorate market liquidity in Australia. They find that naked short-sales contribute to wider market spreads, thinner depth, lower trading volumes, and larger pricing volatility. Those results support the concern of market regulators who restrict the naked short-sales. Similarly, Frino, Lecce, and Lepone (2011) examine the impact of the 2008 short-sale bans in the US on market quality. They find that the short-sale restriction is associated with wider bid-ask spreads, increased price volatility, and reduced trading activity.

Daouk and Charoenrook (2005) study the history of short-selling regulations and practices from 111 countries. They discover that aggregate stock returns are less volatile and market liquidity improves when short-selling is permitted. When countries introduce short-selling schemes, aggregate stock prices increase, raising the cost of capital. In addition, the authors find no evidence that short sale constraints affect the skewness of returns (or lead to market crashes). In agreement, Boulton and Braga-Alves (2010) document that short sale restrictions have a negative effect on various measures of liquidity and price informativeness.

Further, Chen and Rhee (2010) provide empirical evidence that short sales can increase the speed of price adjustment to not only firm-specific information, but also market-wide information, thus improving price discovery. The amount of information incorporated in each trade is higher for shortable stocks than their non-shortable counterparts. Their results are robust in bullish market conditions, in which short sales are not binding.

Bris, Goetzmann, and Zhu (2007) study the effects of short sale regulations in 46 equity markets around the world. They find that price incorporates negative information faster in markets which allow short sales. Short-selling restrictions are associated with reduced informational efficiency at the individual security level. The authors point out that in markets where short sales are prohibited, market returns display less negative skewness.

Similarly, Saffi and Sigurdsson (2011) conduct their study based on the performance of over 12,600 stocks from 26 countries during 2005-2008. They find that stocks with a low lending supply have lower price efficiency. Further, the authors argue that relaxing short-sale constraints does not necessarily increase the price volatility or the occurrence of extreme negative returns, indicating that markets are more efficient when short sales are allowed.

Boehmer, Huszar, and Jordan (2010) examine stocks listed on NYSE, AMEX, and NASDAQ from June 1988 to December 2005. They confirm that short sale restrictions impede the incorporation of negative information into stock prices. However, they point out that good news is also restricted, although short sale restrictions are not binding on the long side. This result contradicts most prior studies.

Cheng, Yan, Zhao, and Chang (2012) study the effects of short-selling restrictions on Initial Public Offering (IPO) stocks in the Taiwan stock market, where short sales are not allowed within the first six months following an IPO. They find that the pricing efficiency of IPO stocks improves after the short-selling restriction is lifted. Further, they show that short sales activities are concentrated in those IPO stocks that have low fundamental ratios and low transaction costs.

Marsh and Payne (2012) investigate how the ban on short sales of financial stocks affects market quality in the UK. Based on transaction-level data, they conduct analysis over the short-selling ban implemented in late 2008 and subsequent removal in early 2009. Results show that the ban does not affect order flow, while trading volume and market liquidity reduce significantly. Market depth on both sides of the limit order book decreases. The price efficiency deteriorates for financial stocks, compared to that of exempt non-financial counterparts. In addition, the authors find that those unfavourable market liquidity symptoms recover after the ban is lifted in 2009.

Boehmer and Wu (2013) examine the impact of short-selling on price discovery, using shorting flow data of NYSE stocks. They find that the intraday informational efficiency improves when the shorting flow is large. The shorting flow is positively related to the speed of price adjustment to public information in monthly and annual horizons. Further, Boehmer and Wu (2013) claim that short sellers change their trading around extreme return events in a way that improves price discovery, and pushes stock prices closer to fundamental value.

Boehmer, Jones, and Zhang (2013) investigate the effect of the US 2008 short sale ban on market quality. They find that the ban severely lowers market quality as measured by bid-ask spreads, price impact, and intraday volatility. They also state that although shorting activity drops by around 77% in large-cap stocks, their prices do not experience a significant change after the short sale ban. In addition, Ni and Pan (2015) show that it takes longer for unfavourable information to be incorporated into share prices during the short sale ban.

Bailey and Zheng (2013) compare distressed financial companies to other companies using NYSE transaction data over a four-year horizon. They find that the short-selling scheme has a stabilising effect on stock prices during the crisis that surrounds the short-selling ban.

Kaplan, Moskowitz, and Sensoy (2013) undertake an experiment to test the market impact of shorting supply. They randomly move the supply of securities available for borrowing to produce an exogenous shock, holding demand and other factors constant. This supply shock reduces stock borrowing costs and increases stock quantities significantly. Results suggest that stock prices, returns, volatility, skewness, and bid-ask spreads do not change due to the shock in the experiment. The authors conclude that the shorting supply does not exert any adverse impact on market efficiency.

Beber and Pagano (2013) compare the market impact of short sale restrictions in 30 countries from 2008 to 2009, based on a data set of 16,491 stocks. Results indicate that short sale restrictions during the 2007 to 2009 crisis harm market liquidity significantly. Small-cap stocks and stocks without listed options experience larger increases in bid-ask spreads. For inter-listed stocks, short sale restrictions in the home country increase market spreads on both home and foreign exchanges. Bans in the foreign jurisdiction only harm liquidity in the foreign market. In addition, the authors find that price discovery is slower under short selling restrictions, especially in bearish markets. Moreover, Beber and Pagano (2013) find no evidence showing that short sale bans can prop up stock prices.

2.2 Index Futures Mispricing

2.2.1 Pricing of Stock Index Futures

A futures contract is theoretically priced based on the spot price of an underlying asset and is affected by other economic factors. The pricing scheme, known as the "cost-of-carry" model, was first introduced by Cornell and French in 1983. The model assumes a perfect capital market, with no taxes or transaction costs, no short selling restrictions, no dividends, and the assets can be divided indefinitely. Cornell and French (1983) conduct empirical research comparing the theoretical futures price for NYSE composite and the market price of S&P 500 index futures contracts. They observe that market prices for stock index futures contracts are generally below the theoretical prices computed through simple arbitrage models. The authors attribute this price difference to the tax effect. Further, they modify the traditional model by taking some factors into account, such as the timing option of common stock owners for taxes, random changes in interest rates and dividends with seasonal volatility.

Modest and Sundaresan (1983) point out that the transaction cost should not be ignored when investors take short positions in the underlying index market. They incorporate the transaction cost component and short sale restrictions effect into the futures pricing model. In addition, Modest and Sundaresan (1983) create the no-arbitrage band of stock index futures.

Modest (1984) further extends the pricing model by incorporating the impact of discrete dividend payments. He divides short sale restrictions into three situations to test whether the arbitrage opportunity exists. Modest (1984) also examines the effect of random interest rates and daily settlement; however, he finds no evidence showing that those two factors are relevant to futures pricing. Stoll and Whaley (1987) develop a pricing model which takes into account transaction costs. They find that no arbitrage profits can be exploited when the actual futures price locates within a certain deviation away from its theoretical value.

Yadav and Pope (1990) examine the pricing efficiency of stock index futures based on a non-US data set, the UK FTSE-100 contract traded on LIFFE. They find that index futures contracts are frequently under-priced against the forward pricing formula. After market deregulation in the UK, the frequency of those mispricing reduces. In addition, the mispricing is observed to be auto-correlated, which indicates that futures mispricing tends to persist in the market. Further, Yadav and Pope (1990) emphasise that the average return of mispricing is very small due to arbitrage trading behaviour.

Klemkosky and Lee (1991) simulate the index arbitrage trading strategies to determine the upper and lower boundaries of futures prices. Their model takes the transaction cost, seasonal dividend payment and stock borrowing rate into account. Specifically, the upper limit of futures price is equivalent to a combination of a short position in index futures and borrowing money. The lower limit of futures price is equivalent to a combination of a long position in index futures and lending money.

Fremault (1991) documents some implications of index arbitrage behaviour on market efficiency. The author identifies three types of traders in both index futures and underlying markets, namely hedgers, speculators and arbitrageurs. The arbitrage trading passes on the hedgers' exposure from one market to speculators in another market. Consequently, the arbitrage trading activity improves the liquidity of two markets, since it can fill the long and short position gaps. Moreover, the arbitrage trading activity can mitigate the mispricing between those two markets. Fremault (1991) argues that index arbitrage can help to reduce information asymmetry between index futures and spot markets, thus improving market efficiency. Similarly, Brennan and Schwartz (1990) point out that the index arbitrage activities force the index futures price close to the theoretical price computed through the “cost-of-carry” model.

2.2.2 Index Futures Mispricing due to Short-Sale Restrictions

Prior literature provides evidence that short-selling restrictions are a significant factor for stock index futures mispricing. Puttonen and Martikainen (1991) investigate the Finnish stock index futures market and agree that transaction costs are the most important factor affecting the futures pricing model. They suggest that actual transaction costs are more appropriate to examine the efficiency of the futures market. Specifically, Puttonen and Martikainen (1991) point out that a different transaction cost estimate should be utilised to evaluate the under-pricing of futures contract than for over-pricing. Results show that short sale restrictions can explain most of index futures under-pricing in the Finnish market.

Pope and Yadav (1994) examine the London market and argue that futures under-pricing cannot be eliminated if short-selling is prohibited, except for traders who already own those stocks. Therefore, futures under-pricing can be attributed to short sale constraints. Kempf (1998) and Fung and Jiang (1999) reach similar conclusions.

Kempf (1998) investigates the German DAX index futures market and discovers that the futures mispricing reverts towards a negative mean value. He points out that short-selling restrictions and early unwinding opportunities are significant factors that affect the behaviour of futures mispricing. The author finds that there is a positive relation between the absolute level of negative mispricing and the time-to-maturity. The holding costs for arbitrage strategies with short positions in stocks increases with time. When the cost of stock borrowing is high, the futures price violates the theoretical levels more frequently. Further, Kempf (1998) finds that index futures mispricing may be eliminated by arbitrage trading, at the same time, however, futures mispricing exists due to arbitrage trading.

Fung and Jiang (1999) conduct an empirical study on the lifting of short sale restrictions in Hong Kong. They find that the prices of index futures and its underlying spot are more closely integrated after the short sale restrictions are removed. Moreover, Fung and Jiang (1999) document that the futures market plays a greater role than the spot market in correcting past pricing errors. The futures market is more efficient than the cash market in updating market information.

Jiang, Fung, and Cheng (2001) further examine the lead-lag relation between index futures and the underlying spot asset under different short-selling rules in Hong Kong from 1993 to 1996. Consistent to the findings of Fung and Jiang (1999), Jiang, Fung, and Cheng (2001) prove that the lifting of short sale constraints improves the informational efficiency of the stock market relative to the index futures. They further incorporate the impact of the two market characteristics, namely market conditions and the magnitude of mispricing. Results demonstrate that when short sale restrictions are removed, the contemporaneous price relation between the futures and spot markets improves, especially in bearish markets and when the index futures contracts are relatively under-priced.

Fung and Draper (1999) investigate the mispricing pattern of the Hong Kong Hang Seng Index futures contracts under three different short-selling regulatory scenarios, namely no short selling, partial short selling and no restrictions. They document that the frequency and magnitude of futures mispricing reduces after the short-selling restrictions are lifted. It also speeds up the process of market adjustment, especially when a long futures strategy (long futures and short stock) is detected. The relaxation of short sales constraints is observed to reduce the magnitude of both over-pricing and under-pricing of the index futures contract.

Draper and Fung (2003) evaluate the impact of government interventions on index futures mispricing in Hong Kong. In 1998, the government bought significant quantities of component stocks of the index in order to resist the backdrop of the Asian Financial Crisis. This government intervention effectively reduces the liquidity of index stocks and impedes short sales. Results suggest that prior to the government intervention, price adjustment in the stock and futures markets is efficient, although the frequency and magnitude of mispricing is high. However, arbitrage efficiency is harmed after the intervention. Hence, discretionary government action can increase risks for arbitrageurs and disrupt the normal market processes.

Gay and Jung (1999) perform an empirical analysis to examine the pricing efficiency of the Korean stock index futures contract (i.e., KOPSI 200 index futures). They find that a significant portion of the futures under-pricing can be explained by transaction costs. However, results reveal that transaction costs alone are not sufficient to answer the persistence of futures under-pricing. The authors attribute this to short sale restrictions, since they observe that the futures under-pricing occurs mostly during periods of downward market price changes. Gay and Jung (1999) examine the appropriateness of the standard "cost-of-carry" model and suggest that an equilibrium pricing model has better explanatory power than the "cost-of-carry" model for persistent under-pricing.

Wang (2010) investigates the index futures contracts traded on the Singapore Exchange Limited (SGX) and the Taiwan Futures Exchange (TAIFEX), using five-minute intraday transaction data. The author finds that relaxing the uptick rule (i.e. lift the short-selling restrictions) improves market efficiency and reduces index futures mispricing. Similarly, Lin, Lee, and Wang (2013) provide evidence that the removal of short-selling restrictions benefits informed trading and strengthens the lead-lag relationship between index futures and underlying markets in Taiwan.

Neal (1996) studies the S&P 500 arbitrage trades during a period in 1989 and concludes that short-selling restrictions do not exert a significant impact on futures mispricing, which is to the contrary of most existing research. The author estimates that around half of the arbitrage trades are undertaken by market participants who already own the underlying stocks. They can avoid short sale restrictions by selling the stock in the market directly. As a result, the short sale restrictions are less binding. In addition, Neal (1996) points out that the implied opportunity costs of arbitrageurs are higher than the risk free rate. Moreover, the average price discrepancy available for arbitrageurs is very small.

In conclusion, due to the short sale restrictions in underlying stock markets, the distribution of index futures mispricing is theoretically predicted to be asymmetric, with more under-pricing than over-pricing. Cornell and French (1983) examine the S&P 500 contracts and support this prediction. Modest and Sundaresan (1983) investigate the S&P 500 and NYSE composite contracts. They find that futures contracts are generally under-priced. The authors attribute that to short-selling restrictions and costs in underlying equities market. Pope and Yadav (1994) discover that the FTSE 100 contracts are more under-priced with a larger magnitude than that of over-pricing. In addition, Brenner, Subrahmanyam, and Uno (1989) observe that Nikkei futures contracts traded on the Singapore International Monetary Exchange (SIMEX) are generally sold at a discount relative to their theoretical value. Gay and Jung (1999) document a persistent under-pricing in the Korean stock index futures market. Cummings and Frino (2011) find that the index futures mispricing (SFE SPI 200) is not symmetrical, with more negative mispricing over positive. This asymmetry is due to the high costs involved in short-selling transactions in the Australian stock market. The negative mispricing cannot be captured by arbitrage strategies, which requires a short position in underlying stocks. Moreover, Lin, Lee, and Wang (2013) find that index futures contracts are more under-priced in Taiwan.

In stark contrast, existing literature also provides evidence showing that index futures are more over-priced than under-priced. Based on transaction-level data, Mackinlay and Ramaswamy (1988) report that the average mispricing of index futures is slightly positive, although small in magnitude. In agreement with the other research, Bhatt and Cakici (1990) observe that the percentage mispricing is small but positive for S&P 500 index futures. They find that more index futures contracts are selling at a premium than at a discount. Fung and Draper (1999) document that index futures are overpriced in Hong Kong. Similar outcomes are achieved by Draper and Fung (2003) in Hong Kong markets, by Chu and Hsieh (2002), and by Richie, Daigler, and Gleason (2008) in US markets.

2.2.3 Other Factors that Drive Index Futures Mispricing

As discussed above, transaction costs are a significant driver for index futures mispricing. The impact of transaction costs are widely considered in existing literature (Modest & Sundaresan, 1983; Modest, 1984; MacKinlay & Ramaswamy, 1988; Puttonen & Martikainen, 1991).

Chung (1991) argues that hidden costs or impediments to arbitrage are not captured by the "cost-of-carry" model when computing the theoretical futures price. The author lists transaction costs involved in an index arbitrage strategy including (1) round-trip commissions to long and short the stocks in the spot market; (2) one commission to open a position in the futures market; (3) one "market impact" cost in the stock market, which is the bid-ask spread; and (4) one "market impact" cost in the futures market. Subsequently, he performs the index-futures mispricing test based on pre-set levels of transaction costs (i.e., 0.5%, 0.75%, and 1%).

Cummings and Frino (2011) point out that the size of futures mispricing is related to both explicit and implicit costs. The explicit costs include fees paid to brokers, exchange charges and short selling costs. The implicit costs include bid-ask spread and market impact costs of opening up positions in both the stock and futures markets.

Gay and Jung (1999) specify the index futures mispricing for different trader groups. Exchange member firms in Korea have greater opportunity to engage in profitable index arbitrage than institutional investors due to the difference in transaction costs. Gay and

Jung (1999) create sets of no-arbitrage bands for various cost assumptions. Similar findings are achieved by Klemkosky and Lee (1991) in US markets.

Moreover, there are a number of explanatory variables, relating to the mispricing behaviour, covered in previous studies, such as variability of dividends (Mackinlay & Ramaswamy, 1988; Cummings & Frino, 2011), interest rate assumptions (Cox, Ingersoll, & Ross, 1981; Cakici & Chatterjee, 1991; Cummings & Frino, 2011), time to maturity of index futures contract (Mackinlay & Ramaswamy, 1988; Merrick, 1989), and liquidity constraints of futures and its underlying market (Butterworth & Holmes, 2000; Roll, Schwartz, & Subrahmanyam, 2007).

Futures market volatility is documented as a relevant factor for index futures mispricing. Merrick (1987) studies the pricing efficiency of the two largest stock index futures markets in the US, namely the S&P 500 index market and the NYSE composite index market. Using daily data, the author finds that market volatility increases the price discrepancies between futures and its underlying spot. Draper and Fung (2003) examine the intraday prices, at 30-second intervals, in the Hong Kong market. Results show that the index futures mispricing is positively related to market volatility. Richie, Daigler, and Gleason (2008) report that mispricing is more frequent in high- and mid-volatility months than in low-volatility months for S&P 500 index futures contracts.

Mackinlay and Ramaswamy (1988) examine intraday transaction data for S&P 500 index futures contracts and its underlying index. Results reveal that the variability of the price change in the index futures market is larger than that in the spot market. The index futures mispricing is path-dependent and increases with time-to-maturity. This positive relation is proved in later studies (Yadav & Pope, 1990, 1994; Brailsford & Hodgson, 1997). Yadav and Pope (1990, 1994) find that early unwinding and rollovers of futures positions contribute to arbitrage profits. Bhatt and Cakici (1990) test the impact of time-to-maturity and dividend yield on the pricing efficiency of S&P 500 index futures, through regression analysis. They find that both of those two variables exert positive effects on futures mispricing. In addition, the positive relationship between time-to-maturity and futures mispricing can be explained by the fact that arbitrageurs require greater price discrepancy to compensate the risks they face long before the expiration of futures contracts.

Interest rate risk affects index futures pricing in two ways. First, interest rates are one essential element in the "cost-of-carry" model, and index arbitrage trading strategies require either borrowing or lending cash for a certain period of time. Second, the marking-to-the-market feature of futures contracts results in the daily reinvestment or borrowing of cash. Cox, Ingersoll, and Ross (1981) compare and examine the relation between forward prices and futures prices. They claim that using the "cost-of-carry" model to price futures contract relies on an assumption of non-stochastic interest rates.

Cakici and Chatterjee (1991) compare the constant interest rate model of futures pricing to stochastic models, based on a data set comprising the daily closing values of S&P 500 futures. Results show that the stochastic model produces better outcomes when the spot interest rate is distant from the long-term mean, or when the speed of adjustment towards this long-term mean is very high. Cakici and Chatterjee (1991) conclude that the quality of the stochastic model depends on the impact of a mean-reversion factor.

Brailsford and Hodgson (1997) study the stock index futures mispricing behaviour in Australia. They find that the futures market leads the price discovery process relative to the stock market. Abnormal trading volume and the volatility of futures prices are positively related to the mispricing of index futures. Cummings and Frino (2011) extend the research of Brailsford and Hodgson (1997) and find that the timing of dividend announcements and the volatility of the spot market are closely related to index futures mispricing. The authors state that interest rate volatility is the primary source of risk faced by arbitrageurs, thus leading to index futures mispricing.

The liquidity of futures and stock markets also influences the pricing relationship. Butterworth and Holmes (2000) compare the pricing efficiency of FTSE 100 and FTSE Mid 250 index futures contracts. They find that mispricing is less frequent and persistent for the FTSE 100 contract than that for the FTSE Mid 250 contract. They explain that the illiquid constituent stocks of the FTSE Mid 250 index in London trigger higher transaction costs, which reduce arbitrage trading activity. Further, Roll, Schwartz, and Subrahmanyam (2007) argue that market liquidity is one determinant of futures mispricing. Higher liquidity eases the establishment of an arbitrage trading position, thereby eliminating mispricing. The authors conclude that liquidity improves the efficiency of the futures-cash pricing system.

Richie, Dailger, and Gleason (2008) investigate factors affecting stock index futures mispricing and arbitrage opportunities for the S&P 500 index. They propose that potential limits to arbitrage are the staleness of the underlying cash index, transaction costs, liquidity constraint, the execution ability of arbitrage strategies, short sale restrictions, and market volatility.

2.2.4 Exchange-Traded Funds as Underlying Assets

In real practice, index arbitrage trading strategies are more complicated than the "cost-of-carry" model, since the stock index itself is not a single asset to trade. MacKinlay and Ramaswamy (1988) point out that assets in the replicating portfolio of index futures contracts are only a close substitute of the underlying assets in theory. A basket of stocks may be closely related to the index. However, the transaction costs and liquidity issues are a strict barrier. Some prior studies adopt Exchange-Traded Funds (ETFs), which track the stock index as the underlying asset for index futures contracts.

Switzer, Varson, and Zghidi (2000) examine the effects of Standard and Poor's Depository Receipt (SPDR) trading on the index futures contracts. They find that positive mispricing of the S&P 500 index futures contract reduces after the SPDR is introduced. As an extension of Bhatt and Cakici's (1990) analysis, Switzer, Varson, and Zghidi (2000) show that the SPDR trading reduces the impact of dividend yield and time-to-maturity on futures mispricing. The authors conclude that SPDR improves the pricing efficiency of the index futures market.

Kurov and Lasser (2002) investigate the impact of the introduction of the NASDAQ 100 index tracking stock on the pricing relationship between NASDAQ 100 futures and the underlying index, using transaction-level futures data. They achieve a similar outcome to Switzer, Varson, and Zghidi (2000) and document that the introduction of the index tracking stock improves the pricing efficiency of index futures contracts. Both the frequency and magnitude of violations in futures price boundaries reduce. In addition, the speed of price correction increases due to the new index tracking stock.

To mitigate the staleness and trading cost issues of the cash index, Richie, Daigler, and Gleason (2008) adopt the S&P 500 SPDR as the underlying asset for the S&P 500 index futures contracts. They find that index futures mispricing exists regardless of the choice of the underlying cash assets. More futures under-pricing is observed when using the SPDR relative to the cash index.

The consistency between the price of index futures contracts and that of its underlying asset is a measure of market efficiency. De Jong and Nijman (1997) point out that if markets are perfectly integrated, efficient and complete, returns on derivatives and underlying securities should be perfectly correlated. However, market frictions prohibit the flow of information across markets.

Budish, Cramton, and Shim (2015) criticise the continuous limit order book market design by allowing an arms race for high frequency traders. The authors examine the price relationship between index futures (S&P 500 E-mini futures contracts) and corresponding ETF (SPDR), using millisecond-level direct-feed exchange data. They document that the return correlation between those two instruments breaks down in high frequency time intervals. This leads to mechanical arbitrage opportunities for high speed traders. In addition, they find that competition does not affect the frequency or magnitude of the arbitrage opportunities. Budish, Cramton, and Shim (2015) argue that the current continuous market design generates mechanical arbitrage rents, which harm market liquidity and induce a "socially wasteful" arms race for trading speed. They advocate that frequent batch auctions can overcome those shortcomings of the continuous limit order book.

Frino, Mollica, Webb, and Zhang (2016) investigate the duration, frequency and profitability of index arbitrage opportunities in Australian markets. They simulate the arbitrage trading strategies using the index futures contract and ETF over the S&P/ASX 200. Consistent with Budish, Cramton, and Shim (2015), they also record a return correlation breakdown at high frequency time intervals. Further, Frino, Mollica, Webb, and Zhang (2016) find that the frequency and profitability of potential arbitrage opportunities are positively related to market volatility and turnover. Moreover, the authors adopt the number of "co-location connections" as a proxy for competition among high frequency traders. Results reveal that the average daily profit, frequency and duration of arbitrage opportunities increases as co-location connections increase in the market. They conclude that a higher level of high frequency trading activity in markets increases the execution risks of arbitrage trading, which increases index futures mispricing.

2.3 Financial Transaction Tax and Market Quality

The concept of a transaction tax was first introduced by James Tobin in 1978. He points out that a transaction tax can mitigate speculation in the foreign exchange market (Tobin, 1978). This concept then has been quickly applied to other financial markets. This section outlines the debate over the impact of financial transaction taxes[1] on market quality.

2.3.1 Theoretical Framework

[1] In this section, the terms "financial transaction tax" and "securities transaction tax" are used interchangeably.

Summers and Summers (1989) discuss the desirability and feasibility of implementing a Securities Transfer Excise Tax (STET), which aims to curb excess short-term speculation and raise tax revenue. Consistent with Tobin's research (1978), the authors argue that STET can mitigate the instability introduced by speculation and lead capital to other business sectors of the economy. This effect outweighs the costs of reduced market liquidity. Further, they estimate that a 0.5% STET rate can raise revenues of more than $10 billion annually in the US.

Stiglitz (1989) claims that a tax on transactions will not harm the major economic functions of the stock market if price volatility does not increase. He finds that a turnover tax can reduce market volatility by discouraging short-term speculative trading. Stiglitz (1989) also predicts that liquidity may improve due to the absence of noise traders.

Schwert and Seguin (1993) review both sides of the arguments over securities transaction taxes. In addition to revenue collection, the tax can reduce excess volatility in the market by discouraging speculative and noise trading. It also increases investors' holding periods, thus encouraging corporate managers to build for the long term. In contrast, a financial transaction tax increases the cost of capital, lowers stock prices and reduces market liquidity. Further, market participants may move their trading activities to overseas markets where the financial transaction tax does not apply.

Subrahmanyam (1998) identifies the negative effects of transaction taxes on market liquidity. He points out that with a transaction tax, informed traders will scale back their aggressive trading activities, and both market liquidity and short-term price discovery decline. Habermeier and Kirilenko (2003) argue that financial transaction taxes exert a negative impact on price discovery, volatility and liquidity. It leads to a reduction in the informational efficiency of markets. Moreover, Matheson (2011) states that the costs triggered by a financial transaction tax outweigh the benefits it brings. He points out that the tax can lower short-term stock prices and trading volume, thus reducing market quality. Financial institutions will pass on such levies to their customers, impeding overall economic development.

Kupiec (1996) investigates the relationship between securities transactions tax and price volatility, using a general equilibrium model. He concludes that a transaction tax can reduce the volatility of the risky asset's price sightly; however, the stock price declines more than the tax revenue collected. Consequently, Kupiec (1996) argues that the tax may increase the volatility of risky asset returns.

Palley (1999) divides market participants into two categories, which are fundamental traders and noise traders. They find that the financial transaction tax can reduce noise trading activities in the market, which benefits fundamental investors. However, the tax can also discourage fundamental investors from trading. The overall effect is a trade-off between those two effects. Further, Song and Zhang (2005) observe that a low proportion of noise traders in the market and low pre-tax volatility are associated with a decline in market volatility after the introduction of the financial transaction tax. Dupont and Lee (2007) develop a static model to examine the impact of the securities transaction tax on depth and bid-ask spreads. They find that the tax increases the market spread and lowers depth when information asymmetry is high. This can result in a market closure if the liquidity providers cease quoting.

2.3.2 Empirical Studies

Prior studies provide some empirical evidence about the impact of a financial transaction tax on various measures of market quality, such as stock price, volatility, trading volume, and liquidity. Umlauf (1993) examines the market impact of the financial transaction tax implemented in Sweden in 1986. He finds that price volatility increases after the transition, while stock prices and trading turnover decline. In addition, he observes that a large proportion of trading activity moves to overseas markets after the introduction of the transaction tax.

Hu (1998) studies 14 securities transaction tax changes in four Asian markets during the period 1975-1994. Results show that an increase in the tax rate is associated with a decline in stock price, whereas price volatility and market turnover are not substantially affected. Green, Maggioni, and Murinde (2000) explore the relationship between transaction costs and price volatility in the UK. They point out that the effect depends on the concept of price volatility. Specifically, they break down price volatility into market volatility and fundamental volatility. The authors surmise that an increase in transaction costs is associated with a decrease in fundamental volatility and an increase in market volatility.

Chou and Wang (2006) examine the impact of a tax rate reduction on the index futures market in Taiwan. Results reveal that trading volume increases and bid-ask spreads decrease after the tax rate cut. The authors conclude that transaction taxes exert a negative effect on trading volume and market spreads. Chou and Wang (2006) do not find evidence showing that price volatility is affected by the transaction tax. Further, they point out that the tax revenue reduces after the rate cut. However, the amount of revenue in the second and third quarters thereafter is higher than that before the tax reduction.

Baltagi, Li, and Li (2006) analyse the market impact of a stamp tax rate increase in China. They document that stock trading volume drops significantly after the transition, whereas price volatility experiences a tremendous increase. Additionally, Sinha and Mathur (2012) report a decrease in trading volume and an increase in price volatility after an increase in the securities transaction tax in India. Further, Phylaktis and Aristidou (2007) find that the effects of a change in the transaction tax on price volatility depend on the market trend. They observe that the price volatility increases in a bullish period in the Greek market, especially for highly traded stocks.

Pomeranets and Weaver (2013) investigate the relation between financial transaction taxes and market quality variables, based on nine modifications to the New York State Securities Transaction Tax. They find that an increase in the tax is associated with an increase in price volatility, wider bid-ask spreads, larger price impact, and lower trading volume.

2.3.3 Modern Financial Transaction Taxes

Modern financial transaction taxes incorporate components that specifically target high frequency traders. Gomber, Haferkorn, and Zimmermann (2016) study the French financial transaction tax, implemented in August 2012. It includes a high frequency trading tax component, which levies 0.01% on the amount of cancelled or modified orders within a half-second time span that exceeds a threshold of 80% of total trading orders on a given trading day. They find that after the transition, trading volume declines. The relative spread widens by 12% and market depth declines by 17%. Further, the financial transaction tax undermines informational efficiency. The authors discover that the price coordination between NYSE Euronext Paris and Chi-X Europe decreases after the implementation of the tax.

Capelle-Blancard and Havrylchyk (2016) adopt a difference-in-difference approach to isolate the impact of the French financial transaction tax from other economic changes, using two control groups (smaller French firms and foreign firms listed on Euronext). They find that the transaction tax reduces stock trading volume, whereas they do not observe significant changes in market liquidity and price volatility. Veryzhenko, Harb, Louhichi, and Oriol (2017) achieve a similar outcome. They find that the introduction of the tax discourages high frequency trading activities in France. However, market liquidity and volatility are observed to be less affected.

Cappelletti, Guazzarotti, and Tommasino (2016) analyse the effects of the Italian financial transaction tax, using a difference-in-difference approach. They report that the tax widens the bid-ask spread and increases price volatility, while the trading volume and stock returns are less affected. Capelle-Blancard (2017) adopts a similar approach to examine the impact of the new tax scheme in Italy. Results indicate that the overall market quality decreases after the initial introduction of the financial transaction tax in the equity market, but this is reversed when the tax scheme extends to the derivatives market. The migration of trading activities from equities to derivatives is observed when there is an asymmetric tax regime.

2.4 Algorithmic Trading and Market Quality

Modern technology changes the way market participants behave and interact with each other. The proliferation of algorithmic trading attracts significant attention from market participants and regulators worldwide. Algorithmic trading is defined as the use of computer algorithms to automatically generate trading decisions over order submission, modification, and cancellation (Hendershott, Jones, & Menkveld, 2011). It has a remarkable speed advantage over other market participants. High frequency trading is a typical type of algorithmic trading. There is no single accurate definition of "high frequency trading". The Securities and Exchange Commission's (SEC) *Concept Release on Equity Market Structure* (2010) describes high frequency traders as, "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis". In addition, the U.S. Commodity Futures Trading Commission (CFTC) Technology Advisory Committee recognises high frequency trading as a subset of algorithmic trading that uses "algorithms for decision making, order initiation, generation, routing, or execution, for each individual transaction without human direction". Further, high frequency trading is usually associated with high speed market connections, high order-to-trade ratios, and neutral inventory positions by the end of each trading day.

2.4.1 Theoretical Framework

The impact of algorithmic trading on market quality spans both sides of arguments. Owing to its speed advantage, algorithmic traders can place and manage orders quickly in response to market information. Froot, Scharfstein, and Stein (1992) point out that short-term speculators play a negative role in market pricing efficiency. Short-term speculators focus on short-term information occurring in the market rather than fundamental information about securities' intrinsic values, thus dismissing price discovery. Gsell (2008) demonstrates that larger volumes executed by algorithmic traders imposes a negative impact on market prices although it appears to lower market volatility.

Cvitanic and Kirilenko (2010) develop a theoretical model to examine the relationship between high frequency traders and transaction prices. They compare the distribution of transaction prices in a market of low frequency traders (humans) before and after the introduction of a high frequency trader (machine). They find that the introduction of a high frequency trader reduces the average transaction price in the market, improves liquidity, and reduces price volatility as market-making high frequency traders update their information in response to news releases.

Jovanovic and Menkveld (2016) build a model to simulate high frequency traders as market makers. They recognise that high frequency traders are faster and more informed than their counterparts. Newly submitted limit orders are either matched with existing limit orders, or are left as a price quote in the order book. The information that arrives before the price quote is matched generates adverse selection risks. The introduction of high frequency traders may restore the trade, since machines can quickly refresh quotes based on information. It allows the high frequency market makers to reduce their exposure to adverse selection as well as their inventory holding costs, thus improving market efficiency. Empirically, Jovanovic and Menkveld (2016) find that high frequency trading can reduce adverse selection costs by 23%, and increase trade frequency by 17%.

Gerig and Michayluk (2010) identify the role of automated market makers in liquidity provisions. They find that algorithmic traders can incorporate all information from trades and ex-post order flows in the market, then modify their quoting behaviour to reduce adverse selection costs and unfavourable inventory imbalances. Hence, algorithmic traders are able to set prices more accurately than traditional market makers, thus improving pricing efficiency. Gerig and Michayluk (2010) show that with an automated market maker, informed traders' execution costs increase, whereas uninformed traders' costs decline. Uninformed investors increase their trading activity and boost total trading volume in the market.

Chung and Lee (2016) categorise high frequency trading activities into three types. First, market-making high frequency traders provide liquidity to the market. They earn profits from the bid-ask spread and utilise their speed advantage to instantly update quotes in the limit order book. Second, arbitrageurs implement trading strategies to exploit the price discrepancies between two portfolios of assets. High frequency traders can analyse market prices and then submit orders to profit from price misalignments ahead of the rest of the market. Third, high frequency traders can act as informed traders and obtain a significant speed advantage. Directional trading relying on new private information can impose a significant impact on the limit order book and asset prices.

2.4.2 Empirical Literature

Empirical research widely documents a positive relationship between message traffic activity and market quality. Specifically, high message traffic and trading activity are associated with increased market liquidity, improved price discovery, and reduced market volatility (e.g., Brogaard, 2010; Hendershott, Jones, & Menkveld, 2011; Hasbrouck & Saar, 2013). Hendershott, Jones, and Menkveld (2011) utilise the order-to-trade ratio as a proxy to measure message traffic activity. They test the market after the implementation of AutoQuote on the NYSE and conclude that algorithmic trading improves market liquidity. Results reveal that algorithmic trading improves quoted and effective spreads, while reducing market depth. Similarly, Castura, Litzenberger, and Gorelick (2010) find that US equity market quality improves along with an increasing ratio of algorithmic trading to total market activity. Results show that bid-ask spreads decrease and market depth increases during the sample period.

The high-speed electronic trading infrastructure allows the implementation of certain high frequency trading strategies which require low latency. Prior literature adopts event study methodology around market structure changes that affect traders' latency capacity. Garvey and Wu (2010) study the execution quality of market participants who are geographically dispersed in the US. They find that traders who locate close to central servers experience faster execution and are subject to lower execution costs.

Boehmer, Fong, and Wu (2015) investigate the relationship between message traffic and market quality for 39 stock exchanges between 2001 and 2009. They discover that exchanges introducing co-location services increase algorithmic trading and high frequency trading activity. The authors observe that market liquidity improves after the introduction of co-location services. Therefore, they conclude a positive relation between algorithmic trading activity and market quality.

Hendershott and Moulton (2011) examine the impact of the introduction of NYSE's Hybrid Market, which increases automation and reduces the execution time for market orders from ten seconds to less than one second. They document an increase in quoted and effective spreads as well as a reduction in the noise component in prices. Hendershott and Moulton (2011) explain that the increase in market spreads is because of an increase in the adverse selection costs caused by anonymous trading.

Riordan and Storkenmaier (2012) investigate the market impact of the co-location services introduced by the Deutsche Boerse and surmise that market liquidity is positively related to trading speed. The infrastructure upgrade in 2007 reduces the time between order submission and confirmation from 50 milliseconds to 10 milliseconds. This dramatically increases the message traffic rate from 2.81 quote updates per 10,000 euros of trading volume to 4.56 quotes. Riordan and Storkenmaier (2012) report that quoted and effective spreads narrow after the system upgrade, whereas the realised spread increases significantly. Specifically, liquidity supplier revenues are estimated to increase by 24,000 euros per firm per day; liquidity demanders can save approximately 4,600 euros per firm per day with the improved trading infrastructure.

Hasbrouck and Saar (2013) study the NASDAQ order-level data from 2007 to 2008 and conclude that low-latency improves market liquidity. Specifically, they find that a decline in latency is associated with narrower bid-ask spreads, increased depth, and reduced price impact. Jarnecic and Snape (2014) examine the equity market in the UK. Results suggest that high frequency traders resolve temporal liquidity imbalances in the limit order book, thus improving market liquidity.

Ye, Yao, and Gai (2013) discover that the minimum time between quotes decreases from 950 nanoseconds to 200 nanoseconds on NASDAQ in 2010. They find no evidence showing that this advanced technology improves market spreads, trading volume, or variance ratios. They observe that the order cancellation ratio and short-term volatility increases, and market depth reduces during the sample period. In addition, Zhang (2010) compares price volatility for a high frequency trading interval (1995-2009) with a period without high frequency trading (1985-1994). Zhang (2010) finds that heightened levels of high frequency trading is accompanied by high market volatility. He points out that high frequency trading restricts the market's ability to incorporate fundamental information into the stock price, and high frequency trading causes stock prices to overreact around earnings announcement. Analysing the behaviour of algorithmic traders during periods of variable volatilities, Groth (2011) points out that algorithmic traders do not modify their trading strategies in response to changes in volatility. Therefore, Groth (2011) argues that there is no evidence showing that periods of high market volatility are caused by algorithmic traders withdrawing liquidity from the market.

Frino, Mollica, and Webb (2014) examine the impact of co-location services on the liquidity of futures contracts traded on the Australian Securities Exchange (ASX) in 2012. Results indicate that low latency leads to a lower bid-ask spread and an increase in market depth. Hence, the authors conclude that co-location improves market efficiency with which high frequency traders are able to make markets.

Similarly, Brogaard, Hagstromer, Norden, and Riordan (2015) study the effect of an optional co-location upgrade at NASDAQ OMX Stockholm. They find that the co-location service is favoured by market makers as it boosts their trading speed to reduce exposure to adverse selection and relax inventory constraints. The latency upgrade improves bid-ask spread and depth, with short-term price volatility remaining stable. The authors surmise that increasing market makers' trading speed can improve market liquidity.

In summary, those studies discussed above suggest a positive relationship between algorithmic trading proxies and market quality. Common proxies adopted are message traffic and latency improvement. There are studies examining the impact of algorithmic trading on market quality using proprietary data sets. Hendershott and Riordan (2009) obtain an order-level data set from the Deutsche Boerse's Automated Trading Program. They are able to directly identify algorithmic traders' quotes and trades. They find that algorithmic traders play dynamic roles in the market. Algorithmic traders closely monitor changes in market liquidity; they consume liquidity when it is cheap, and they supply liquidity when it is expensive, thus smoothing out liquidity over time. The authors suggest that algorithmic trading improves price discovery by placing more efficient quotes, and algorithmic trading consumes liquidity to move the price towards its fundamental value.

Carrion (2013) obtains a unique data set that identifies the activity of 26 high frequency traders on NASDAQ during 2008 and 2009. Results show that high frequency traders profit when providing liquidity but lose when consuming liquidity, and they engage in successful intra-day market timing. The author finds that bid-ask spreads widen on trades where high frequency traders supply liquidity, and that bid-ask spreads tighten on trades where high frequency traders demand liquidity, which indicates that high frequency traders on average provide liquidity when it is sparse and consume liquidity when it is abundant. In addition, it is observed that high frequency trading participation is positively related to price discovery.

Brogaard, Hendershott, and Riordan (2014) use the same data set and sample period with Carrion (2013). The authors find that high frequency traders trade in the direction of permanent price changes and in the opposite direction of transitory pricing errors. The direction of high frequency trading is related to public information release. They identify that aggressive high frequency trading activities impose adverse selection costs on passive low-speed counterparts. However, the liquidity supplying activities of high frequency traders are more significant, thereby reducing the overall adverse selection costs. In contrast to Carrion (2013), Brogaard, Hendershott, and Riordan (2014) discover that high frequency traders profit when consuming liquidity, and lose when providing liquidity.

Hagstromer and Norden (2013) identify two types of high frequency traders on NASDAQ OMX Stockholm, namely market-making high frequency traders and opportunistic high frequency traders. They report that market-making high frequency traders have higher order-to-trade ratios, lower latency and lower inventory than opportunistic high frequency traders. Hagstromer and Norden (2013) argue that the market-making high frequency traders supply more liquidity and reduce short-term volatility.

Malinova, Park, and Riordan (2013) examine the impact of high frequency trading activity on Canadian market efficiency. After the Investment Industry Regulatory Organisation of Canada (IIROC) implemented the Integrated Fee Model (IFM), high frequency trading activity reduces significantly in both absolute terms and as a percentage of total market activity. Results reveal that bid-ask spreads widen, market depth declines, and institutional traders' costs increase when high frequency trading message traffic is low. Lepone and Sacco (2013) find similar results by examining the market impact of the same event.

Financial literature in recent years also provides some evidence concerning the negative effects imposed by high frequency trading. Kirilenko, Kyle, Samadi, and Tuzun (2017) investigate the behaviour of high frequency trading during the "Flash Crash" on 6 May 2010, using a comprehensive set of transaction-level data in the E-Mini S&P 500 futures market. They find that high frequency traders are initially the passive liquidity suppliers, but quickly become aggressive liquidity consumers to balance their outstanding inventory exposure. They conclude that high frequency traders may increase the price volatility by withdrawing from supplying liquidity and even competing for liquidity as they manage their inventory positions. High frequency traders can negatively affect the market stability during periods of extreme market stress.

Lee (2015) analyses the role of high frequency trading in the Korean stock index futures market and discovers that high frequency trading activities do not provide liquidity or improve market efficiency. Further, the author finds that high frequency trading is detrimental to the price discovery process. Foucault, Homber, and Rosu (2016) argue that the impact of high frequency trading on price discovery is less obvious. Their theoretical model demonstrates that high frequency traders concentrate on short-term price changes and news. Therefore, they do not really contribute to price discovery, but still increase adverse selection costs.

Bongaerts and Van Achter (2016) develop a dynamic model to analyse how liquidity provision by high frequency traders affects market stability. Fast traders have both trading and information-processing speed, which leads to efficient resource allocation and increases market liquidity. However, market liquidity may deteriorate during periods of volatility. Consistent with Bongaerts and Van Achter (2016), Brogaard, Hendershott, and Riordan (2017) examine the impact of high frequency trading activity on market liquidity during the period of the 2008 short sale ban in the US. They conclude that some high frequency traders' activities are detrimental to liquidity during the extremely volatile period.

There is some academic concern that high frequency traders can generate negative externalities on other participants in the market. Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) investigate algorithmic trading on macroeconomic news, through examining the price adjustment of index futures and Exchange-Traded Funds to announcement surprises. They discover that algorithmic trading improves market efficiency. However, they also suggest that this contribution to market efficiency comes at the expense of slower traders. Results suggest that trading profit is negatively related to quote intensity, indicating that algorithmic trading is highly competitive.

Biais, Foucault, and Moinas (2015) examine the impact of high frequency trading on other market participants. The authors recognise that high frequency traders can profit from their speed advantage. However, a high level of high frequency trading activity increases adverse selection costs of the slower traders; thus, high frequency trading generates negative externalities. Biais, Foucault, and Moinas (2015) point out that larger institutions are more likely, than smaller institutions, to adopt high frequency trading strategies, which require large fixed investment in technology. In equilibrium, small institutions tend to become less informed and exit the market when high frequency trading becomes prevalent.

Cartea and Penalva (2012) analyse the interactions between three types of traders in the market, namely liquidity traders, professional traders and high frequency traders. They find that high frequency traders utilise their speed advantage to profit from trading ahead of slower traders. Further, high frequency trading increases trading volume as well as the noise of prices.

Several prior studies shed some light on the profitability and competition of high frequency traders. Baron, Brogaard, and Kirilenko (2012) claim that high frequency trading is highly profitable. They, for instance, estimate that high frequency traders earn over $29 million in the E-Mini S&P 500 futures contract in the month of August 2010, using transaction level data with user ID. The profit of high frequency traders is contributed by opportunistic traders, institutional traders, retail traders and non-high frequency trading market makers. Further, they find that this profit is consistent and positively related to traders' speed. New entrants have a higher propensity to underperform and exit, which generates an uneven playing field among market participants.

Kozhan and Tham (2012) measure the impact of execution risk in high frequency trading through arbitrage strategies. They argue that competition among high frequency traders triggers execution risks, which harm market efficiency. Computer algorithms generating the same order at the same time to exploit an arbitrage opportunity causes a crowding effect. This can push the market prices of financial instruments away from their fundamental values.

2.4.3 Market Regulations for Algorithmic Trading

As discussed above, a strong body of literature documents the negative market impact imposed by certain algorithmic trading (high frequency trading) activities. Consequently, restrictive regulations over those activities are proposed or implemented in many jurisdictions around the world.

Chung and Lee (2016) surmise that there are various forms of high frequency trading-related regulations discussed by authorities around the world. First, modern financial transaction taxes charge a high frequency trading tax for excessive orders submitted by market participants; the market impact of these regulations are further discussed in the following section. Second, minimum order resting times force all orders to stay in the order book for at least a certain time periods. Third, introducing structural delays in order processing can mitigate the technology arms races. For instance, Budish, Cramton, and Shim (2015) propose a frequent batch auctions market design to replace the current continuous limit-order book market structure.

2.5 Dark Trading and Market Quality

The proliferation of dark trading attracts considerable attention from both regulators and market participants. Unlike traditional trading venues, dark pools allow traders to submit orders without pre-trade transparency. They are designed to provide protection for institutional orders from information leakage and market impact. Dark trading then is favoured by traders who aim to pursue best execution. The impact of dark trading on market quality is widely documented in the literature, from both theoretical and empirical perspectives.

2.5.1 Theoretical Discussion

There are many theoretical studies discussing the effect of dark trading on equity market efficiency. Hendershott and Mendelson (2000) develop a theoretical model to demonstrate the interaction between a crossing network and a dealer market. In traditional dealer markets, the execution is guaranteed but the transaction costs can be significant. In contrast, orders in crossing network are executed on time-priority only, without dealer intervention. The execution costs of crossing networks is low, but execution is not guaranteed. The low-cost feature of crossing network attracts additional orders to the market, hence injecting liquidity. With the increased level of liquidity, low-willingness traders (in terms of execution) enter the market and compete with high-willingness traders. Under the execution rule of time-priority only, high-willingness traders can be crowded out by low-willingness traders if low-willingness traders submit their orders earlier.

Degryse, Van Achter, and Wuyts (2009) further extend Hendershott and Mendelson's model (2000) by examining three information settings: transparency, partial opaqueness, and complete opaqueness. They point out that the crossing network can trigger execution risks for certain market participants. Traders who have a strong desire to transact may face lower execution probability in the dark.

Ye (2012) advances an extension of Kyle's (1985) model to simulate equity market trading conditions. In the model, informed traders are able to choose to submit their orders to traditional exchanges or dark pools. He argues that the optimal trading strategy for an informed trader is to split their orders between lit markets and crossing networks. Informed traders then migrate a portion of their trades from the lit market to the dark. Therefore, introducing a dark pool can lower the adverse selection risks, price discovery, and price volatility in traditional exchanges.

In accordance with Ye's (2012) findings, Bloomfield, O'Hara, and Saar (2015) suggest that both informed and uninformed traders migrate a portion of their orders from the lit market to dark pools, after introducing a new dark venue. However, they find that informed traders move a larger portion of their orders than that of uninformed traders.

Buti, Rindi, and Werner (2017)'s model studies the determinants of dark pool activity and its impact on market quality. They explain that there is a positive relationship between dark pool activity and the depth of the limit order book. Their research provides mixed predictions on the impact of dark trading on market quality. Although the introduction of a dark trading venue will cause the order migration from the lit market to the dark, they also document that introducing a dark pool can attract additional orders and trades in aggregate, therefore increasing market liquidity. Boulatov and George (2013) further recognise the positive effect of dark trading on market quality. They suggest that dark trading increases the competition among liquidity providers, thus narrowing spreads and improving market efficiency.

In stark contrast, Zhu (2014) reaches the opposite conclusion to Ye's (2012) model. The author extends the notion of "execution risks" in the model of Degryse, Van Achter, and Wuyts (2009). Informed traders tend to cluster on the same side of the order book, thus facing a higher probability of non-execution. Due to the low execution probability in dark venues, informed traders have to execute their orders in the lit market at an unfavourable price to the price without the dark pool. Dark trading then results in the segregation of market participants. Impatient informed traders prefer trading in the lit market to submitting orders to the dark. Therefore, introducing dark venues will increase the adverse selection risks in the lit market, reducing market liquidity (Zhu, 2014). Moreover, the author claims that the segregation of traders lowers the noisiness of demand and supply in the lit market, and improves price discovery.

Yin (2005) states that market fragmentation increases search costs and reduces competition among liquidity providers, thereby harming liquidity and price discovery. Kratz and Schoeneborn (2014) identify the existence of adverse selection risks in dark pools, which increases the execution costs of dark trading. They point out that traders tend to use dark trading before the lit market execution, reducing information leakage.

Comerton-Ford and Putnins (2015) summarise the two contradictory theories raised by Ye (2012) and Zhu (2014). Ye's (2012) model assumes that an informed trader is a monopolist, who does not face the risks of non-execution in the dark pool. However, Zhu (2014) assumes that there are many competing informed traders in the market; they face low execution probability in a dark pool and unexecuted orders may suffer costly delays.

2.5.2 Empirical studies

Numerous empirical studies contribute to the debate about the impact of dark trading on market quality. Conrad, Johnson, and Wahal (2003) document that institutional traders in the US achieve lower execution costs through alternative trading systems than on the exchange. Traders submit their orders to the alternative trading system to reduce information leakage, and they then fulfil their unexecuted orders in the lit market. Naes and Odegaard (2006) find that institutional traders (the Norwegian Petroleum Fund), who send their orders first to dark pools and then to the lit market, enjoy lower level of explicit execution costs for the dark component. Similar results are achieved by Bessembinder, Panayides, and Venkataraman (2009), using a sample of Euronext-Paris stocks, and Brandes and Domowitz (2010), evaluating the impact of the implementation of MiFID in Europe.

However, Naes and Odegaard (2006) argue that the implicit costs due to non-execution in dark venues fully offset the reduction in explicit costs, leaving total costs stable. Similarly, Altunata, Rakhlin, and Waelbroeck (2010) find that all cost savings from dark trading are lost due to adverse selection. Hatheway, Kwan, and Zheng (2014) further show that adverse selection risk in dark trading venues is 60% to 80% less than that in lit markets.

Annand and Weaver (2004) analyse the effects of suspension and re-introduction of hidden orders in Canada in 1996 and in 2002. They find that there is a substitution effect between lit market depth and hidden orders. The re-introduction of hidden orders in 2002 increases market depth in aggregate. However, Fong, Madhavan, and Swan (2004) find no evidence showing that crossing networks cannibalise the liquidity in the lit market in Australia.

Ready (2010) evaluates the drivers of trading volume in three dark crossing networks (Liquidnet, Posit and Pipeline), using a proprietary data set. He reports that there is a positive relationship between dark trading volume and stock daily turnover, while dark trading is less active for those stocks that have higher levels of information asymmetry. This finding is consistent with Zhu's (2014) model that informed traders prefer to submit their orders in lit markets due to execution risks in dark pools.

Fong, Swan, and Madhavan (2001) discover that institutional trading interests and market liquidity are the key determinants of the activeness of dark trading in the Australian market. Buti, Rindi, and Werner (2011) also show that dark trading is more active for stock-days that have narrower spreads, larger market depth, low price volatility, and larger turnover. Dark trading is less active when trading is more informed. The impact of dark trading on market efficiency is less obvious. Similar findings are reported by He and Lepone (2014), investigating the relationship between dark trading in Australia and market quality.

O'Hara and Ye (2011) examine the US market, using the market share of trade reporting facilities (TRF) as a proxy for the amount of dark trading. They find that fragmentation reduces market spreads and execution speed as well as increasing short-term price volatility. They conclude that dark fragmentation does not exert a negative impact on market quality.

In contrast, Weaver (2011) investigates the relationship between dark fragmentation and five measures of market spreads, which are quoted spread, effective spread, realised spread, price impact and return volatility, using a similar data set (but a later sample period) as O'Hara and Ye's (2011) analysis. He observes that internalisation increases market spreads and reduces liquidity. Stocks with a high level of dark trading are associated with higher price impact and higher price volatility. Nimalendran and Ray (2014) also observe that the bid-ask spread increases after dark trades occur in the US crossing network.

Degryse, De Jong, and Van Kervel (2015) examine the impact of dark and lit market fragmentation on market efficiency, using data from the Dutch market. They find that lit market fragmentation improves quoted spreads, realised spreads, and effective spreads. It reduces the execution costs and boosts competition between liquidity providers across venues. However, it is observed that dark trading reduces market depth and increases the price impact of transactions. Degryse, De Jong, and Van Kervel (2015) explain that dark trading pushes informed traders clustering in a lit market, which increases adverse selection risks and reduces market liquidity. This finding is consistent to that in Zhu's (2014) model.

Gresse (2012) evaluates the implementation of MiFID in Europe and documents that lit market fragmentation improves market liquidity, and market competition can reduce spreads. In addition, the author finds that internalisation does not exert a negative impact on market efficiency. Kwan, Masulis, and McInish (2015) analyse the competition between traditional exchanges and dark venues in the US. With the introduction of a minimum pricing increment regulation, lit markets experience significant limit order queues. Market participants then migrate their trades from lit exchanges to dark pools. This regulation gives a competitive advantage to dark pools and increases market fragmentation in the US. The authors argue that this uneven playing field, generated by the regulator, is detrimental to market quality.

Comerton-Forde and Putnins (2015) investigate the relationship between dark trading and price discovery in Australia. They suggest that dark trades are less informed than lit trades and discover that dark venues attract less-informed order flows migrating from lit markets. Consistent with Zhu's (2014) study, dark trading results in the concentration of informed traders in the lit exchange. This effect increases in adverse selection risk, quoted spreads, and price impact in the lit market. They conclude that high levels of dark trading harm price discovery, and thus overall pricing efficiency, while low levels of dark trading are benign or even beneficial for informational efficiency. Specifically, they find that the impact of dark trading on informational efficiency turns negative when dark trading exceeds 10% of total daily turnover in a given stock in the Australian market.

Foley and Putnins (2014) examine the impact of dark trading restrictive regulations in Australia and Canada. They observe that the amount of dark trading reduces substantially after the implementation of the Minimum Price Improvement (MPI) rule. However, they find no significant improvement in lit market liquidity under the new rule. Comerton-Forde, Malinova, and Park (2016) reach a similar conclusion using proprietary trader-level data in Canada. They find that the MPI reduces the volume of dark trading significantly; however, it does not exert an impact on aggregate market quality.

Further, Foley and Putnins (2016) divide dark trading into two types: dark limit order markets and dark midpoint crossing systems. The authors find that dark limit order markets reduce market spreads and increase information efficiency by encouraging aggressive competition in liquidity provision. They do not find a significant relationship between dark midpoint crossing systems and market quality.

2.6 Options Market Liquidity

The bid-ask spread is one of the essential indicators to measure market liquidity. Two theoretical approaches analyse the determinants of bid-ask spread in market microstructure literature, namely inventory-based models and information-based models.

The inventory-based approach suggests that quoted prices and sizes reflect the non-equilibrium inventory positions of market makers. Theoretical models assume that market makers are uninformed, and that they do not actively acquire information other than the order flow in the market. Further, market makers are considered to face no adverse selection risks. Prior studies argue that the bid-ask spread is positively associated with the security's price and volatility; however, it is negatively impacted by trading volume (e.g., Stoll, 1978; Amihud & Mendelson, 1980; Ho & Stoll, 1981).

Alternatively, the information-based approach concentrates on the adverse selection risks faced by market makers in the presence of information asymmetry. The information-based models assume that market makers are uninformed towards the intrinsic value of securities. These models predict that market makers increase bid-ask spreads to compensate the adverse selection risks from trading with informed traders (e.g., Bagehot, 1971; Copeland & Galai, 1983; Glosten & Milgrom, 1985; Madhavan, 1992; Foster & Viswanathan, 1994).

These two theoretical approaches are applied in the equity options market microstructure literature, which documents the impact of these two factors on the hedging costs of options market makers, thus the market liquidity. Options market makers use the bid-ask spread to manage their inventory exposures (e.g., Ho & Macris, 1984; Jameson & Wilhelm, 1992). Ho and Macris (1984) apply the inventory-based model to examine the behaviour of options market makers on the American Stock Exchange (AMEX). They show that market makers adjust bid and ask quotes when their inventory holdings deviate from their desired levels. They find that bid-ask spreads are positively related to price volatility.

Jameson and Wilhelm (1992) argue that options market makers face hedging risk and option volatility risk. Specifically, options market makers need to continuously hedge their positions using underlying assets as part of their inventory management. Market makers also need to consider the stochastic nature of the options volatility. These two risks are both positively related to the bid-ask spread of options traded on the Chicago Board Options Exchange (CBOE).

Giannetti, Zhong, and Wu (2004) develop a theoretical model to simulate options market making. They suggest that conventional inventory models are not sufficient to describe the options market spread. Options market makers hedge their inventory position by trading the underlying security. This hedging process generates additional transaction costs, which should be incorporated within the options market bid-ask spread.

Battalio and Schultz (2011) examine the impact of the 2008 Short Sale Ban on the equity options market. They discover that bid-ask spreads for options written on the banned stocks increase substantially, and they attribute this phenomenon to the inability of options market makers to hedge within the underlying stock market due to the short sale ban.

Wu, Liu, Lee, and Fok (2014) shed some light on the importance of inventory management on option market spreads. They break down the rebalancing costs into two types: rebalancing costs due to inventory position changes, and rebalancing costs due to delta changes. They report that rebalancing costs due to inventory changes are much more influential than those due to delta changes. A stable inventory position can reduce options market spreads substantially.

Muravyev (2016) decomposes the price impact of trades into two categories: inventory risk and asymmetric information components. The author finds that the inventory risk component is significantly larger than the asymmetric information components. In addition, Muravyev (2016) finds that past order imbalances have a strong predictive power for option returns. Further, prior literature identifies the relationship between information asymmetry and options market spread (e.g., Manaster & Rendleman, 1982; Stehpan & Whaley, 1990; Easley, O'Hara, & Srinivas, 1998; Chan, Chung, & Fong, 2002; Charkravarty, Gulen, & Mayhew, 2004).

Easley, O'Hara, and Srinivas (1998) investigate the informational role of trading volume in options market. They build an asymmetric information model in which informed traders can trade in options or underlying stock markets. The authors find that options market are an alternative market in which informed traders can profit from their private information. The trading volume in the options market conveys information about future stock prices. Easley, O'Hara, and Srinivas (1998) confirm an important informational role in options market.

Charkravarty, Gulen, and Mayhew (2004) examine the contribution of options market to price discovery. They estimate the options markets accounts for 17% of total contributions to price discovery, based on a sample of stock and options data over five years. The authors find that options market price discovery is related to trading volume, market spreads, and price volatility. They show that informed traders trade in both stock and options markets.

Bartram, Fehle, and Shrider (2008) compare the bank-issued options that traded on EuWax, where market makers face minimum adverse selection risk, and traditional options that trade on EuRex. They compute that the average bid-ask spread for the EuWax options is 4.2%, while that for the EuRex options is 8.8%. Hence, the adverse selection component constitutes more than half of the percentage bid-ask spread for Eurex options. Ahn, Kang, and Ryu (2008) investigate the KOSPI 200 index options traded on the Korean Exchange (KRX). They estimate that the adverse selection component accounts for 35% and 39% of the bid-ask spread for call and put options, respectively. Further, they find that adverse selection costs are positively related to the proportion of foreign investors in the options market. Moreover, Cao and Wei (2010) investigate the US options market and argue that information asymmetry exerts a more significant impact on options market liquidity than inventory risk.

Huh, Lin, and Mello (2015) build a model to analyse the effects of hedging activities by options market makers facing informed trading. They find that options market makers' hedging activities motivated by adverse selection risk increase bid-ask spreads in both stock market and options markets. Results indicate that such an impact is larger when the options market makers hedge with the underlying stocks than with other options. The authors discover that options market makers' hedging activities significantly influence the trading behaviour of informed traders in the market.

However, there is some empirical evidence showing that adverse selection risk is not a significant factor for options market spreads. Vijh (1990) investigates the relationship between information asymmetry and bid-ask spreads in the options market using a data set from the CBOE. He discovers that the impact of adverse selection risk on the bid-ask spread of the CBOE options is insignificant. In addition, Neal (1992) conducts a study on a sample of 26 AMEX options and 15 CBOE options. He finds that the adverse selection component of the option bid-ask spread is negligible.

Lee and Yi (2001) find similar results as Vijh (1990) that large-sized option trades do not exert a significant impact on option prices. They also investigate the effect of small-sized option trades, and find that adverse selection risk imposes a more substantial influence on the options market than on the underlying stock market for small-sized trades.

Beyond the inventory-based and information-based approaches, some researchers find that the option market liquidity is closely related to its underlying spot market liquidity. Cho and Engle (1999) raise the famous "derivative hedge theory", which states that if options market makers can perfectly hedge their inventory exposures in underlying stock markets, the stock market liquidity will determine the bid-ask spread in the options market. The inventory risks and adverse selection risks are irrelevant in this theory. They find that the bid-ask spread in the options market is positively related to that in the stock market. Based on a sample of covered warrants traded in Italy, Petrella (2006) investigates the different options market making costs components (initial hedging, rebalancing, and order processing). Results suggest that the market spread of the option is positively related to the spread of its underlying asset.

Mayhew (2002) points out that the bid-ask spread in options markets is driven by the level of inter-market competition. He compares the market spread of single-listed options (only listed on CBOE) and multiple-listed options and reports that multiple-listed options have lower quoted and effective spreads. De Fontnouvelle, Fishe, and Harris (2003) further extends Mayhew's (2002) study, incorporating a structural transition that increases inter-market competition in option markets. They find that quoted and effective spreads decrease with an increased level of competition. The effective spread of call and put options experiences a 31% and 39% decrease during their sample period, respectively. They eliminate the effect of hedging costs in their study by observing a stable underlying market spread and option delta.

Prior studies document how the option bid-ask spread relates to the option parameters. George and Longstaff (1993) examine the cross-sectional distribution of bid-ask spreads and trading activity in the S&P 100 index options market. Results show that the bid-ask spread is positively related to the option's time-to-maturity and its premium, while it is negatively related to its delta and the level of trading activity.

Wei and Zheng (2010) document three variables, namely option return volatility, time-to-maturity, and moneyness, as the liquidity determinants of equity options market. They define option return volatility as the option price elasticity multiplied by the stock return volatility. Besides the commonly recognised liquidity determinants (such as underlying stock return volatility and option trading volume), the option price volatility is observed to have a significant impact on options' proportional bid-ask spreads. They estimate that the inventory risk component, which is measured through the option return volatility, accounts for more than 45% of the bid-ask spread. In addition, Wei and Zheng (2010) identify the maturity-substitution effect and moneyness-substitution effect on the spread variation of individual equity options.

There are a broad range of approaches to measure options market liquidity. Yet, no consensus has been reached about the most appropriate measurement. Aitken and Comerton-Forde (2003) surmise that the various liquidity measures can be divided into two main categories: trade-based and order-based. Trade-based approaches involve trading value, volume and turnover. These measurements are ex-post, which focus on past trading activity and do not necessarily imply the liquidity for future transactions. Order-based approaches include bid-ask spreads and quoted depth, which are considered to be better proxies. Aitken and Comerton-Forde (2003) argue that order-based measures can capture both the cost and the ability to trade immediately. Amihud and Mendelson (1986) point out that the bid-ask spread can be viewed as the price the market maker demands for providing liquidity services and immediacy of execution.

2.7 Hypothesis Development

This section translates the literature reviewed in the previous sections into testable hypotheses; these hypotheses are subsequently tested in this dissertation.

2.7.1 Short-Sale Restrictions and Index Futures Mispricing

Short sale restrictions are widely implemented in many jurisdictions around the world. Prior studies provide empirical evidence showing that short sale restrictions generally exert a negative impact on market quality. It is observed that restrictions can result in lower trading activities (e.g., Chan, Kot, & Yang, 2010; Frino, Lecce, & Lepone, 2011), stock over-valuation (e.g., Jones & Lamont, 2002; Chan, Kot, & Yang, 2010), lower market liquidity (e.g., Daouk & Charoenrook, 2005; Frino, Lecce, & Lepone, 2011), higher price volatility (e.g., Ho, 1996; Daouk & Charoenrook, 2005; Frino, Lecce, & Lepone, 2011), and slower price discovery process (e.g., Boulton & Braga-Alves, 2010; Chen & Rhee, 2010).

A position in a futures contract can be replicated by its underlying asset, thus futures prices should be consistent with the price of the spot market. The “cost-of-carry” model provides guidance as to how to compute the theoretical futures price. Several prior studies document that a number of market factors can push the futures price away from its theoretical value. This difference is referred to as “futures mispricing”.

The literature suggests that short-selling restrictions are a significant factor for stock index futures mispricing. Fung and Draper (1999) find that the removal of short-selling restrictions reduces the frequency and magnitude of index futures mispricing in Hong Kong. Kempf (1998) and Fung and Jiang (1999) reach qualitatively similar conclusions. On the contrary, if the owners of the underlying assets act on futures under-pricing quickly (or the over-pricing of the underlying assets), short sale restrictions may not have a significant impact on futures pricing, especially futures under-pricing. By directly examining S&P 500 arbitrage trades during a period in 1989, Neal (1996) presents evidence that futures pricing is not significantly affected by short sale restrictions.

Further, due to short sale restrictions, the distribution of index futures mispricing is theoretically predicted to be asymmetric, with more under-pricing than over-pricing. Existing literature reviewed in Section 2.2 widely documents this phenomenon (e.g., Cornell & French, 1983; Modest & Sundaresan, 1983; Lin, Lee, & Wang, 2013). A plethora of literature also reports that index futures are more frequently over-priced than under-priced (e.g., Mackinlay & Ramaswamy, 1988; Draper & Fung, 2003; Richie, Daigler, & Gleason, 2008).

As the above discussion indicates, it is difficult to predict the relationship between short sale restrictions and futures pricing. Hence, the following two hypotheses are tested in this dissertation.

Hypothesis 3.1: The mispricing of CSI 300 index futures is symmetric.

Hypothesis 3.2: Short sale restrictions in equities markets have no impact on the pricing efficiency of the CSI 300 index futures contracts relative to the spot index.

2.7.2 Message Traffic Regulatory Restrictions and Relative Pricing Efficiency of Index Futures Contract

Along with the proliferation of high frequency trading in global markets, regulations are proposed and implemented by many market authorities. Financial transaction taxes are a prevalent method designed to curb excess market volatility, as well as collecting revenue for governments (e.g., Tobin, 1978; Schwert & Seguin, 1993). However, past studies report that financial transaction taxes can impose a negative impact on market quality. It is observed that financial transaction taxes are associated with lower trading volume, wider bid-ask spreads, and higher price volatility (Chou & Wang, 2006; Pomeranets & Weaver, 2013). Further, modern financial transaction tax schemes incorporate a tax component that specifically targets high frequency trading activities. Given this, the market impact of financial transaction taxes depends on the role of high frequency trading in capital markets.

The literature reviewed in the previous sections suggests that the market impact of high frequency trading is mixed. Prior research demonstrates a positive relationship between algorithmic trading and market quality. Algorithmic trading activities can reduce bid-ask spreads, increase market depth, lower price volatility, and improve price discovery (e.g., Brogaard, 2010; Hendershott, Jones, & Menkveld, 2011). Arbitrageurs who employ fast trading speeds are able to better exploit price misalignments between related markets, thus improving market pricing efficiency. However, some academic research in more recent years expresses concerns over the negative externalities brought about by high frequency trading. They document that some high frequency trading activities consume liquidity in the limit order book and increase market volatility. During periods of extreme market stress, high frequency trading activities can significantly harm market stability; an example case is the “Flash Crash” (Kirilenko, Kyle, Samadi, & Tuzun, 2017). In addition, the increased competition among high frequency traders may drive the market price of financial instruments away from their fundamental value (Kozhan & Tham, 2012).

As the above discussion suggests, there is an empirical question about the relationship between restrictions on algorithmic trading activity and relative pricing efficiency between index futures and Exchange-Traded Fund markets. Hence, the following three hypotheses are tested in this dissertation.

> **Hypothesis 4.1:** The introduction of message traffic regulatory restrictions has no impact on the trading volume of equity-like instruments.

> **Hypothesis 4.2:** The introduction of message traffic regulatory restrictions has no impact on the price volatility of equity-like instruments.

> **Hypothesis 4.3:** The introduction of message traffic regulatory restrictions has no impact on return correlation between index futures and index ETFs.

2.7.3 Dark Trading Regulations and Options Market Liquidity

Existing literature highlights a relationship between dark trading and equities market quality. Ye (2012) and Boulatov and George (2013) recognise the positive effects of dark trading on market quality. They point out that dark trading can narrow market spreads, lower adverse selection risks, reduce price volatility, and thus improve market efficiency. However, Zhu (2014) argues that dark trading increases the adverse selection risks in the lit market and reduces market liquidity. In addition, abundant literature indicates that dark trading does not exert a significant impact on aggregate market quality (e.g., Foley & Putnins, 2014; Comerton-Forde, Malinova, & Park, 2016).

The literature reviewed in the previous sections suggests that options market liquidity is related to that of its underlying market (e.g., Cho & Engle, 1999; Petrella, 2006). Specifically, the bid-ask spread in the options market reflects the costs faced by options market makers to hedge against inventory risks and adverse selection risks (e.g., Ahn, Kang, & Ryu, 2008; Battalio & Schultz, 2011).

Based on the discussions above, the potential impact of dark trading regulations on options market liquidity are two-fold. First, dark trading activity widens bid-ask spreads in equities markets. Consequently, the options market liquidity is predicted to reduce. Second, dark trading discourages informed traders to acquire costly private information, thereby reducing the aggregate amount of information in the market. Options market makers thus face a lower level of adverse selection risks from informed traders. Therefore, the options market liquidity is predicted to increase. Hence, the following hypothesis is tested in this dissertation.

> **Hypothesis 5.1:** Restrictive dark trading regulations have no impact on options market liquidity through measurements such as percentage bid-ask spreads, quoted depth, percentage effective spreads, realised spreads, and price impact.

2.8 Summary

This chapter reviews the literature related to the issues examined in this dissertation and develops several hypotheses that are tested in the following chapters. Chapter 3 examines the impact of short-selling restrictions on the pricing efficiency of index futures contracts in China. Chapter 4 analyses the effects of message traffic regulatory restrictions on the relative pricing efficiency of index futures contracts against Exchange-Traded Funds that track the index. Chapter 5 investigates the relationship between restrictive dark trading regulations and equity options market liquidity.

Chapter 3 – The Impact of Short Sales Restriction on Index Futures Pricing: Evidence from China

3.1 Introduction

Theoretical analysis and empirical evidence suggest that short sales restrictions may exert a significant effect on the efficiency of index futures pricing relative to its underlying cash index. The literature review in Section 2.2 illustrates that futures prices and the corresponding underlying prices are determined such that arbitrage opportunities do not exist. The relative pricing relationship is maintained by arbitrageurs who can capture profits from misalignment between futures and the underlying prices. However, various studies document significant misalignment between the stock index futures price and the corresponding underlying index level in numerous markets.

This chapter extends the understanding of the relationship between short sales restrictions and futures pricing, on which there is disagreement in the literature as reviewed in Section 2.2. Two hypotheses are developed and tested in this chapter, based on short sales restrictive regulations implemented in mid-2015 in China. The first hypothesis (H3.1) predicts that the mispricing of CSI 300 index futures is symmetric. The second hypothesis (H3.2) predicts that short sales restrictions do not exert a substantial effect on the pricing efficiency of the CSI 300 index futures contracts relative to the spot index.

The remainder of this chapter is structured as follows. Section 3.2 provides institutional details of the CSI 300 Index and the corresponding futures (CSI 300 futures) as well as regulations on short-selling in China. Section 3.3 presents the data and descriptive statistics. Section 3.4 outlines the research design. Section 3.5 reports the empirical results. Section 3.6 provides results of robustness tests. Section 3.7 concludes.

3.2 Institutional Details and Recent Regulatory Changes

The CSI 300 Index (China Securities Index 300), which underlies the CSI 300 futures, is a market capitalisation weighted index that consists of 300 A-share stocks listed on the Shanghai Securities Exchange (SSE) and Shenzhen Securities Exchange (SZSE). The constituent stocks account for about 70% of the total market capitalisation of both stock exchanges. Index points are generated during the trading hours for both the SSE and the SZSE: from 9:30 am to 11:30 am and from 1:00 pm to 3:00 pm.

CSI 300 futures trade on the China Financial Futures Exchange (CFFEX). The contract unit is computed by the CSI 300 index point multiplied by RMB 300. The trading time for the CSI 300 index futures is from 9:15 am to 11:30 am and from 1:00 pm to 3:15 pm. On the last trading day (the third Friday), the futures market closes at 3:30 pm. Futures contracts are cash settled based on the settlement price calculated using the average index points in the last two trading hours on the settlement day. Quarterly contracts expire in March, June, September, and December. Non-quarterly contracts expire in the other months. On any given trading day, there exist four futures contracts: “current month”, “next month” and the “final months” of the next two quarters, with expiry dates in the current month, next month, next quarter, and the quarter after.

In mid-2015, China’s stock market experienced a sharp decline. On 4 August 2015, Chinese regulators imposed restrictions on short-selling in the equity market. Market participants who borrow shares for short-selling are not permitted to cover their positions within a trading day. The new rule discourages short-selling by short-term arbitrageurs, since short-sellers are now forced to hold their positions overnight, therefore being exposed to greater risk including any public information disclosures before the market opens the following day ("China Limits Stock Market," 2015). Some brokerage firms in China suspended their short-selling services temporarily after the rule change, including Citic Securities and Huatai Securities ("China Stocks Rise," 2015).

3.3 Data and Descriptive Statistics

Intraday data for the CSI 300 stock index futures and the underlying stock index are sourced from the Thomson Reuters Tick History (TRTH) data service. The data set contains the following: (1) the price (index point) for CSI 300 futures contracts (the CSI 300 Index) for each one-minute interval; and (2) the open, close, highest and lowest prices each trading day. For CSI 300 futures, trading volume (number of contracts traded) each trading day is included. The dividend yield for the CSI 300 Index is obtained from Bloomberg. The interest rate is the one-year benchmark lending rate in China, which is issued and maintained by the People's Bank of China.

The sample period in this study ranges from 30 April 2015 to 10 November 2015. The most actively traded contract (with the largest number of contracts traded) is chosen each trading day. Since during the "roll periods", the trading behaviour may differ significantly from the normal trading period, trading during these days are removed from the sample.[2]

[2] The nearest expiry contract has the largest trading volume among the four contracts on a given day. However, close to the monthly expiration date (the third Friday of the month), the next nearest-to-expiry futures contract becomes the most actively traded contract. During the sample period for CSI 300 futures, this occurs two to five trading days before the futures contract's expiration date ("roll periods").

Four trading days before and after the regulatory change are removed from the sample. The final sample contains 110 trading days, with 55 days each before and after the event. To mitigate the possible effect of irregular trading behaviour, trades 10-minutes prior to the market close are eliminated. The intraday data for the empirical analysis are from 9:31 am to 11:20 am and from 1:01 pm to 2:50 pm; in total there are 220 one-minute intervals each trading day.

Table 3-1 reports the descriptive statistics for CSI 300 futures contracts during the sample period. *Volatility* is defined as the natural logarithm of the highest price divided by the lowest price each trading day. *Trading Volume* is the total trading volume (number of contracts traded) of the CSI 300 futures contract chosen each trading day. *Futures price* is the daily closing price of the futures contract. The futures market is less volatile after the event; the average futures volatility decreases from 0.0553 to 0.0423. The trading volume of futures contracts drops considerably after the implementation of short-selling restrictions, which is consistent with previous studies (e.g., Reed, 2007; Chan, Kot, & Yang, 2010). After the event, the average daily volume of futures is 467,784 contracts, which is less than one third of that before the event (1,660,043 contracts). The futures market saw the average daily price fall from 4,600 to 3,395.

Table 3 - 1
Descriptive Statistics

This table reports descriptive statistics for CSI 300 futures surrounding the regulatory change. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. *Volatility* is defined as the natural logarithm of the highest price divided by the lowest price each trading day. *Trading Volume* is the total trading volume (number of contracts traded) of the CSI 300 futures contract chosen each trading day. *Futures price* is the daily closing price of the futures contract.

		Pre-period (N = 55 days)	*Post-period (N = 55 days)*
Volatility	*Mean*	0.0553	0.0423
	Standard Deviation	0.0321	0.0272
	Minimum	0.0149	0.0149
	Median	0.0458	0.0283
	Maximum	1.3170	1.1850
Trading volume	*Mean*	1,660,043	467,784
	Standard Deviation	410,401	768,997
	Minimum	414,476	11,664
	Median	1,642,710	16,232
	Maximum	2,594,682	2,425,793
Futures price	*Mean*	4,600	3,395
	Standard Deviation	546	310
	Minimum	3,463	2,822
	Median	4,674	3,377
	Maximum	5,335	4,033

3.4 Research Design

The theoretical futures price is based on the "cost-of-carry" model (e.g., Cornell & French, 1983; Harris, 1989; Brennan & Schwartz, 1990; Chung, 1991; Yadav & Pope, 1994) as follows:

$$TP = Ie^{[(r-d)T]} \tag{3-1}$$

where, for each one-minute interval; *TP* is the theoretical futures price; *I* is the CSI 300 index point; *T* is the time to expiry (in years); *d* is the annual dividend yield; and *r* is the annualised risk-free interest rate. The theoretical futures price is calculated in one-minute time intervals for each trading day during the sample period. Then, various futures price bands, which consist of the upper and lower bounds around a theoretical price, are determined as in Chung (1991) and Richie, Daigler, and Gleason (2008).

Following Richie, Daigler, and Gleason (2008), mispricing in this study is measured relative to seven levels of transaction costs: 0, 0.25, 0.50, 0.75, 1.00, 1.25, and 1.50%.[3] Then, the upper and lower theoretical futures price boundaries are constructed. The upper (*UB*) and lower (*LB*) price boundaries for each one-minute interval are defined as follows:

$$UB = TP \times (1 + TC) \tag{3-2}$$

$$LB = TP \times (1 - TC) \tag{3-3}$$

where *TP* is the theoretical futures price and *TC* is the pre-determined transaction cost.

The futures price is compared with theoretical futures price bands defined above in each one-minute interval. If the futures price is greater than the upper boundary, the futures contract is regarded as being "over-priced". Arbitrageurs may take a short position in futures contracts and a long position in the underlying stocks ("short futures strategy"). In contrast, if the futures price is below the lower boundary, the futures contract is considered "under-priced". To exploit this arbitrage opportunity, investors take a long

[3] For marginal retail investors in China, the transaction costs of implementing an index futures trading strategy add up to approximately 52 basis point. This includes exchange fee, title transfer fee, brokerage cost, stamp duty, and market impact cost. However, this does not include the cost of stock lending if the trading strategy requires stock short-selling.

position in futures contracts and a short position in the underlying stocks ("long futures strategy"). It should be noted that mispricing (either under-pricing or over-pricing) does not necessarily mean market inefficiency since: (i) the transaction cost benchmarks may not fully represent true transaction costs in China, and (ii) there could be other rational factors driving the deviation of the futures price from the theoretical value implied by Equation (3-1).

To isolate the impact of the regulatory change on futures pricing, the following regression is estimated:

$$MIS_t = \beta_0 + \beta_1 Event_t + \beta_2 Volatility_t + \beta_3 Volume_t + \beta_4 Trend_t + \varepsilon_t \tag{3-4}$$

where the unit of observation is a trading day. For the analysis of frequency of mispricing, MIS_t represents the proportion of futures mispricing (sum of over-pricing and under-pricing), over-pricing, and under-pricing on trading day t. For the regressions of the size of mispricing, MIS_t is defined as the average relative size of mispricing, the absolute deviation of the futures price from the upper (lower) boundary for over-pricing (under-pricing) divided by the futures price on trading day t. $Event_t$ takes the value of zero if trading day t belongs to the pre-event period (from 30 April 2015 to 28 July 2015) and one during the post-event period (from 10 August 2015 to 10 November 2015). $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at the 1% and 99% levels. Table 3-2 presents the correlation coefficient matrix for the four independent variables. After the regulatory event, futures market volatility and futures contract trading volume reduce, statistically significant at 5% and 1% levels, respectively. Futures market movement does not show a clear change after the event.

Table 3 - 2
Correlation Matrix

This table reports the correlation matrix of the independent variables for the regressions in this study. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by the lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. *Trend* is a dummy variable that takes the value of zero if the futures price moves up during a given trading day, and one otherwise. For each variable, the first row presents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*	*Trend*
Event	1	-0.2150*	-0.7450**	-0.1093
		(0.0241)	(<0.0001)	(0.2559)
Volatility	-0.2150*	1	0.4098**	0.1370
	(0.0241)		(<0.0001)	(0.1536)
Volume	-0.7450**	0.4098**	1	0.1381
	(<0.0001)	(<0.0001)		(0.1503)
Trend	-0.1093	0.1370	0.1381	1
	(0.2559)	(0.1536)	(0.1503)	

3.5 Results

3.5.1 Frequency of Mispricing

Table 3-3 reports the number and percentage of under-pricing, over-pricing, and mispricing (either under-pricing or over-pricing) subject to seven levels of hypothetical transaction costs, ranging from 0 to 1.50% in the period before and after the event. Binomial tests reveal that the difference between under-pricing and over-pricing is statistically significant at the 1% level subject to all levels of the transaction costs in both periods. Results also indicate that for all transaction cost levels after the regulatory change, futures contracts are more frequently mispriced, with under-pricing dominating over-pricing. At the 0.25% transaction cost level, 83% of futures prices fall outside either the upper or lower theoretical futures price boundary before the transition, whereas 99% of the futures prices are mispriced under the new short sale rule. At the highest transaction cost level (1.50%), futures contracts are mispriced in 75% of the total number of one-minute intervals after the event, whereas about 30% of observations show mispricing in the pre-event period.

Results also reveal that futures under-pricing is considerably more prevalent than futures over-pricing after the transition, which is consistent with prior research (e.g., Cornell & French, 1983; Gay & Jung, 1999; Lin, Lee, & Wang, 2013). This finding, however, contradicts Hypothesis 3.1, i.e., that the mispricing of CSI 300 index futures is symmetric. Under the new rule, the frequency of futures over-pricing is approximately 0% at all levels of transaction costs, and the minimum frequency of futures under-pricing is 75%.

Table 3-4 presents the regression results of the daily relative frequency of futures mispricing (either under-pricing or over-pricing) on the following independent variables: $Event_t$, $Volatility_t$, $Volume_t$, and $Trend_t$. The coefficient of $Event_t$ is positive and statistically significant at the 1% level for transaction cost levels from 0.25% to 1.25%, and at the 5% significance level under the 1.5% transaction cost assumption. This implies that futures contracts are more frequently mispriced under the new short sale rule after controlling for $Volatility_t$, $Volume_t$, and $Trend_t$. This finding is inconsistent with Hypothesis 3.2, that the short sale restriction in equities market has no impact on the pricing efficiency of the CSI 300 index futures contracts relative to spot index. The coefficients for $Volatility_t$ and $Volume_t$ are not statistically distinguishable from zero at conventional significance levels for all levels of transaction costs, suggesting that they are not related to the frequency of futures mispricing. The coefficient of $Trend_t$ is statistically different from zero at the 5% level for transaction cost levels ranging from 0.75% to 1.5%; futures mispricing (subject to transaction cost levels of 0.75% – 1.5%) is more likely to occur during falling markets in both periods.

Next, regressions are estimated for futures over-pricing and under-pricing separately. Table 3-5 presents the regression results of the relative frequency of over-pricing on futures' volatility, volume, and market direction. The coefficient of $Event_t$ is negative and statistically different from zero at the 1% level for the transaction levels from 0 to 0.5%, and at the 5% level of significance under the 0.75% transaction cost assumption, indicating that futures over-pricing is less frequent in the post-event period after controlling for volatility, volume, and market direction. The coefficients for $Volatility_t$, $Volume_t$, and $Trend_t$ are not statistically significant at either the 1% or 5% significance levels for all levels of transaction costs; none of the control variables are associated with the frequency of futures over-pricing.

Table 3 - 3
Frequency of Mispricing Surrounding the Regulatory Change

This table reports the number and proportion of futures under-pricing, over-pricing, and no mispricing subject to seven levels of predetermined transaction costs (ranging from 0 to 1.50%). The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. *N* is the number of observations in each period. * (**) indicates statistical significance at 5% (1%) levels based on a binomial test.

Transaction Cost (%)	*Pre-period*				*Post-period*			
	N	*Under-pricing*	*No Mispricing*	*Over-pricing*	*N*	*Under-pricing*	*No Mispricing*	*Over-pricing*
0	12,100	7,458	0	4,642	12,100	12,089	0	11
		62%	0%	38%**		100%	0%	0%**
0.25	12,100	6,341	2,060	3,699	12,100	11,951	148	1
		52%	17%	31%**		99%	1%	0%**
0.50	12,100	5,198	4,061	2,841	12,100	11,539	560	1
		43%	34%	23%**		95%	5%	0%**
0.75	12,100	4,237	5,766	2,097	12,100	10,952	1,148	0
		35%	48%	17%**		91%	9%	0%**
1.00	12,100	3,419	6,996	1,685	12,100	10,491	1,609	0
		28%	58%	14%**		87%	13%	0%**
1.25	12,100	2,879	7,850	1,371	12,100	9,803	2,297	0
		24%	65%	11%**		81%	19%	0%**
1.50	12,100	2,615	8,447	1,038	12,100	9,055	3,045	0
		22%	70%	9%**		75%	25%	0%**

Table 3 - 4
Regressions of Frequency of Mispricing

This table reports the regression results of the daily proportion of futures mispricing (sum of over-pricing and under-pricing). The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. The unit of observation is a trading day. Regressions are estimated for six levels of predetermined transaction costs (ranging from 0.25% to 1.50%). The results for the transaction cost of zero are not presented since under that condition futures are mispriced in each one-minute interval. $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0.25	0.8131**	0.1610**	0.8430	-3.2380	0.0285	0.1885	110
	(<0.0001)	(<0.0001)	(0.1442)	(0.5186)	(0.3068)		
0.50	0.5221**	0.3206**	1.5960	0.6526	0.0774	0.2268	110
	(0.0019)	(<0.0001)	(0.1215)	(0.9582)	(0.0859)		
0.75	0.2331*	0.4466**	2.0510	8.0240	0.1071*	0.2570	110
	(0.4022)	(<0.0001)	(0.0949)	(0.6909)	(0.0484)		
1.00	0.1966	0.4950**	2.1380	3.0760	0.1084*	0.2869	110
	(0.5101)	(<0.0001)	(0.1058)	(0.8884)	(0.0456)		
1.25	0.3529	0.4556**	2.5390	-14.9200	0.1223*	0.2865	110
	(0.3286)	(<0.0001)	(0.0704)	(0.5685)	(0.0243)		
1.50	0.5611	0.3832*	2.9540	-34.5900	0.1231*	0.2743	110
	(0.2423)	(0.0116)	(0.0660)	(0.3205)	(0.0281)		

Table 3 - 5
Regressions of Frequency of Over-pricing

This table reports the regression results of the daily proportion of futures over-pricing. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of predetermined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day *t*. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day *t*. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day *t*, and one otherwise. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	*N*
0	0.3746**	-0.3792**	0.0432	2.6780	-0.0543	0.2640	110
	(<0.0001)	(<0.0001)	(0.9724)	(0.7526)	(0.2111)		
0.25	0.3044**	-0.3041**	0.2948	0.7813	-0.0450	0.2030	110
	(0.0004)	(0.0011)	(0.8132)	(0.9224)	(0.2913)		
0.50	0.2319**	-0.2336**	0.3982	-0.7438	-0.0146	0.1388	110
	(0.0043)	(0.0081)	(0.6974)	(0.9108)	(0.6720)		
0.75	0.1609*	-0.1706*	0.3241	-0.7428	0.00884	0.0862	110
	(0.0200)	(0.0332)	(0.7033)	(0.8966)	(0.7046)		
1.00	0.1099*	-0.1327	-0.0505	1.8390	0.0101	0.0562	110
	(0.0495)	(0.0684)	(0.9440)	(0.7189)	(0.6418)		
1.25	0.0750	-0.1047	-0.2751	3.1620	0.0141	0.0437	110
	(0.1342)	(0.1073)	(0.6352)	(0.4746)	(0.5487)		
1.50	0.0524	-0.0775	-0.2215	2.3520	0.0185	0.0321	110
	(0.1974)	(0.1381)	(0.6118)	(0.4931)	(0.4863)		

Table 3-6 presents the results of the regression analysis for futures under-pricing as the dependent variable. The regressions control for the effects of futures' volatility, volume, and market trend on futures under-pricing. Contrary to the results of the regressions of futures over-pricing, the coefficient of $Event_t$ is positive and statistically significant at the 1% level for all transaction levels. Controlling for futures' volatility, volume, and market trend, futures under-pricing is more likely to occur under the new short sale rule. The coefficient of $Volatility_t$ is positive and statistically different from zero at the 5% level for transaction cost levels ranging from 1.25% to 1.5%, indicating that higher futures volatility is associated with more frequent futures under-pricing. The coefficient of $Trend_t$ is positive and statistically significant at the 5% level for transaction cost levels of 1.25% and 1.5%; futures under-pricing is more frequent when the futures prices decline. It is also shown that futures trading volume has no statistically significant relation with futures under-pricing at conventional significance levels.

Overall, regression results reveal that futures under-pricing occurs more frequently across all transaction cost levels, while futures over-pricing occurs less frequently at transaction cost levels ranging from 0 to 0.75% under the new short sale rule. The results demonstrate that short-selling restrictions impose costs to the arbitrage trading strategies by short-term arbitrageurs who do not own the underlying assets in the presence of futures under-pricing (or over-pricing of the underlying assets), resulting in more persistent futures under-pricing. This finding is inconsistent with Hypothesis 3.2.

Table 3 - 6
Regressions of Frequency of Under-pricing

This table reports the regression results of the daily proportion of futures under-pricing. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of predetermined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The p-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0	0.6254**	0.3792**	-0.0432	-2.6780	0.0543	0.2640	110
	(<0.0001)	(<0.0001)	(0.9747)	(0.7526)	(0.2111)		
0.25	0.5084**	0.4654**	0.5502	-4.0360	0.0738	0.3506	110
	(<0.0001)	(<0.0001)	(0.6871)	(0.6420)	(0.0892)		
0.50	0.2903	0.5542**	1.1980	1.3690	0.0920	0.3912	110
	(0.0899)	(<0.0001)	(0.4054)	(0.9144)	(0.0599)		
0.75	0.07224	0.6172**	1.7270	8.7670	0.0983	0.3949	110
	(0.7943)	(<0.0001)	(0.2046)	(0.6612)	(0.0625)		
1.00	0.0867	0.6277**	2.1880	1.2360	0.0982	0.4222	110
	(0.7725)	(<0.0001)	(0.0812)	(0.9545)	(0.0546)		
1.25	0.2778	0.5604**	2.8160*	-18.1000	0.1083*	0.4029	110
	(0.4366)	(<0.0001)	(0.0183)	(0.4767)	(0.0332)		
1.50	0.5079	0.4619**	3.1880*	-37.0900	0.1062*	0.3587	110
	(0.2826)	(0.0022)	(0.0216)	(0.2741)	(0.0405)		

3.5.2 Magnitude of Mispricing

This section examines the relative size of mispricing: the daily average absolute deviation of the futures price from the upper (lower) boundary for over-pricing (under-pricing) divided by the futures price. Table 3-7 reports the daily average size of the futures mispricing (either under-pricing or over-pricing) and under-pricing before and after the regulatory change. Given that there are only a few observations with over-pricing in the post-event period, over-pricing is not separately examined. The average relative mispricing (either under-pricing or over-pricing) in the post-event period is greater than that in the pre-event period, which is statistically significant at the 1% level for all levels of transaction costs. Even at the highest transaction cost level (1.5%), the difference is economically large; the average relative mispricing increases from 0.96% to 1.82%. Regarding futures under-pricing, the increase is statistically significant at the 1% level for transaction cost levels ranging from 0% to 0.75%, and at the 5% significance level for the transaction cost level of 1%.

Table 3-8 presents the regression results of the daily average magnitude of futures mispricing on $Event_t$, $Volatility_t$, $Volume_t$, and $Trend_t$. The analysis is conducted with seven levels of pre-determined transaction cost levels, ranging from 0 to 1.50%. The coefficient of $Event_t$ is positive and statistically significant at the 5% level for transaction cost levels from 0 to 0.25%. Consistent with Fung and Draper (1999), the relative size of mispricing is greater under the new short sale rule after controlling for $Volatility_t$, $Volume_t$, and $Trend_t$. Again, this finding is inconsistent with Hypothesis 3.2, that short sale restrictions do not affect the futures pricing efficiency. The coefficient of $Volatility_t$ is positive and statistically distinguishable from zero at the 5% level for the transaction cost level of 0.25%, suggesting that higher futures volatility is associated with larger futures mispricing in magnitude at this transaction level only. The coefficient of $Trend_t$ is positive and statistically significant at the 5% level for transaction cost levels ranging from 0 to 0.50% and the transaction cost level of 1%; the size of futures mispricing is larger when futures prices decline. The coefficient of $Volume_t$ is not statistically distinguishable from zero at conventional significance levels.

Table 3 - 7
Size of Mispricing Surrounding the Regulatory Change

This table reports the daily average of the relative magnitude of futures mispricing. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. Seven levels of pre-determined transaction costs are adopted (ranging from 0 to 1.50%). * (**) denotes statistical significance at the 5% (1%) level for the difference in the means before and after the event. *N* is the number of observations.

Transaction Cost (%)	*Mispricing (%)*			*Under-pricing (%)*		
	N	*Pre-period*	*Post-period*	*N*	*Pre-period*	*Post-period*
0	110	1.3387	2.9865**	101	1.2783	2.9869**
0.25	110	1.1476	2.7341**	98	1.1866	2.7341**
0.50	108	1.0150	2.4880**	94	1.1390	2.4880**
0.75	102	0.9591	2.2936**	87	1.1782	2.2936**
1.00	91	1.0009	2.1911**	79	1.2343	2.1911*
1.25	84	1.0149	2.0048**	74	1.2708	2.0048
1.50	80	0.9566	1.8226**	71	1.2247	1.8226

Table 3 - 8
Regressions of Size of Mispricing

This table reports the regression results of the daily relative size of mispricing: the absolute deviation of the futures price from the upper (lower) boundary for over-pricing (under-pricing) divided by the futures price. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the most actively traded contract. The sample includes 110 trading days, with 55 trading days each before and after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of pre-determined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The p-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0	-0.0184	0.0236*	0.1547	1.4682	0.0038*	0.2897	110
	(0.5845)	(0.0382)	(0.0522)	(0.5373)	(0.0271)		
0.25	-0.0202	0.0230*	0.1551*	1.4649	0.0037*	0.2857	110
	(0.5464)	(0.0422)	(0.0489)	(0.5362)	(0.0311)		
0.50	-0.0213	0.0219	0.1511	1.4679	0.0035*	0.2688	108
	(0.5233)	(0.0527)	(0.0543)	(0.5345)	(0.0383)		
0.75	-0.0201	0.0204	0.1430	1.3616	0.0031	0.2356	102
	(0.5444)	(0.0728)	(0.0796)	(0.5628)	(0.0755)		
1.00	-0.0168	0.0188	0.1347	1.1025	0.0038*	0.1984	91
	(0.6197)	(0.1098)	(0.1217)	(0.6434)	(0.0400)		
1.25	-0.0157	0.0172	0.1480	0.9596	0.0033	0.1708	84
	(0.6287)	(0.1384)	(0.1107)	(0.6737)	(0.0691)		
1.50	-0.0170	0.0163	0.1391	1.0401	0.0028	0.1444	80
	(0.5911)	(0.1569)	(0.1417)	(0.6390)	(0.1479)		

3.6 Robustness Tests

To ascertain the robustness of the results of the regression analyses in Section 3.5 with respect to the sample construction, an alternative index futures contract selection method is utilised. In this section, the index futures contracts selected are the nearest-to-expiry contract for each trading day. In addition, the "roll periods", discussed in Section 3.3, remain in the sample. Consequently, the sample in this section contains 121 trading days, with 61 days before and 60 days after the regulatory change. Regression results are presented in Tables 3-9, 3-10, 3-11, and 3-12. With a different index futures contract selection method, the coefficients of the regulatory event are not significantly altered for the frequency of the index futures mispricing (over-/under-pricing). Further, for the magnitude of mispricing, the coefficient of $Event_t$ is positive and statistically significant at the 5% level for transaction cost levels from 0 to 0.50%. Results of these additional tests indicate that the regression results in Section 3.5 are robust to the selection of futures contract.

Table 3 - 9
Regressions of Frequency of Mispricing (Nearest-to-Expiry Contracts)

This table reports the regression results of the daily proportion of futures mispricing (sum of over-pricing and under-pricing). The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the nearest-to-expiry contract. The sample includes 121 trading days, with 61 trading days before and 60 trading days after the transition. The unit of observation is a trading day. Regressions are estimated for six levels of predetermined transaction costs (ranging from 0.25% to 1.50%). The results for the transaction cost of zero are not presented since under that condition futures are mispriced in each one-minute interval. $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The p-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0.25	0.6266**	0.1894**	1.1729*	9.7348	-0.0279	0.1413	121
	(<0.0001)	(<0.0001)	(0.0366)	(0.2881)	(0.3033)		
0.50	0.1672	0.3748**	2.1823*	24.4164	-0.0026	0.1814	121
	(0.4967)	(<0.0001)	(0.0186)	(0.1799)	(0.9563)		
0.75	-0.1062	0.4941**	2.6377*	30.7681	0.0296	0.2256	121
	(0.7467)	(<0.0001)	(0.0179)	(0.2070)	(0.5803)		
1.00	-0.1139	0.5337**	2.6659*	24.0058	0.0356	0.2537	121
	(0.7415)	(<0.0001)	(0.0271)	(0.3545)	(0.5065)		
1.25	0.0836	0.4829**	3.0675*	3.1236	0.0504	0.2477	121
	(0.8287)	(<0.0001)	(0.0168)	(0.9136)	(0.3510)		
1.50	0.3335	0.3996**	3.5297*	-19.6792	0.0517	0.2315	121
	(0.4728)	(0.0021)	(0.0178)	(0.5688)	(0.3346)		

Table 3 - 10
Regressions of Frequency of Over-pricing (Nearest-to-Expiry Contracts)

This table reports the regression results of the daily proportion of futures over-pricing. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the nearest-to-expiry contract. The sample includes 121 trading days, with 61 trading days before and 60 trading days after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of predetermined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The p-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0	0.4445**	-0.3663**	0.0650	-5.3430	0.0027	0.2127	121
	(0.0007)	(<0.0001)	(0.9622)	(0.6701)	(0.9504)		
0.25	0.2892**	-0.2777**	0.4076	-0.9495	0.0134	0.1712	121
	(0.0063)	(0.0008)	(0.7431)	(0.9295)	(0.7406)		
0.50	0.1557*	-0.2007**	0.4791	2.6840	-0.0033	0.1276	121
	(0.0330)	(0.0079)	(0.6279)	(0.7371)	(0.9182)		
0.75	0.0873	-0.1429*	0.3699	3.1502	0.0125	0.0809	121
	(0.1260)	(0.0345)	(0.6437)	(0.6517)	(0.5552)		
1.00	0.0486	-0.1102	-0.0046	5.1067	0.0116	0.0525	121
	(0.3120)	(0.0714)	(0.9945)	(0.4468)	(0.5486)		
1.25	0.0251	-0.0868	-0.2242	5.7975	0.0144	0.0407	121
	(0.5555)	(0.1104)	(0.6734)	(0.3254)	(0.4922)		
1.50	0.0162	-0.0649	-0.1761	4.2550	0.0180	0.0305	121
	(0.6170)	(0.1360)	(0.6582)	(0.3441)	(0.4493)		

Table 3 - 11
Regressions of Frequency of Under-pricing (Nearest-to-Expiry Contracts)

This table reports the regression results of the daily proportion of futures under-pricing. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the nearest-to-expiry contract. The sample includes 121 trading days, with 61 trading days before and 60 trading days after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of predetermined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The p-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The p-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0	0.5555**	0.3662**	-0.0650	5.3430	-0.0027	0.2127	121
	(<0.0001)	(<0.0001)	(0.9622)	(0.6701)	(0.9504)		
0.25	0.3372*	0.4673**	0.7672	10.6616	-0.0143	0.2791	121
	(0.0416)	(<0.0001)	(0.5695)	(0.4402)	(0.7498)		
0.50	0.0115	0.5755**	1.7033	21.7325	0.0007	0.3180	121
	(0.9614)	(<0.0001)	(0.1975)	(0.2381)	(0.9895)		
0.75	-0.1935	0.6370**	2.2678	27.6178	0.0170	0.3417	121
	(0.5422)	(<0.0001)	(0.0662)	(0.2427)	(0.7424)		
1.00	-0.1625	0.6440**	2.6706*	18.8991	0.0240	0.3716	121
	(0.6294)	(<0.0001)	(0.0201)	(0.4512)	(0.6340)		
1.25	0.0585	0.5698**	3.2932**	-2.6955	0.0362	0.3528	121
	(0.8765)	(<0.0001)	(0.0027)	(0.9224)	(0.4714)		
1.50	0.3171	0.4654**	3.7176**	-24.1068	0.0350	0.3097	121
	(0.4846)	(0.0002)	(0.0041)	(0.4708)	(0.4748)		

Table 3 - 12
Regressions of Size of Mispricing (Nearest-to-Expiry Contracts)

This table reports the regression results of the daily relative size of mispricing: the absolute deviation of the futures price from the upper (lower) boundary for over-pricing (under-pricing) divided by the futures price. The new short sale rule took effect on 4 August 2015. Four trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 30 April 2015 and 28 July 2015. *Post-period* is between 10 August 2015 and 10 November 2015. The futures contract examined for each trading day is the nearest-to-expiry contract. The sample includes 121 trading days, with 61 trading days before and 60 trading days after the transition. The unit of observation is a trading day. Regressions are estimated for seven levels of pre-determined transaction costs (ranging from 0 to 1.50%). $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. $Trend_t$ is a dummy variable that takes the value of zero if the futures price moves up during trading day t, and one otherwise. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

Transaction Cost (%)	*Constant*	$Event_t$	$Volatility_t$	$Volume_t$	$Trend_t$	R^2	N
0	-0.0210	0.0227*	0.1712*	1.6619	0.0015	0.2770	121
	(0.4842)	(0.0245)	(0.0241)	(0.4392)	(0.3380)		
0.25	-0.0223	0.0220*	0.1710*	1.6198	0.0014	0.2745	121
	(0.4554)	(0.0279)	(0.0227)	(0.4471)	(0.3312)		
0.50	-0.0223	0.0207*	0.1658*	1.5488	0.0015	0.2569	118
	(0.4536)	(0.0391)	(0.0272)	(0.4646)	(0.3100)		
0.75	-0.0192	0.0190	0.1558*	1.2991	0.0015	0.2227	110
	(0.5253)	(0.0647)	(0.0464)	(0.5439)	(0.3476)		
1.00	-0.0130	0.0174	0.1460	0.8135	0.0029	0.1885	96
	(0.6723)	(0.1063)	(0.0895)	(0.7042)	(0.1155)		
1.25	-0.0124	0.0160	0.1602	0.6948	0.0024	0.1666	89
	(0.6722)	(0.1303)	(0.0816)	(0.7342)	(0.1803)		
1.50	-0.0149	0.0158	0.1486	0.8466	0.0024	0.1443	83
	(0.6181)	(0.1502)	(0.1171)	(0.6813)	(0.1969)		

3.7 Conclusions

This chapter investigates the relationship between the pricing of CSI 300 futures and short-selling restrictions in China. Specifically, the impact of a recent regulatory change on the pricing of CSI 300 futures is examined. On 4 August 2015, the new regulation on short-selling took effect for Chinese shares. Under the new short sale rules, investors who borrow shares for short-selling are not allowed to cover their positions within a trading day. This study examines how the frequency and size of futures mispricing changes after this regulatory transition.

This chapter provides evidence that futures under-pricing occurs more frequently at various transaction cost levels ranging from 0 to 1.5%, while futures over-pricing occurs less frequently under transaction cost levels ranging from 0 to 0.75% after the regulatory change. Results also show that the relative size of futures mispricing increases significantly at the transaction cost levels from 0 to 0.25% after the regulatory change. Results could be driven by changes in short-term arbitrageurs' behaviour in response to the regulatory change. Note that short-term arbitrageurs who prefer realising profits within a trading day are less incentivised to trade when futures under-pricing (or over-pricing of the underlying assets) is observed. This implies that market participants are likely to observe futures under-pricing more frequently under the new short sales rule.

Appendix 3.1

Table 3 - 13 Contract Specifications for the CSI 300 Index Futures Contract

Underlying index	CSI 300 Index
Contract multiplier	CNY 300
Unit	Index point
Tick size	0.2 points
Contract months	Monthly: current month, next month, next two calendar quarters (four contracts in total)
Trading hours	09:30 am – 11:30 am and 01:00 pm – 03:00 pm
Limit up/down	+/– 10% of settlement price on the previous trading day
Margin requirement	8% of the contract value
Last trading day	Third Friday of the contract month, postponed to the next business day if it falls on a public holiday
Delivery day	Third Friday, same as "Last trading day"
Settlement method	Cash settlement

For further information refer to http://www.cffex.com.cn/en_new/sspz/hs300zs/

Chapter 4 – Message Traffic Restrictions and Relative Pricing Efficiency: Evidence from Index Futures Contracts and Exchange-Traded Funds

4.1 Introduction

Prior studies provide mixed conclusions with respect to the impact of message traffic regulatory restrictions on inter-market pricing efficiency. The potential effects are two-fold, which are mutually contradicting. On the one hand, message traffic restrictions potentially reduce algorithmic trading (high frequency trading) activity. Arbitrageurs face higher execution costs to implement their trading strategies, and based on this, the speed of price adjustment between index futures and Exchange-Traded Fund (ETF) markets is predicted to be lower. Therefore, the return correlation between these two instruments is expected to decline. On the other hand, a significant quantity of literature suggests that financial transaction taxes, as well as message traffic restrictions, may remove some noise traders from the market, as well as reducing competition among algorithmic traders (high frequency traders). Consequently, the limit order book is more stable and the return correlation is expected to increase under more restrictive regulations.

The objective of this chapter is to contribute to the literature by investigating the relationship between message traffic restrictions and relative pricing efficiency. More specifically, this chapter examines the impact of message traffic restrictions on return correlation between index futures and ETFs in four countries, namely Australia, Canada, Italy, and France. Based on the literature reviewed in Sections 2.3 and 2.4, three hypotheses are developed and tested in this chapter. The first hypothesis (H4.1) predicts that the message traffic regulatory restrictions have no impact on the trading volume of equity-like instruments. The second hypothesis (H4.2) predicts that the message traffic regulatory restrictions have no impact on the price volatility of equity-like instruments. The third hypothesis (H4.3) predicts that the introduction of message traffic regulatory restrictions have no impact on return correlation between index futures and ETFs.

This chapter is organised as follows. Section 2 provides institutional details of stocks indices and their corresponding futures contracts and ETFs in four countries as well as the message traffic restriction policies. Section 3 presents the data sample and descriptive statistics. Section 4 summarises the research design. Section 5 reports the empirical results. Section 6 provides two additional tests. Section 7 concludes.

4.2 Institutional Details

4.2.1 Index Futures Contracts and Exchange-Traded Funds (ETFs)

The analysis in this chapter is based on four pairs of financial instruments (index futures contracts and ETFs). Introduced in 2000, the S&P/ASX 200 index is composed of the largest 200 stocks listed on the Australian Securities Exchange (ASX). This index is float-adjusted and commonly used to measure the performance of the Australian equity market. The SFE SPI 200^{TM} Index Futures (SPI Futures) is the most actively traded equity index futures contract written on the S&P/ASX 200 Index. Trading of the SPI Futures is based on an electronic limit order book that follows a price-time priority rule. The minimum tick size is one index point, valued at 25 Australian dollars. The contracts follow a March-June-September-December quarterly maturity cycle. The daytime trading session is from 9:50 am to 4:30 pm on the ASX. The ASX also lists the SPDR S&P/ASX 200 Fund (STW), an ETF maintained by State Street Global Advisors. This ETF seeks to closely track the return of S&P/ASX 200 Index. The STW is traded on a centralised limit order book, following the price-time priority rule. Investors can trade the shares of the STW anytime during the trading session, from 10:00 am to 4:00 pm, on both the listed exchanges in Australia.

In Canada, the S&P/TSX 60 Index is an equity market index, which consists of the largest 60 stocks by market capitalisation listed on the Toronto Stock Exchange (TSX). The S&P/TSX 60 index standard futures contract (TSX Futures) is the main stock index futures traded in the Montreal Exchange. The contract is denominated in index points, expressed to two decimal places. Each index point of the TSX Futures is equivalent to 200 Canadian dollars. The TSX Futures follows a March-June-September-December quarterly maturity cycle, and it is traded between 9:30 am to 4:15 pm. In addition, the iShares S&P/TSX 60 Index ETF (XIU) is an ETF that seeks to replicate the performance of the S&P/TSX 60. The XIU commenced trading in 1999 and is maintained by BlackRock Asset Management Canada Limited. This fund is the most liquid stock index ETF in Canada, and it is publicly traded on the TSX. The trading hours of the XIU are identical to listed shares on the exchange (9:30 am to 4:00 pm).

In Italy, the FTSE MIB (Milano Italia Borsa) Index is the primary benchmark equity index. The index consists of the 40 most actively traded stocks listed on Borsa Italiana's MTA and MIV markets. FTSE MIB Index Futures (MIB Futures) are written over the

FTSE MIB Index, trading on Borsa Italia. The MIB Futures are quoted in index points, valued at 5 Euros. The minimum tick size is 5 index points. The MIB Futures follows a March-June-September-December quarterly maturity cycle. Its continuous trading hours are from 9:00 am to 5:40 pm. In addition, LYXOR UCITS ETF FTSE MIB (ETFMIB) is an ETF that seeks to track the performance of the FTSE MIB index. It is denominated in Euros. The continuous trading hours are 9:00 am to 5:25 pm.

In France, the CAC 40 Index contains the 40 largest stocks by free-float market capitalisation. It is the most widely used indicator of the Paris equities market. The CAC 40 index futures (CAC Futures) are the main derivatives contract written on the CAC 40 index. The CAC Futures is denominated in index points, which is equivalent to 10 Euros. The expiration month of the CAC Futures is up to 60 months. The CAC Futures has a central limit order book, which applies a price-time priority rule, trading from 8:00 am to 10:00 pm. In addition, the Lyxor UCITS ETF CAC 40 (CAC ETF) is the most actively traded fund, which tracks the performance of the CAC 40 index. The CAC ETF is continuously traded between 9:00 am and 5:30 pm.

4.2.2 Regulations

In Australia, the Cost Recovery Scheme (CRS) was implemented on 1 January 2012 by the Australian Securities & Investments Commission (ASIC), which is the capital market regulatory authority in Australia. Through CRS, ASIC allocates costs to regulated entities to fund their market supervision services. In addition to the fixed component of fees and costs, market participants are charged variable fees based on their proportion of the total number of transactions and message traffic for securities executed on the ASX and Chi-

X. The message traffic costing component of CRS only applies to equities market, which includes shares, ETFs, and managed funds.

In Canada, the Integrated Fee Model (IFM) took effect on 1 April 2012. It was enacted by the Investment Industry Regulatory Organisation of Canada (IIROC), the national self-regulatory organisation that oversees all investment dealers and trading activity on debt and equity marketplaces in Canada. Similar to the CRS in Australia, the IFM is a fee model allocating IIROC's market regulation costs (e.g., technology costs) to market participants. The cost allocation to each market participant is on a pro rata basis, based on the number of messages sent and trades executed.

In Europe, the EU Commission proposed to introduce the financial transaction tax. Although the proposal was postponed, some member states have already implemented their state-version of financial transaction tax, such as France and Italy. In France, the financial transaction tax was imposed on 1 August 2012. It applies to the transfer of ownership of equity instruments issued by a French firm, of which the market capitalisation is larger than one billion euros as at 1 January 2012. Equity instruments, in that bill, are defined as shares and other securities that could give access to capital or voting rights. Therefore, the taxable instruments in the French financial transaction tax regime specifically exclude ETFs and financial contracts. The effective tax rate is 0.2% of the acquisition value. In addition, high frequency trading activities are subject to a 0.01% tax if trading is carried out in France. In that bill, high frequency trading is defined as program trading with amendments or cancellation of orders exceeding two-thirds of transmitted orders.

In Italy, the financial transaction tax was implemented on 1 March 2013 in its equity market. Within the scope of the Italian financial transaction tax, transactions of equity instruments issued by Italian companies with a capitalisation higher than 500 million Euros are to be taxed at 0.22% if executed over-the-counter (OTC), and 0.12% if executed on a regulated market.[4] The definition of equity instruments above includes shares and equity-like instruments, such as ETFs. Six-months later, the Italian financial transaction tax was extended to the derivatives market (2 September 2013).[5] The tax on OTC derivatives applied at a fixed rate according to the type of derivatives involved and its notional value. Derivatives executed on regulated markets can have a reduced tax rate equal to 20% of the ordinary fixed rate. Similar to that in France, an additional high frequency trading tax was imposed for the trading of financial instruments (both equities and derivatives) executed by a computer algorithm that automatically makes decisions (e.g., send, modify and cancel orders) in a time frame shorter than 0.5 seconds. Italian financial transaction tax levies at a rate of 0.02% on any portion of the order (beyond a certain threshold) that are modified or cancelled on a daily basis. The tax is borne by the person on whose behalf the relevant orders are executed.

4.3 Data

Intraday data for the index futures contracts and ETFs for the four markets are sourced from Thomson Reuters Tick History (TRTH). The data contain: (1) the price, time, and volume of each trade; (2) the price, time, and size of quotes that affect the best available bid and ask quotes in the central limit order book; and (3) the open, close, highest, and lowest prices during each trading day.

[4] In 2014, those rates reduced to 0.2% and 0.1%, respectively.

[5] The implementation date for the financial transaction tax in derivative markets was initially set at 1 July 2013, however, it was postponed to 2 September 2013.

To mitigate the infrequent trading issue, the most actively traded futures contract, with the largest daily trading volume, is chosen for each trading day. The continuous trading hours of index futures and ETF markets are not the same. Therefore, for analytical purposes, any observations of futures and ETFs before the other markets open, or after the other market closes, are excluded from the sample. Further, to minimise the effect of irregular trading behaviour of financial instruments shortly after the market opens and before the market closes, as well as increasing the pricing accuracy of ETFs, 30-minutes after the open of trading, and before the close of trading, is eliminated from the sample. Specific time periods for each of the four markets are described below:

- Australia: the continuous trading hours for equity and futures markets are from 10:00 am to 4:00 pm, and from 9:50 am to 4:30 pm, respectively. The daily time frame used for analysis is from 10:30 am to 3:30 pm.
- Canada: the continuous trading hours for equity and futures markets are from 9:30 am to 4:00 pm, and from 9:30 am to 4:15 pm, respectively. The daily time frame for analysis is from 10:00 am to 3:30 pm.
- Italy: the continuous trading hours for equity and futures markets are from 9:00 am to 5:30 pm, and from 9:00 am to 5:40 pm, respectively. The daily time frame for analysis is from 9:30 am to 5:00 pm.
- France: the continuous trading hours for equity and futures markets are from 9:00 am to 5:30 pm, and from 8:00 am to 10:00 pm, respectively. The daily time frame for analysis is from 9:30 am to 5:00 pm.

The event studies in this chapter are based on a sample of 180 trading days centred around the event date, with observations during the three trading days before and after the implementation of message traffic restriction policies eliminated. Specific event dates for each of the four markets are described below:

- Australia: The Cost Recovery Scheme (CRS) was implemented on 1 January 2012. The sample period in the event study is from 22 August 2011 to 16 May 2012.
- Canada: The Integrated Fee Model (IFM) took effect on 1 April 2012. The sample period in the event study is from 17 November 2011 to 14 August 2012.
- Italy: The Financial Transaction Tax (FTT) was implemented on 1 March 2013 in the equity market. The sample periods are from 16 October 2012 to 12 July 2013. In addition, the FTT extends to derivatives market on 2 September 2013. A separate analysis is conducted to examine this, with a sample period from 22 April 2013 to 15 January 2014.
- France: The French FTT was implemented on 1 August 2012. The sample period in this study is from 19 March 2012 to 7 December 2012.

4.4 Research Design

The analysis in this chapter is based on the return correlation between two instruments: index futures contracts and ETFs. The correlation derives from the synchronised return for two instruments on a daily basis (Budish, Cramton, & Shim, 2015). We use the mid-price returns sampled at one-second time intervals. The return refers to the percentage change in the mid-point price, which is the average of the best available bid and ask quotes. We simulate limit order books with best bid and ask quotes for futures and ETFs based on the quote and trade data in the market.

$$Midpoint_t = \frac{Bidprice_t + Askprice_t}{2} \tag{4-1}$$

$$Return_t = \frac{Midpoint_t - Midpoint_{t-1}}{Midpoint_{t-1}} \tag{4-2}$$

where, for each one-second interval: $Midpoint_t$ is the midpoint of the best available bid and ask quotes in the limit order book at time *t*; $Bidprice_t$ is the price of the best quote in the bid side of the order book at time *t*; $Askprice_t$ is the price of the best quote in the ask side of the order book at time *t*.

To isolate the impact of the regulatory change on return correlation, the following regression is estimated:

$$Correl_t = \beta_0 + \beta_1 Event_t + \beta_2 Volatiltiy_t + \beta_3 Volume_t + \varepsilon_t \tag{4-3}$$

where the unit of observation is a trading day. $Correl_t$ represents the return correlation between those two instruments on trading day t. $Event_t$ takes the value of zero if trading day t belongs to the pre-event period, and one during the post-event period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. The *p*-values are computed based on Newey-West standard errors. To reduce the effect of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. Tables 4-1, 4-2, 4-3, and 4-4 present the correlation coefficient matrix for the independent variables in the four markets.

Table 4 - 1
Correlation Matrix – Australia

This table presents the correlation matrix of the independent variables for the regressions in this study. The regulatory event is the Cost Recovery Scheme (CRS), which was implemented on 1 January 2012 in Australia. Three trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 22 August 2011 and 23 December 2011. *Post-period* is between 6 January 2012 and 16 May 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*
Event	1	-0.6786**	-0.4383**
	-	(<0.0001)	(<0.0001)
Volatility	-0.6786**	1	0.5336**
	(<0.0001)	-	(<0.0001)
Volume	-0.4383**	0.5336**	1
	(<0.0001)	(<0.0001)	-

Table 4 - 2
Correlation Matrix – Canada

This table presents the correlation matrix of the independent variables for the regressions in this study. The regulatory event is the Integrated Fee Model (IFM), which was implemented on 1 April 2012 in Canada. Three trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 17 November 2011 and 27 March 2012. *Post-period* is between 5 April 2012 and 14 August 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*
Event	1	0.0896	-0.0102
	-	(0.2316)	(0.8918)
Volatility	0.0896	1	0.4278**
	(0.2316)	-	(<0.0001)
Volume	-0.0102	0.4278**	1
	(0.8918)	(<0.0001)	-

Table 4 - 3
Correlation Matrix – Italy

This table presents the correlation matrix of the independent variables for the regressions in this study. The regulatory event is the Financial Transaction Tax (FTT), which was implemented on 1 March 2013 in Italy. Three trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 16 October 2012 and 25 February 2013. *Post-period* is between 6 March 2013 and 12 July 2013. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*
Event	1	0.0407	0.4423**
	-	(0.5875)	(<0.0001)
Volatility	0.0407	1	0.4722**
	(0.5875)	-	(<0.0001)
Volume	0.4423**	0.4722**	1
	(<0.0001)	(<0.0001)	-

Table 4 - 4
Correlation Matrix – France

This table presents the correlation matrix of the independent variables for the regressions in this study. The regulatory event is the Financial Transaction Tax (FTT), which was implemented on 1 August 2012 in France. Three trading days before and after the regulatory change are removed from the sample. *Pre period* is between 19 March 2012 and 26 July 2012. *Post period* is between 6 August 2012 and 7 December 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*
Event	1	-0.4683**	-0.3567**
	-	(<0.0001)	(<0.0001)
Volatility	-0.4683**	1	0.4734**
	(<0.0001)	-	(<0.0001)
Volume	-0.3567**	0.4734**	1
	(<0.0001)	(<0.0001)	-

4.5 Empirical Results

4.5.1 Univariate Results

Table 4-5 reports descriptive statistics for index futures contracts and ETFs in four jurisdictions before and after the implementation of message traffic restrictions. The futures/ETF price is the daily closing price of the futures contract/ETF share. *Volatility* is defined as the natural logarithm of the highest price divided by the lowest price each trading day. *Trading Volume* is the total trading volume (number of contracts/shares traded) of the futures contract/ETF.

In Australia, the average closing prices of the SPI Futures and the STW increase, which are statistically significant at 1% after the implementation of the CRS. The SPI Futures is less volatile; the daily price volatility decreases from 0.0237 to 0.0131. The trading volume of the futures contract drops considerably after the transition. Similar changes are observed in the ETF market. The average daily price volatility decreases from 0.0127 to 0.0076. In addition, the average daily volume of the STW in the post-event period is 180,875, which is only 58% of the volume before the event. Both changes are statistically significant at the 1% level. Those results are consistent with previous research that a transaction/message tax reduces trading volume (e.g., Baltagi, Li, & Li, 2006; Matheson, 2011) and price volatility (e.g., Stiglitz, 1989; Schwert & Seguin, 1993; Kupiec, 1996). However, those results are not consistent with either Hypothesis 4.1 or Hypothesis 4.2.

In Canada, the price of index futures and the ETF decreases after the introduction of the IFM. In contrast to the Australian market, the TSX Futures and the XIU price volatility do not experience substantial changes with the implementation of the message traffic restrictions. These results are consistent with some previous research that shows the restrictive regulations do not necessarily reduce market volatility (e.g., Habermeier & Kirilenko, 2003; Chou & Wang, 2006). This finding is consistent with Hypothesis 4.2. Further, it is observed that the trading volume of the XIU decreases approximately 21% after the policy event, which is statistically significant at the 1% level. This finding is inconsistent with Hypothesis 4.1. In addition, the trading volume of the TSX Futures does not experience a substantial change after the transition.

In Italy, the prices of the two instruments are less affected by the implementation of the financial transaction tax in the equity market. Results reveal that both the futures and ETF market volatility remain stable during the sample period. This finding is consistent with Hypothesis 4.2. However, it is observed that the trading volume of the futures contract and the ETF increase by 34% and 22% respectively, both of which are statistically significant at the 1% level. These results are inconsistent with Hypothesis 4.1.

In France, the price of the CAC Futures and the CAC ETF increase after the financial transaction tax is implemented. Both of these two markets are less volatile after the transition. In addition, the trading volume of these two instruments decreases significantly. The average daily trading volume of the CAC Futures declines 23%, from 147,646 to 112,317. The average daily trading volume of the CAC ETF drops 28%, from 658,480 to 476,111. The decrease in price volatility and trading volume is statistically significant at the 1% level.

Table 4-6 reports descriptive statistics for the daily return correlation between index futures and ETFs in the four countries. It is further supported by Figures 4-1 and 4-2, which plot the daily return correlations across the sample period. Preliminary results reveal that the average daily return correlation in Australia increases from 0.2441 to 0.3509 after the introduction of the CRS. This increase is statistically significant at the 1% level. Similarly, the average daily return correlation in Canada increases from 0.1782 to 0.2411 after the transition, statistically significant at 1% level. These results illustrate that the return correlation between index futures and ETFs improves after the implementation of the message restriction regulations in these two countries. In Italy, the average daily return correlation decreases from 0.2836 in the pre-sample to 0.2576 in the post-sample. This drop is statistically significant at 1% level. It shows that the financial transaction tax lowers the pricing consistency between index futures and ETF in Italy. In

France, the average daily correlation does not experience a substantial change around the implementation of the financial transaction tax. Overall, there does not appear to be a consistent impact of the message traffic restrictions on relative pricing efficiency between index futures and index ETFs.

Table 4 - 6
Descriptive Statistics - Return Correlations

This table reports descriptive statistics for the daily return correlations between index futures and ETFs within the sample period before and after the message traffic restriction policies are imposed in four countries (Australia, Canada, Italy, and France). The message traffic restriction policies are the Cost Recovery Scheme in Australia (1 January 2012), the Integrated Fee Model in Canada (1 April 2012), and the Financial Transaction Tax in Italy (1 March 2013) and France (1 August 2012). Three trading days before and after the regulatory changes are removed from the sample. *Pre- periods* are Australia: 22 August 2011 – 23 December 2011; Canada: 17 November 2011 – 27 March 2012; Italy: 16 October 2012 – 25 February 2013; and France: 19 March 2012 – 26 July 2012. *Post-periods* are Australia: 6 January 2012 – 16 May 2012; Canada: 5 April 2012 – 14 August 2012; Italy: 6 March 2013 – 12 July 2013; and France: 6 August 2012 – 7 December 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. * (**) denote statistical significance at the 5% (1%) level.

Countries	*Pre-event*	*Post-event*	*Difference*
Australia	0.2441	0.3509	0.1069**
Canada	0.1782	0.2411	0.0629**
Italy	0.2836	0.2576	-0.0261**
France	0.5722	0.5905	0.0183

Table 4 - 5
Descriptive Statistics – Market Variables

This table reports descriptive statistics for four variables within the sample period before and after the message traffic restriction policies are imposed in four countries (Australia, Canada, Italy, and France). The message traffic restriction policies are the Cost Recovery Scheme in Australia (1 January 2012), the Integrated Fee Model in Canada (1 April 2012), and the Financial Transaction Tax in Italy (1 March 2013) and France (1 August 2012). Three trading days before and after the regulatory change are removed from the sample. *Pre periods* are Australia: 22 August 2011 – 23 December 2011; Canada: 17 November 2011 – 27 March 2012; Italy: 16 October 2012 – 25 February 2013; and France: 19 March 2012 – 26 July 2012. *Post periods* are Australia: 6 January 2012 – 16 May 2012; Canada: 5 April 2012 – 14 August 2012; Italy: 6 March 2013 – 12 July 2013; and France: 6 August 2012 – 7 December 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Futures Price* is the daily closing price of index futures contracts. *Futures Volume* is the total trading volume (number of contracts traded) of the index futures contract chosen each trading day. *Futures Volatility* is defined as the natural logarithm of the highest price divided by the lowest price each trading day. Those three measures are repeated for Exchange-Traded Funds (ETFs). * (**) denote statistical significance at the 5% (1%) level.

		Futures Price	*Futures Volatility (%)*	*Futures Volume*	*ETF Price*	*ETF Volatility (%)*	*ETF Volume*
Australia	Pre-CRS	4,164	2.37	45,844	39.58	1.27	309,249
	Post-CRS	4,264	1.31	33,183	40.18	0.76	180,875
	Change	99**	-0.06**	-12,660**	0.60**	-0.51**	-128,374**
Canada	Pre-IFM	694.9	1.30	13,185	17.51	1.09	7,083,838
	Post-IFM	665.1	1.39	12,612	16.76	1.15	5,621,077
	Change	-29.8**	0.09	-573	-0.75**	0.06	-1,462,762**
France	Pre-FTT	3,167	2.23	147,646	32.19	1.89	658,480
	Post-FTT	3,462	1.52	112,317	34.61	1.29	476,111
	Change	295**	-0.71**	-35,330**	2.41**	-0.60**	-182,369**
Italy	Pre-FTT	16,269	1.82	21,261	16.38	1.95	981,966
	Post-FTT	16,083	1.87	28,573	16.40	1.95	1,202,339
	Change	-186	0.05	7,312**	0.02	0.00	220,373**

Figure 4 - 1
Daily Return Correlation in Australia and Canada

This figure plots the daily return correlation between index futures contracts and index ETFs within the sample period before and after the message traffic restriction policies are imposed in Australia and Canada. The message traffic restriction policies are the Cost Recovery Scheme (CRS) in Australia (1 January 2012) and Integrated Fee Model (IFM) in Canada (1 April 2012). Three trading days before and after the regulatory change are removed from the sample. *Pre periods* are Australia: 22 August 2011 – 23 December 2011; and Canada: 17 November 2011 – 27 March 2012. *Post periods* are Australia: 6 January 2012 – 16 May 2012; and Canada: 5 April 2012 – 14 August 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition.

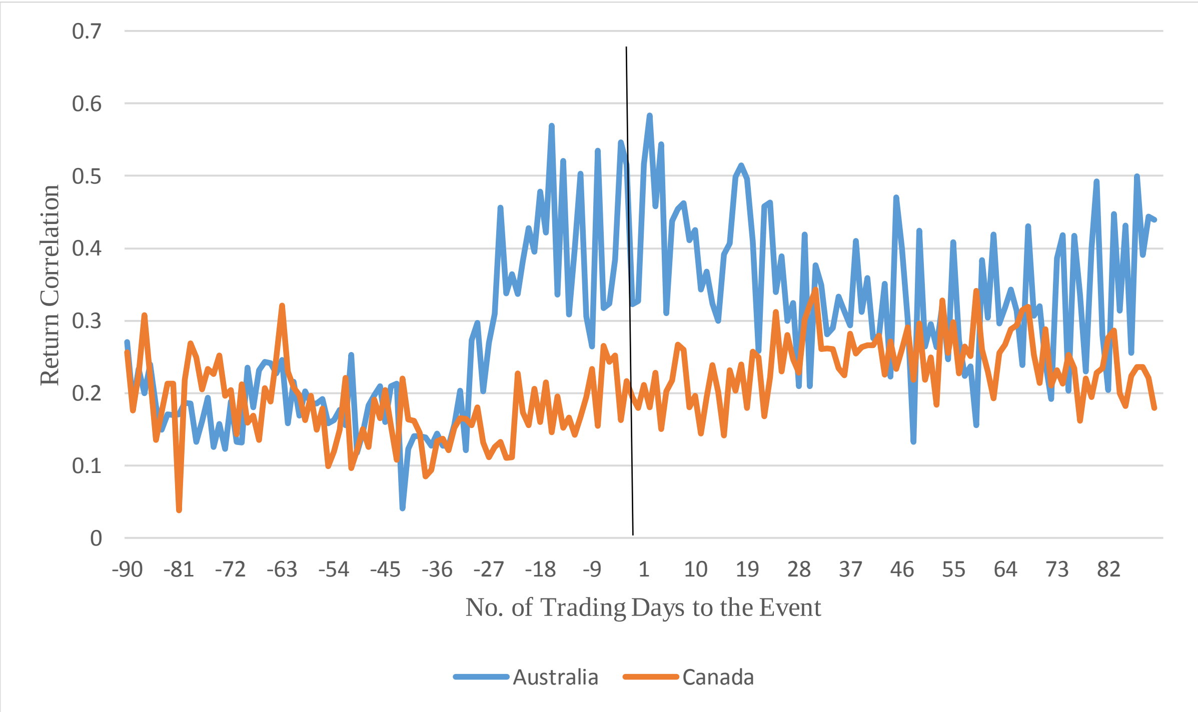
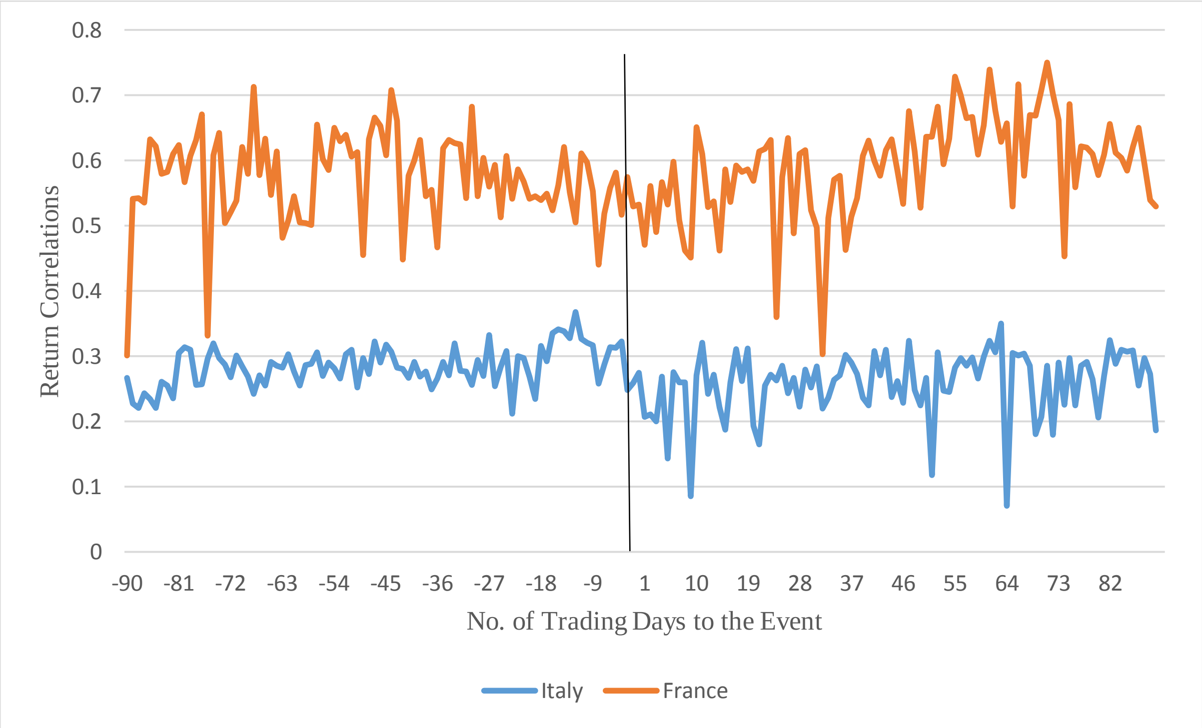


Figure 4 - 2
Daily Return Correlation in France and Italy

This figure plots the daily return correlation between index futures contracts and index ETFs within the sample period before and after the message traffic restriction policies are imposed in France and Italy. The message traffic restriction policies are the Financial Transaction Tax (FTT) in Italy (1 March 2013) and France (1 August 2012). Three trading days before and after the regulatory change are removed from the sample. *Pre periods* are Italy: 16 October 2012 – 25 February 2013; and France: 19 March 2012 – 26 July 2012. *Post periods* are Italy: 6 March 2013 – 12 July 2013; and France: 6 August 2012 – 7 December 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition.



4.5.2 Multivariate Analysis

Prior research suggests that price volatility and trading volume of the market may influence the pricing efficiency between two markets. Therefore, we incorporate two control variables, which are futures market volatility and futures contract trading volume, to isolate the impact of changes due to market conditions. Table 4-7 reports the regression results of the daily return correlation on message traffic restriction event, futures market volatility, and futures trading volume. In Australia, the coefficient of $Event_t$ is positive and statistically significant at the 1% level after controlling for market volatility and trading volume; the return correlation between the SPI Futures and the STW increases after the introduction of the CRS. This finding is inconsistent with Hypothesis 4.3. Futures market volatility and futures contract trading volume are not significantly related to return correlations during the sample period.

In Canada, it is observed that the return correlation increases, statistically significant at the 1% level after the introduction of the IFM. Again, this finding is inconsistent with Hypothesis 4.3. In addition, the coefficient of futures volatility is positive and statistically significant at the 5% level. This suggests that when the futures market is more volatile, the return correlation between the TSX Futures and the XIU is higher. The futures trading volume is not significantly related to the relative pricing consistency.

In Italy, the coefficient of the Event dummy variable is negative and statistically significant at the 1% level. It indicates that the return correlation between two securities reduces after the implementation of the financial transaction tax in equities market on 1 March 2013. This finding is inconsistent with Hypothesis 4.3. Results also highlight that futures price volatility and futures contract trading volume do not impose a significant impact on the price relationship between the MIB Futures and the ETFMIB. In France, the coefficient of the event dummy variable is not statistically significant. This indicates that the financial transaction tax does not exert a significant impact on the price correlation. Neither futures market volatility nor futures contract trading volume impose a significant effect on the return correlation between these two instruments

From the above analysis, the message traffic restriction policies in Australia and Canada impose a similar effect on the return correlation between the index futures and index ETFs. The regulatory authorities in these two countries allocate the market regulation costs to participants based on the proportion of trades and quotes they submit. In this situation, the relative pricing efficiency improves when the message traffic restriction policies come into effect. In Italy, the high frequency trading tax, which levies on the value of orders from high frequency trading firms, lowers the pricing correlations between index futures and index ETF. However, the high frequency trading tax in France does not have a similar effect. Although the French financial transaction tax is implemented in the equity market, the tax bill specifically excludes financial derivatives contracts and ETFs. Therefore, the message traffic restrictions on the underlying equity market do not exert a direct impact on the return correlation between index futures and ETFs. This serves as a controlling scenario, indicating that the restriction on the index ETF affects the relative pricing efficiency between index futures and ETFs.

Table 4 - 5
Regressions of Return Correlation with Control Variables

This table reports the regression results of the return correlation between index futures and ETFs. The message traffic restriction policies are the Cost Recovery Scheme in Australia (1 January 2012), the Integrated Fee Model in Canada (1 April 2012), and the Financial Transaction Tax in Italy (1 March 2013) and France (1 August 2012). Three trading days before and after the regulatory change are removed from the sample. *Pre periods* are Australia: 22 August 2011 – 23 December 2011; Canada: 17 November 2011 – 27 March 2012; Italy: 16 October 2012 – 25 February 2013; and France: 19 March 2012 – 26 July 2012. *Post periods* are Australia: 6 January 2012 – 16 May 2012; Canada: 5 April 2012 – 14 August 2012; Italy: 6 March 2013 – 12 July 2013; and France: 6 August 2012 – 7 December 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. $Event_t$ takes the value of zero if the trading day belongs to the pre-event period, and one otherwise. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. $Volume_t$ is natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. N is the number of observations.

	Constant	$Event_t$	$Volatility_t$	$Volume_t$	R^2	N
Australia	0.5640	0.0929**	-0.3636	-29.1155	0.1965	180
	(0.0909)	(0.0035)	(0.7735)	(0.3645)		
Canada	0.0964	0.0608**	1.6550*	6.5326	0.3375	180
	(0.1620)	(<0.0001)	(0.0407)	(0.3893)		
France	0.7110*	0.0145	-0.0689	-11.5963	0.0019	180
	(0.0163)	(0.4363)	(0.9558)	(0.6554)		
Italy	0.4300**	-0.0263**	-0.1701	-14.2981	0.1317	180
	(0.0003)	(0.0027)	(0.8074)	(0.2529)		

4.6 Robustness Tests

4.6.1 Introduction of the Australian Liquidity Centre (ALC)

On 20 February 2012, the ASX introduced a co-location service, named the Australian Liquidity Centre (ALC), for trading of equities and derivatives instruments. The new facility allows market participants to co-locate their computer servers next to exchange servers (ASX Trade for equities and ASX Trade24 for futures trading). The introduction of the co-location service widens the playground of high-frequency traders by significantly reducing trading latency. Since the implementation date of co-location service is within our sample period, we add an additional dummy variable into the regression as follows:

$$Correl_t = \beta_0 + \beta_1 Event_t + \beta_2 Colo_t + \beta_3 Volatility_t + \beta_4 Volume_t + \varepsilon_t \tag{4-4}$$

where the unit of observation is a trading day. $Correl_t$ represents the return correlation between index futures and ETF on trading day t. $Event_t$ is a dummy variable, representing the implementation of the CRS. It takes the value of zero if trading day t is either before the implementation of the CRS or after the introduction of the ALC, and it takes the value of one otherwise. $Colo_t$ is a dummy variable, describing the introduction of the ALC. It takes the value of zero if trading day t belongs to the pre-ALC period and one during the post-ALC period. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by the lowest futures price on trading day t. $Volume_t$ is the natural logarithm of the futures trading volume divided by 1,000 for trading day t. The correlation coefficient matrix is presented in Table 4-8. Table 4-9 reports the regression results of the daily return correlation on message traffic restriction events, introduction of co-location services, futures market volatility and futures contract trading volume. We observe that after the co-location service is introduced, the price correlation between index futures and index ETF increases. After controlling for that factor, the impact of message traffic restrictions on price correlation remains positive and statistically significant. This suggests that the regression results for Australian markets in Section 4.5 are robust.

Table 4 - 6
Correlation Matrix – Australia (Co-location)

This table presents the correlation matrix of the independent variables for the regressions in this study. The regulatory change is the Cost Recovery Scheme (CRS), which was implemented on 1 January 2012 in Australia. Three trading days before and after the regulatory change are removed from the sample. *Pre period* is between 22 August 2011 and 23 December 2011. *Post period* is between 6 January 2012 and 16 May 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day is either before the implementation of the CRS or after the introduction of ALC, and it takes the value of one otherwise. *Co-lo* denotes the introduction of co-location services by ASX on 20 February 2012. It takes the value of zero for the period between 22 August 2011 and 17 February 2012, and one for the period between 20 February 2012 and 16 May 2012. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Co-lo*	*Volatility*	*Volume*
Event	1	-0.3162**	-0.2727**	-0.3047**
	-	(<0.0001)	(0.0002)	(<0.0001)
Co-lo	-0.3162**	1	-0.5041**	-0.2240**
	(<0.0001)	-	(<0.0001)	(0.0025)
Volatility	-0.2727**	-0.5041**	1	0.5336**
	(0.0002)	(<0.0001)	-	(<0.0001)
Volume	-0.3047**	-0.2240**	0.5336**	1
	(<0.0001)	(0.0025)	(<0.0001)	-

Table 4 - 7
Regression Results of Return Correlation with Control Variables and Co-location

This table reports the regression results of the return correlation between index futures and ETFs. The message traffic restriction policy is the Cost Recovery Scheme (CRS), which was implemented on 1 January 2012 in Australia. Three trading days before and after the regulatory change are removed from the sample. *Pre period* is between 22 August 2011 and 23 December 2011. *Post period* is between 6 January 2012 and 16 May 2012. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. $Event_t$ takes the value of zero if the trading day is either before the implementation of the CRS or after the introduction of ALC, and it takes the value of one otherwise. $Co\text{-}lo_t$ denotes the introduction of co-location services by ASX on 20 February 2012. Co-location take value of zero for the period between 22 August 2011 and 17 February 2012 and one for period between 20 February 2012 and 16 May 2012. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. $Volume_t$ is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

Constant	$Event_t$	$Co\text{-}lo_t$	$Volatility_t$	$Volume_t$	R^2	*N*
0.4344	0.1407**	0.0678*	-0.8280	-15.9347	0.2514	180
(0.1924)	(0.0001)	(0.0308)	(0.4970)	(0.6173)		

4.6.2 Italian Financial Transaction Tax in Futures Markets

On 2 September 2013, the Italian financial transaction tax regime further extended to its derivatives market after which high frequency trading firms in the futures market faced an additional high frequency trading tax. We further examine the impact of this event on the return correlation between these two instruments. Results in Table 4-10 reveal that after the financial transaction tax extends to the futures market, the price of index futures and ETF increases, statistically significant at the 1% level. The daily futures trading volume declines from 24,517 to 21,691, which is statistically significant at the 5% level, and the ETF trading volume increases from 989,184 to 1,229,187, statistically significant at the 1% level. In addition, the futures market is less volatile after the financial transaction tax is implemented: the daily volatility reduces from 1.79% to 1.50%.

Regression analysis is undertaken to examine the impact of this event on the relative pricing efficiency between the two instruments. The correlation coefficient matrix is presented in Table 4-11. Table 4-12 reports the regression results of the daily return correlation against the introduction of the financial transaction tax, futures market volatility, and futures contract trading volume. The coefficient of the tax regulatory event is positive and statistically significant at the 1% level. It demonstrates that the return correlation between index futures and ETF improves after the Italian financial transaction tax extends to its derivatives market. Neither futures market volatility nor futures contract trading volume has a significant effect on the daily return correlation.

Table 4 - 8
Descriptive Statistics – FTT in Italian Derivatives Market

This table reports descriptive statistics for three variables within the sample period before and after the implementation of message traffic restriction policies in Italian derivatives market on 2 September 2013. Three trading days before and after the regulatory change are removed from the sample. *Pre period* is between 22 April 2013 and 27 August 2013. *Post period* is between 5 September 2013 and 15 January 2014. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Futures Price* is the daily closing price of index futures contracts. *Futures Volume* is the total trading volume (number of contracts traded) of the index futures contract chosen each trading day. *Futures Volatility* is defined as the natural logarithm of the highest price divided by the lowest price each trading day. Those three measures are repeated for Exchange-traded Funds (ETFs). * (**) denote statistical significance at the 5% (1%) level.

	Futures Price	*Futures Volatility (%)*	*Futures Volume*	*ETF Price*	*ETF Volatility (%)*	*ETF Volume*
Pre-event	16,505	1.79	24,517	16.73	1.86	989,184
Post-event	18,588	1.50	21,691	18.68	1.66	1,229,187
Change	2,083**	0.29**	-2,826*	1.95**	-0.20	240,002**

Table 4 - 9
Correlation Matrix – Italy

This table presents the correlation matrix of the independent variables for the regressions in this chapter. The regulatory event is the Financial Transaction Tax (FTT), which was implemented on 2 September 2013 in Italian derivatives market. Three trading days before and after the regulatory change are removed from the sample. *Pre-period* is between 22 April 2013 and 27 August 2013. *Post-period* is between 5 September 2013 and 15 January 2014. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. *Event* takes the value of zero if the trading day belongs to the pre-event period, and one during the post-event period. *Volatility* is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. *Volume* is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. For each variable, the first row represents the correlation coefficients. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis.

	Event	*Volatility*	*Volume*
Event	1	-0.2336**	-0.1741*
	-	(0.0016)	(0.0195)
Volatility	-0.2336**	1	0.4496**
	(0.0016)	-	(<0.0001)
Volume	-0.1741*	0.4496**	1
	(0.0195)	(<0.0001)	-

Table 4 - 10
Regressions of Return Correlation with Control Variables – Italy

This table reports regression results of the return correlation between index futures and ETFs. The message traffic restriction policy took effect on 2 September 2013 in Italian derivatives market. Three trading days before and after the regulatory change are removed from the sample. *Pre period* is between 22 April 2013 and 27 August 2013. *Post period* is between 5 September 2013 and 15 January 2014. The futures contract examined for each trading day is the most actively traded contract. The sample includes 180 trading days, with 90 trading days each before and after the transition. $Event_t$ takes the value of zero if the trading day belongs to the pre-event period, and one otherwise. $Volatility_t$ is defined as the natural logarithm of the highest futures price divided by lowest futures price each trading day. $Volume_t$ is the natural logarithm of the total futures trading volume (number of contracts traded) divided by 1,000 each trading day. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

Constant	$Event_t$	$Volatility_t$	$Volume_t$	R^2	*N*
0.3032*	0.0444**	-0.0677	-4.8912	0.1372	180
(0.0265)	(0.0007)	(0.9409)	(0.7262)		

4.7 Conclusions

This chapter investigates the impact of message traffic regulatory restrictions on the relative pricing efficiency of futures markets. It focuses on the effect of message traffic restrictions on the return correlation of index futures contracts and ETFs that track the stock index. An event study is performed based on the implementation of four restrictive policies in Australia (the Cost Recovery Scheme), Canada (the Integrated Fee Model), France (the Financial Transaction Tax), and Italy (the Financial Transaction Tax). It is observed that after the message traffic restrictions are implemented, the trading volume and price volatility of both ETFs and index futures in Australia and France decrease. In addition, less ETF shares are traded in Canada, and more futures contracts are traded after the financial transaction tax is implemented in the Italian equities market.

The regression results indicate that the daily return correlation in Australia, Canada, and Italy experience a change after the transition. In addition, the direction of the changes vary across the three markets. Specifically, this study documents that price correlation improves in Australia and Canada after the introduction of the new market regulations, where market supervision cost allocation is based on the number of trades and quotes. In Italy, the price correlation decreases after the implementation of the financial transaction tax, which charges on the value of trades and orders. Further, results from the French market show that the financial transaction tax in the underlying stock market does not exert a direct effect on the pricing efficiency of index futures against the corresponding index ETFs.

Appendix 4.1

Table 4 - 11
Contract Specifications for index futures in four countries

	Australia	Canada	Italy	France
Underlying index	S&P/ASX 200	S&P/TSE 60	FTSE-MIB	CAC 40
Exchange	Australian Securities Exchange	Montreal Exchange	Borsa Italiana	Euronext
Contract multiplier	A$25	C$200	€5	€10
Unit	Index point	Index point	Index point	Index point
Tick size	1 point	0.1 point	5 Index points	0.5 index points
Contract months	March/June/September/December up to six quarter months ahead and the nearest two non-quarterly expiry months	March/June/September/December	March/June/September/December	3 monthly, 3 quarterly (from March/June/September/December), 8 half-yearly maturities from June/December cycle
Trading hours	09:50 am – 04:30 pm (day session)	09:30 am to 04:15 pm (regular session)	09:00 am – 05:40 pm	08:00 am – 10:00 pm (central order book)
Last trading day	Third Thursday of the settlement month	Third Thursday of the contract month	Third Friday of the expiry month	Third Friday of the delivery month
Settlement method	Cash settlement	Cash settlement	Cash settlement	Cash settlement

For further information refer to
Australia: http://www.asx.com.au/products/index-derivatives/asx-index-futures-contract-specifications.htm;
Canada: https://www.m-x.ca/produits_indices_sxf_en.php;
Italy: https://www.lseg.com/sites/default/files/content/documents/%E2%80%A2LSEG_ITA_Products_Factsheet_v10.pdf;
France: https://derivatives.euronext.com/en/products/index-futures/FCE-DPAR/contract-specification

Chapter 5 - Dark Trading Regulations and Option Market Liquidity: Evidence from Canada

5.1 Introduction

Existing literature widely suggests that dark trading exerts negative impacts on equity market efficiency. Dark trading can cause the segregation of market participants, with more informed traders clustering in the lit market. Hence, the adverse selection risk in lit markets increases in line with the level of dark trading activity. Previous research also shows that dark trading harms price discovery and reduces information in aggregate. In addition, the literature reviewed in Section 2.6 shows that options market quality is strongly related to the market efficiency of its underlying asset. Specifically, the derivative hedging theory explains that the option market bid-ask spread is determined by the liquidity of its underlying stock market (Cho & Engle, 1999). The objective of this chapter is to provide empirical evidence on the relationship between dark trading and the options market liquidity.

In 2012, the Investment Industry Regulatory Organisation of Canada (IIROC) imposed a new dark trading regulation, referred to as “Minimum Price Improvement” (“MPI”). This restrictive regulation is observed to substantially reduce dark trading as a proportion of total market turnover. This transition provides a natural experiment to examine the impact of dark equity trading on options market quality.

This chapter bridges the gap in the literature by empirically investigating the relationship between dark trading and option market liquidity. Based on the literature reviewed in Chapter 2, one hypothesis is developed and tested in this chapter. The hypothesis (H5.1) predicts that the restrictive dark trading regulations exert no impact on options market liquidity, through measurements of percentage bid-ask spreads, quoted depth, percentage effective spreads, realised spreads, and price impact.

The remainder of this chapter is structured as follows. Section 5.2 provides institutional details of the Canadian equities and options markets, and regulations over dark trading in Canada. Section 5.3 presents the data. Section 5.4 outlines the research design. Section 5.5 reports empirical results. Section 5.6 provides results of robustness tests. Section 5.7 concludes.

5.2 Institutional Details

5.2.1 Canadian equities and option market

In Canada, the Toronto Stock Exchange (TSX) is the main stock listing venue. In addition, there are five Alternative Trading Systems (ATS) in operation during the sample period. Stocks can be traded continuously with pre-trade transparency on those markets (lit markets), namely Alpha, Chi-X, Pure Trading, TMX-Select, and Omega.[6] Further, there are four markets in which orders can be submitted without pre-trade transparency, which are MatchNow (ITG), Alpha Intraspread, Chi-X and TSX. MatchNow and Alpha Intraspread are referred to as 'dark pools', in which only dark orders can be submitted.

[6] A sixth lit venue (Chi-X 2) was introduced in April 2013 after the sample period.

Therefore, dark orders are traded against other dark orders in those two venues. However, on the TSX and Chi-X, dark and lit orders interact and can trade with each other. In October 2012, Alpha Intraspread merged with Alpha (ATS). Thereafter, dark and lit orders could trade with others in Alpha, similar to the TSX and Chi-X. The equity options contracts are actively traded on the Montreal Exchange, and there are designated market makers in the options market. The trading hours are from 9:30 am to 4:00 pm.

5.2.2 Dark trading regulations

The Investment Industry Regulatory Organisation of Canada (IIROC) maintains and enforces the Universal Market Integrity Rules (UMIR) in Canada. On 13 April 2012, IIROC announced changes (notice 12-0130) to the UMIR, which came into effect on 15 October 2012. These changes imposed a minimum price improvement by dark orders of one full tick relative to the prevailing National Best Bid and Offer (NBBO). If the spread is already constrained to one tick size, dark orders are allowed at the midpoint of the NBBO. The new rule allows an exemption for dark orders larger than either 50 standard trading units (STU), which are usually 5,000 shares, or $100,000. Such large size dark orders can be executed at the NBBO, without providing any price improvement, as long as they give priority to lit orders at the same price on the same trading venue.

Prior to the transition, all dark orders were required to provide some level of price improvement. However, the required amount of price improvement was not specified legislatively. Both MatchNow and Intraspread offered the midpoint price improvement (50% improvement of NBBO). In addition, MatchNow and Intraspread provided 20% and 10% price improvements over the NBBO, respectively. To comply with the new regulations, all trading venues providing dark orders were required to adjust the types of dark orders provided. For MatchNow and Intraspread, orders offering 20% and 10% price improvement were terminated on 15 October 2012. After the change, Intraspread retained the midpoint price improvement and offered the NBBO execution for large size dark orders. MatchNow did not add the NBBO execution for large size dark orders, only retaining the midpoint price improvement.

5.3 Data

Intraday data for the Canadian options market is sourced from Thomson Reuters Tick History (TRTH). The data set contains: (1) the price, time, and volume of all trades; (2) the price, time and size of quotes that affect the best available bid and ask in the central limit order book; and (3) the close price, trading volume, and the implied volatility for each option series each day. In addition, the data set includes intraday data for underlying stocks traded on the Toronto Stock Exchange, including the open, close, highest, and lowest price each trading day.

The new dark trading regulation was implemented on 15 October 2012. The sample period in this analysis ranges from 27 August 2012 to 30 November 2012, seven weeks either side of the event.[7] The event study in the research is based on a sample of 64 trading days.[8] To avoid the compounding effect from another regulatory change over short-

[7] On 1 December 2012, TSX implemented a connection speed update. Therefore, we end the sample period at 30 November 2012.

[8] Six days of observations are eliminated from the sample period. Pre-event period: 3 September 2012: Labour Day in Canada; 8 October 2012: Thanksgiving Day in Canada. Post-event period: 29 and 30 October 2012: US markets close due to Hurricane Sandy; 22 November 2012: US Thanksgiving Day; and 23 November 2012: US Black Friday.

selling rules,[9] which was also implemented on 15 October 2012 by the IIROC, we focus on inter-listed stocks in this chapter.

To minimise the infrequent trading issue, the three most actively traded call/put options contracts, with the largest daily trading volume, are chosen for each trading day. To achieve an equal weight of options, 12 underlying stocks are selected. Those stocks have at least three call and put options traded every day within the sample period. The list of stocks is presented in Appendix 5-1 (Table 5-12). As a result, we have 488 call option series and 632 put option series in the sample. To mitigate the possible effects of irregular trading behaviour, ten minutes after the market open and prior to the market close are removed. As a result, the intraday data for the analysis is from 9:40 am to 3:50 pm.

5.4 Method

The common liquidity measurements are market spreads. In this chapter, we use quoted spreads, best depth, effective spreads, one-minute realised spreads, and one-minute price impact (Hendershott, Jones, & Menkveld, 2011).[10] The quoted spread measures the liquidity in the limit order book and refers to the lowest price at which an investor wants to sell (best ask) and the highest price at which an investor is willing to buy (best bid). The quoted spreads in this chapter are calculated relative to the prevailing midpoint price.

$$midpoint_{i,t} = \frac{bid\_price_{i,t} + ask\_price_{i,t}}{2}$$

[9] On 15 October 2012, IIROC modified rules over short-selling for non-interlisted securities. This short sale rule gives exemptions to inter-listed stocks.

[10] Quoted spread, effective spread, realised spread, and price impact are measured in half-spread and presented in percentage points.

(5-1)

$$Quoted\_spread_{i,t} = \frac{ask\_price_{i,t} - bid\_price_{i,t}}{2 \times midpoint_{i,t}}$$

(5-2)

where $ask\_price_{i,t}$ ($bid\_price_{i,t}$) denotes the price of the best ask (bid) for option i at time t. We calculate the quoted spread for each order submission, amendment, cancellation, and transaction. The daily quoted spread is calculated as time-weighted averages at one-minute intervals.

The best depth measures the available order volume at the level of the best bid and ask quotes in the limit order book.

$$Best\_depth_{i,t} = \frac{bid\_size_{i,t} + ask\_size_{i,t}}{2}$$

(5-3)

where $ask\_size_{i,t}$ ($bid\_size_{i,t}$) denotes the size of the best ask (bid) for option i at time t. Similar to quoted spreads, we calculate the daily best depth as the time-weighted average at one-minute intervals.

Effective spreads measure the execution costs that a liquidity consumer has to pay. It is defined as the difference between the execution price and the midpoint of the best bid and ask quotes prevailing at the time of execution.

$$Effective\_spread_{i,t} = D_{i,t} \times \frac{trade\_price_{i,t} - midpoint_{i,t}}{midpoint_{i,t}}$$

(5-4)

where $D_{i,t}$ denotes the direction of the trade at time t for option i. It equals +1 for buyer-initiated trades and -1 for seller-initiated trades. We estimate the trade direction using the method in Lee and Ready (1991). $Trade\_price_{i,t}$ represents the execution price of trade at time t for option i. $Midpoint_{i,t}$ is the midpoint of the best bid and ask price for option i at time t prior to each trade. For each option each day, we calculate the effective spread as a share volume-weighted average across all trades that day.

Further, the change in a liquidity provider's revenue is measured by decomposing the effective spread into the realised spread and the price impact. The realised spread measures the transitory component of the effective spread. We measure revenue to liquidity providers using the one-minute realised spreads, assuming that liquidity providers are able to close their position one minute after the trade. The realised spread is defined as follows:

$$Realised\_spread_{i,t} = D_{i,t} \times \frac{trade\_price_{i,t} - midpoint_{i,t+1min}}{midpoint_{i,t}} \tag{5-5}$$

where $D_{i,t}$ denotes the direction of the trade at time t for option i. It equals +1 for buyer-initiated trades and -1 for seller-initiated trades. $Trade\_price_{i,t}$ represents the execution price of trade at time t for option i. $Midpoint_{i,t+1min}$ is the midpoint price of the best bid and ask for option i at one minute after the time of trade t. For each option each day, we calculate the realised spread as a share volume-weighted average across all trades that day.

The permanent component of the spread reflects the portion of the spread that arises due to the presence of informed liquidity traders. We measure gross losses to liquidity demanders using the one-minute price impact of a trade. The price impact is defined as follows:

$$Price\_impact_{i,t} = D_{i,t} \times \frac{midpoint_{i,t+1min} - midpoint_{i,t}}{midpoint_{i,t}}$$

(5-6)

where $D_{i,t}$ denotes the direction of the trade at time t for option i. It equals +1 for buyer-initiated trades and -1 for seller-initiated trades. $Midpoint_{i,t}$ and $midpoint_{i,t+1min}$ are the midpoint price of the best bid and ask for option i at the time of trade t and one minute after that trade, respectively. For each option each day, we calculate the price impact as a share volume-weighted average across all trades that day.

To determine if the dark trading regulatory event exerts an impact on the options market liquidity, the following regression is estimated:

$$MS_{i,t} = \beta_0 + \beta_1 Event_{i,t} + \beta_2 TTM_{i,t} + \beta_3 M_{i,t} + \beta_4 V_{i,t} + \beta_5 \sigma_{o_{i,t}} + \beta_6 \sigma_{s_{i,t}} + \varepsilon_{i,t}$$

(5-7)

where the unit of observation is option-day. $MS_{i,t}$ represents the daily average market spread/depth, namely quoted spread, best depth, effective spread, realised spread, and price impact, for option i on day t. $Event_{i,t}$ takes the value of zero if trading day t belongs to the pre-event period (from 27 August 2012 to 12 October 2012), and one during the post-event period (from 15 October 2012 to 30 November 2012). Time-to-maturity

($TTM_{i,t}$) is the difference between the current date of the option and the expiry date. Moneyness ($M_{i,t}$) is the ratio of closing spot (strike) price to strike (closing spot) price of call (put) option for option *i* on day *t*. $V_{i,t}$ denotes the natural logarithm of the total daily option trading volume for option *i* on day *t*. Option volatility ($б_{oi,t}$) is the implied volatility of option *i* on day *t*. Stock volatility ($б_{si,t}$) is defined as the natural logarithm of highest stock price divided by the lowest stock price on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regression are winsorised at the 1% and 99% levels. Tables 5-1 and 5-2 present the correlation coefficient matrix for call and put options, respectively.

Table 5 - 1
Covariance Matrix for Call Option

This table reports the correlation matrix of the independent variables for the regression analysis of call option contracts in this chapter. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The call option contracts examined for each trading day are the top three most actively traded contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days, with 7 weeks each before and after the transition. *Event* takes the value of zero if the trading day belongs to pre-event period, and one during the post-event period. *TTM* (days) denotes the time-to-maturity, which is the difference between current date and the expiry date of an option contract. The moneyness (*M*) of a call option series is calculated as the closing spot price divided by the strike price. Option volume (*V*) is the natural logarithm of the total option trading volume (number of contracts traded) each trading day. Option volatility (*бo*) is the implied volatility for option each trading day. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price each trading day.

	Event	*TTM*	*M*	*V*	*бo*	*бs*
Event	1	0.0035	-0.0340	0.0498*	-0.0419*	0.0031
		(0.8682)	(0.1028)	(0.0169)	(0.0445)	(0.8819)
TTM	0.0035	1	-0.1495**	-0.1634**	0.0231	-0.1276**
	(0.8682)		(<0.0001)	(<0.0001)	(0.2673)	(<0.0001)
M	-0.0340	-0.1495**	1	-0.0262	-0.1499**	-0.1431*
	(0.1028)	(<0.0001)		(0.2080)	(<0.0001)	(<0.0001)
V	0.0498*	-0.1634**	-0.0262	1	-0.0042	0.1029**
	(0.0169)	(<0.0001)	(0.2080)		(0.8395)	(<0.0001)
бo	-0.0419*	0.0231	-0.1499**	-0.0042	1	0.6657**
	(0.0445)	(0.2673)	(<0.0001)	(0.8395)		(<0.0001)
бs	0.0031	-0.1276**	-0.1431*	0.1029**	0.6657**	1
	(0.8819)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	

Table 5 - 2
Covariance Matrix for Put Option

This table reports the correlation matrix of the independent variables for the regression analysis of put option contracts in this chapter. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The put option contracts examined for each trading day are the top three most actively traded contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days, with 7 weeks each before and after the transition. *Event* takes the value of zero if the trading day belongs to pre-event period, and one during the post-event period. *TTM* (days) denotes the time-to-maturity, which is the difference between current date and the expiry date of an option contract. The moneyness (*M*) of a put option series is calculated as the strike price divided by the closing spot price. Option volume (*V*) is the natural logarithm of the total option trading volume (number of contracts traded) each trading day. Option volatility (*бo*) is the implied volatility for option each trading day. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price each trading day.

	Event	*TTM*	*M*	*V*	*бo*	*бs*
Event	1	-0.0267	0.0486*	0.0462*	-0.0529*	0.0031
		(0.2001)	(0.0198)	(0.0267)	(0.0111)	(0.8819)
TTM	-0.0267	1	-0.2600**	-0.1236**	0.1202**	-0.0974**
	(0.2001)		(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
M	0.0486*	-0.2600**	1	0.0945**	-0.3390**	-0.0138
	(0.0198)	(<0.0001)		(<0.0001)	(<0.0001)	(0.5067)
V	0.0462*	-0.1236**	0.0945**	1	-0.1204**	0.0630**
	(0.0267)	(<0.0001)	(<0.0001)		(<0.0001)	(0.0025)
бo	-0.0529*	0.1202**	-0.3390**	-0.1204**	1	0.6233**
	(0.0111)	(<0.0001)	(<0.0001)	(<0.0001)		(<0.0001)
бs	0.0031	-0.0974**	-0.0138	0.0630**	0.6233**	1
	(0.8819)	(<0.0001)	(0.5067)	(0.0025)	(<0.0001)	

5.5 Empirical Results

5.5.1 Univariate tests

Table 5-3 reports the total number of contracts traded, average price and size of contracts, average moneyness, and time-to-maturity of options contracts. The sample contains a total of 19,787 transactions for call options and 10,113 transactions for put options. The moneyness of an option series is calculated as the closing spot (strike) price divided by the strike (closing spot) price for call (put) options. Time-to-maturity (TTM) is computed as the difference between the date of trade and the expiry date. Panel B of Table 5-3 reports the descriptive statistics across three moneyness categories: in-the-money options (ITM) where moneyness is greater than 1.1; at-the-money (ATM) options where moneyness is between 0.9 and 1.1; and out-of-the-money (OTM) where moneyness is less than 0.9. Preliminary results suggest that the majority of the trades are concentrated in the ATM category (93.17% of all trades for call options, and 87.84% for put options), followed by the OTM category. The ITM category accounts form the least portion of total transactions. Panel C of Table 5-3 reports summary statistics divided into three TTM categories: greater than 90 days, between 30 and 90 days, and less than 30 days to maturity. Results show that trades that are less than 30 days to maturity make up the greatest proportion of the sample, followed by 30-90 days to maturity.

Table 5 - 3
Descriptive Statistics for Option Contracts

This table reports descriptive statistics for call and put options. Panel A describes the full sample. Panel B splits the sample into three moneyness categories. The moneyness of an option series is calculated as the closing spot (strike) price divided by the strike (closing spot) price for call (put) options. Moneyness categories are defined as at-the-money (ATM) if it is between 0.9 and 1.1, in-the-money (ITM) if greater than 1.1, and out-of-the-money (OTM) if less than 0.9. Panel C describes the sample in three time-to-maturity (TTM) categories. Time-to-maturity is the difference between current date of an option and its expiration date. *Trade Premium* is the average of the options premiums ($) in the sample. *Moneyness* is the average moneyness of call (put) options in the sample. *Time-to-Maturity* is the average time-to-maturity (days). *Trade Size* is the average trade size (contracts).

	Number of Trades	Trade Premium ($)	Moneyness	Time-to-maturity (days)	Trade size (contracts)
PANEL A: Overall					
Call	19,787	1.10	0.98	53.07	48.78
Put	10,113	1.22	0.97	67.77	52.94
PANEL B: Moneyness					
Call					
ATM	18,435	0.99	0.99	47.87	45.39
ITM	443	6.17	1.16	121.73	54.74
OTM	909	0.76	0.86	125.17	114.49
Put					
ATM	8,883	1.17	0.99	50.63	56.48
ITM	130	7.66	1.20	155.68	25.51
OTM	1,100	0.90	0.84	177.35	27.63
PANEL C: Time-to-Maturity					
Call					
> 90 days	3,624	2.08	0.97	157.34	29.31
30 - 90 days	6,835	0.99	0.98	48.04	69.12
< 30 days	9,328	0.79	0.99	16.24	41.43
Put					
> 90 days	1,916	2.46	0.93	224.72	31.30
30 - 90 days	3,268	1.19	0.97	46.76	54.40
< 30 days	4,929	0.76	0.99	16.58	60.38

Table 5-4 compares the average price, moneyness, time-to-maturity, and size of each transaction before and after the implementation of the new dark trading regulation. It also presents five measures of market quality, namely quoted spread, best depth, effective spread, realised spread, and price impact. For call options, the average trade price reduces, while the trade size increases after the regulatory transition, statistically significant at the 1% level. The average moneyness is reduced after the event. The average quoted spread, best depth, and effective spread are larger under the new regulation. For put options, the average trade price per transaction increases, statistically significant at the 5% level. The average moneyness increases, while average time-to-maturity declines in the post-event sample period. The best depth of put options increases after the transition.

Table 5 - 4
Descriptive Statistics for Options Market Spreads

This table reports descriptive statistics for call and put options surrounding the regulatory change. The new dark trading regulation took effect on 15 October 2012. *Pre-period* is between 27 August 2012 and 12 October 2012. *Post-period* is between 15 October 2012 and 30 November 2012. The call (put) option contracts examined for each trading day are the top three most actively traded contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days, with 7 weeks each before and after the transition. *Trade Premium* is the average of the options premiums ($). *Moneyness* of an option series is calculated as the closing spot (strike) price divided by the strike (closing spot) price for call (put) options. *Time-to-Maturity* is the difference between current date of an option contract and its expiration date. *Trade Size* is the average trade size (contracts). *Quoted spread* (%) is the bid-ask spread of prevailing best bid and ask in the limit order book relative to its midpoint. *Best depth* is the average size of prevailing best bid and ask. *Effective spread* (%) is the difference between the trade price and the midpoint at the time of execution relative to that midpoint. *Realised spread* (%) and *price impact* (%) are calculated analogously using the quote midpoint 1-minute after the trade. The t-test is used to test the difference in the mean values across the regulatory change. *(**) denotes statistical significance at the 5% (1%) level.

	Call Options		Put Options	
	Pre-event	Post-event	Pre-event	Post-event
Trade Premium	1.24**	0.94**	1.25*	1.19*
Moneyness	0.99**	0.98**	0.97**	0.98**
Time-to-Maturity	53.34	52.77	70.65**	60.48**
Trade Size	35.92**	63.12**	39.72	67.26
Quoted Spread	5.83**	7.10**	6.04	6.65
Best Depth	70.36**	76.38**	62.70**	70.22**
Effective Spread	3.37**	4.17**	3.38	3.50
Realised Spread	0.92	1.29	0.95	0.75
Price Impact	2.35	2.54	2.38	2.67

5.5.2 Multivariate Analysis

Table 5-5 reports the regression results of market spreads for call option contracts. Consistent with existing literature, market spreads are affected by a number of liquidity determinants. For relative quoted spreads, the coefficient of event is positive and statistically significant at the 1% level. It indicates that the relative bid-ask spread in the call options market increases after the implementation of dark trading regulations in

Canada. This finding is inconsistent with Hypothesis 5.1. Time-to-maturity and moneyness of call option contracts are negatively related to the quoted spread, statistically significant at the 1% level. The coefficient of the option's implied volatility is negative and statistically significant at the 5% level. It shows that the quoted spread is lower when the call option market is more volatile. Further, the daily trading volume is positively related to the call option market's relative bid-ask spread.

Results for best depth indicate that the average size available at the best bid and ask quotes in the limit order book increases after the transition, statistically significant at the 5% level. This result is inconsistent with Hypothesis 5.1. Time-to-maturity, moneyness, option market volatility and underlying stock volatility are all negatively related to the best depth. The call options contract trading volume exerts a positive effect on the average bid and ask size in the limit order book.

For percentage effective spread, the coefficient of event is positive and statistically significant at the 1% level, after controlling for other liquidity determinants. It demonstrates that traders face higher execution costs in the call options market after the introduction of dark trading regulations. This finding is inconsistent with Hypothesis 5.1. Time-to-maturity, moneyness, and underlying stock volatility exert negative impacts on percentage effective spreads, statistically significant at the 1% level. The coefficient of option trading volume is positive at the 1% level.

For one-minute realised spreads, the dark regulatory event does not impose a substantial impact. It shows that the revenue of liquidity providers in the call options market, measured at one-minute lags, does not change significantly after the event. Time-to-maturity, moneyness, and underlying stock volatility are negatively related to the realised spread. Similarly, the coefficient of the dark trading regulatory event is not statistically significant for one-minute price impact measurement after controlling for other market factors. Time-to-maturity, moneyness, and option volatility are negatively related to price impact, whereas option trading volume is positively related to the price impact. Those results are consistent with Hypothesis 5.1.

Table 5-6 presents the regression results of market spreads for put options during the sample period. For quoted spreads, the coefficient of event is positive and statistically significant at the 5% level after controlling for other liquidity determinants. It suggests that the relative bid-ask spread increases after the implementation of new dark trading regulations. This finding is inconsistent with Hypothesis 5.1. Time-to-maturity, moneyness, and the underlying stock market volatility play a negative role in relative quoted spread measurement.

Table 5 - 5
Regressions of Market Spreads of Call Options

This table reports the regression results of the daily average market spreads for call options. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded call option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days. The unit of observation is an option contract per trading day. Regressions are estimated for five measures of market liquidity, namely quoted spread, best depth, effective spread, realised spread, and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a call option series is calculated as the closing spot price divided by the strike price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Quoted Spread	55.3918**	0.9996**	-0.0233**	-50.5174**	0.6897**	-0.0605*	-0.3991	0.1619	2,294
	(<0.0001)	(0.0019)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0271)	(0.1122)		
Best Depth	130.1690**	4.6155*	-0.0537**	-77.3544**	7.9160**	-0.6027**	-4.3308*	0.1081	2,294
	(<0.0001)	(0.0333)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0002)	(0.0136)		
Effective Spread	32.2080**	0.5849**	-0.0129**	-30.8676**	0.5962**	0.0078	-0.5588**	0.1505	2,279
	(<0.0001)	(0.0051)	(<0.0001)	(<0.0001)	(<0.0001)	(0.6569)	(0.0002)		
Realised Spread	10.7976**	0.2996	-0.0038**	-10.2050**	0.1366	0.02058	-0.4536**	0.0232	2,264
	(<0.0001)	(0.0745)	(0.0003)	(<0.0001)	(0.1447)	(0.1537)	(0.0005)		
Price Impact	17.3781**	0.1259	-0.0067**	-15.8779**	0.3467**	-0.0430**	0.0839	0.0994	2,263
	(<0.0001)	(0.3558)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.4013)		

For best depth, the coefficient of the event dummy variable is positive and statistically significant at the 1% level. It shows that the limit order book becomes deeper after the event. This result is inconsistent with Hypothesis 5.1. Time-to-maturity, moneyness, and option market volatility are all negatively related to best depth. The options contract trading volume exerts a positive impact on best depth.

Unlike call options, the regulatory event does not impose a significant impact on put option percentage effective spreads. It indicates that the execution cost in the put options market does not experience significant changes due to the implementation of dark trading regulations. This finding is consistent with Hypothesis 5.1. Time-to-maturity, moneyness, and underlying stock volatility are negatively related to the effective spread measure. The coefficient of options contract trading volume is positive and statistically significant at the 5% level.

For realised spreads, measured at one minute intervals, the regulatory event does not exert a significant impact. Time-to-maturity, moneyness, option trading volume and underlying stock market volatility are negatively related to the realised spread. Similarly, the coefficient of the event dummy variable is less substantial for price impact measurement. These results are consistent with Hypothesis 5.1. Time-to-maturity, moneyness and underlying stock market volatility are negatively related to price impact, whereas options contract trading volume is positively related. Results suggest that the cost of liquidity demanders, and the revenue of liquidity providers, is less affected by the new dark trading regulation.

Table 5 - 6
Regressions of Market Spreads of Put Options

This table reports the regression results of the daily average market spreads for put options. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded put option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample include 64 trading days. The unit of observation is an option contract per trading day. Regressions are estimated for five measures of market liquidity, namely quoted spread, best depth, effective spread, realised spread, and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a put option series is calculated as the strike price divided by the closing spot price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Quoted Spread	45.8613**	0.7059*	-0.0174**	-39.4109**	0.3230	-0.0165	-0.8262**	0.1589	2,300
	(<0.0001)	(0.0314)	(<0.0001)	(<0.0001)	(0.0896)	(0.4834)	(<0.0001)		
Best Depth	90.3868**	6.2011**	-0.0312**	-25.2994*	4.3869**	-0.6326**	-1.6060	0.0763	2,300
	(<0.0001)	(0.0016)	(<0.0001)	(0.0247)	(<0.0001)	(<0.0001)	(0.2931)		
Effective Spread	24.9294**	0.1547	-0.0097**	-21.9664**	0.2351*	0.0074	-0.4932**	0.1411	2,244
	(<0.0001)	(0.4191)	(<0.0001)	(<0.0001)	(0.0378)	(0.6074)	(<0.0001)		
Realised Spread	11.5716**	-0.0352	-0.0032**	-9.0498**	-0.3932**	0.0092	-0.1700*	0.0349	2,237
	(<0.0001)	(0.8456)	(<0.0001)	(<0.0001)	(0.0001)	(0.4711)	(0.0219)		
Price Impact	13.3064**	0.2429	-0.0059**	-12.4063**	0.5245**	-0.0144	-0.2265*	0.0944	2,236
	(<0.0001)	(0.1157)	(<0.0001)	(<0.0001)	(<0.0001)	(0.2065)	(0.0270)		

5.6 Robustness Tests

5.6.1 Multivariate analysis on a transaction basis

The unit of observation of the regression analysis in Section 5.5 is option-day. To further examine the intraday market liquidity, we undertake regression analysis focusing on each option trade. The following regression is estimated:

$$MS_{i,t} = \beta_0 + \beta_1 Event_{i,t} + \beta_2 TTM_{i,t} + \beta_3 M_{i,t} + \beta_4 V_{i,t} + \beta_5 \sigma_{o_{i,t}} + \beta_6 \sigma_{s_{i,t}} + \varepsilon_{i,t} \quad (5\text{-}8)$$

where the unit of observation is a transaction. $MS_{i,t}$ represents the market spread, namely effective spread, realised spread, and price impact, for each trade of option i on day t. $Event_{i,t}$ takes the value of zero if trading day t belongs to the pre-event period (from 27 August 2012 to 12 October 2012), and one during the post-event period (from 15 October 2012 to 30 November 2012). Time-to-maturity ($TTM_{i,t}$) is the difference between the current date of the option and the expiry date. Moneyness ($M_{i,t}$) is the ratio of closing spot (strike) price to strike (closing spot) price of call (put) option for option i on day t. $V_{i,t}$ denotes the natural logarithm of the total daily option trading volume for option i on day t. Option volatility ($бo_{i,t}$) is the implied volatility of option i on day t. Stock volatility ($бs_{i,t}$) is defined as the natural logarithm of highest stock price divided by the lowest stock price on trading day t. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regression are winsorised at the 1% and 99% levels.

Table 5-7 reports the regression results of market spreads for all call option transactions. The coefficient of event is positive and statistically significant at the 1% level after controlling for other liquidity determinants. It indicates that traders in call option markets suffer from higher transaction costs under the new dark trading regulations. This result is consistent with the daily average measurement results in Section 5.5.2, and is inconsistent with Hypothesis 5.1. Time-to-maturity, moneyness, option market volatility, and underlying stock price volatility are all negatively related to the percentage effective spread, whereas option contract trading volume exerts a positive impact on the effective spread.

For realised spreads and price impact, we do not observe a clear direction of change due to the new regulatory event. These results are consistent with the daily average measurement results and with Hypothesis 5.1. Time-to-maturity, moneyness, option and underlying stock volatility are negatively related to realised spreads; option trading volume is positively related. There is a negative relationship between price impact and several market determinants, including time-to-maturity, moneyness and option price volatility. Underlying stock price volatility is positively related to price impact.

Table 5-8 presents the regression results of trade-based market spreads for all put option transactions. The new MPI rule does not exert a significant impact on put option market liquidity, in terms of percentage effective spreads, realised spreads, and price impact. Instead, these three measures are affected by some liquidity determinants widely discussed in existing literature, such as time-to-maturity, moneyness, option trading volume, option price volatility, and underlying stock price volatility. Therefore, findings in Section 5.5.2 are robust for transaction-based measures of put options.

Table 5 - 7
Regressions of Market Spreads of Call Options (per trade)

This table reports the regression results of the market spreads for call options per trade basis. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded call option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days. The unit of observation is an option contract transaction. Regressions are estimated for three measures of market liquidity, namely effective spread, realised spread, and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a call option series is calculated as the closing spot price divided by the strike price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Effective Spread	30.1042**	0.3117**	-0.0180**	-26.3287**	0.2559**	-0.0638**	-0.1387**	0.1326	18,053
	(<0.0001)	(0.0017)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0084)		
Realised Spread	12.6312**	0.1001	-0.0040**	-11.6203**	0.1446**	-0.0152*	-0.2698**	0.0158	18,007
	(<0.0001)	(0.3064)	(<0.0001)	(<0.0001)	(0.0026)	(0.0352)	(<0.0001)		
Price Impact	15.4980**	0.1401	-0.0127**	-12.4608**	0.0708	-0.0601**	0.2097**	0.0505	17,996
	(<0.0001)	(0.0619)	(<0.0001)	(<0.0001)	(0.0631)	(<0.0001)	(<0.0001)		

Table 5 - 8
Regressions of Market Spreads of Put Options (per trade)

This table reports the regression results of the market spreads for put option per trade basis. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded put option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days. The unit of observation is an option contract transaction. Regressions are estimated for three measures of market liquidity, namely effective spread, realised spread, and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a put option series is calculated as the strike price divided by the closing spot price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Effective Spread	28.5398**	-0.0655	-0.0105**	-25.8805**	0.3486**	-0.0196*	-0.3528**	0.1339	9,209
	(<0.0001)	(0.6647)	(<0.0001)	(<0.0001)	(0.0001)	(0.0535)	(<0.0001)		
Realised Spread	11.0418**	-0.2416	-0.0035**	-10.8416**	0.1122	0.0149	-0.1211	0.0179	9,191
	(<0.0001)	(0.0635)	(<0.0001)	(<0.0001)	(0.1176)	(0.0991)	(0.1315)		
Price Impact	16.8463**	0.1264	-0.0066**	-14.2282**	0.1701**	-0.0364**	-0.1405	0.0483	9,186
	(<0.0001)	(0.2953)	(<0.0001)	(<0.0001)	(0.0072)	(<0.0001)	(0.0506)		

5.6.2 Market Spreads with Alternative Time Interval Assumptions

The realised spread and price impact in the above analysis are calculated based on the assumption that market makers are able to close their positions at the mid-point one-minute after each transaction. Further, we conduct additional tests on three-minute and ten-minute realised spreads and price impact. Results, in Table 5-9, show that the three-minute realised spread and price impact for both call and put options remain unchanged after the transition. Similarly, the ten-minute measurements are also less affected by the new regulation.

Table 5 - 9
Descriptive Statistics for Option Market Spreads (Alternative Time Interval)

This table reports descriptive statistics for call and put options surrounding the regulatory change. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The call (put) option contract examined for each trading day is the top three most actively traded contracts for each underlying stock. The sample includes 64 trading days, with seven weeks each before and after the transition. *Realised spread* (%) and *price impact* (%) are calculated analogously using the quote midpoint 3-minute and 10-minute after the trade. The t-test is used to test the difference in the mean values across the regulatory change. *(**) denotes statistical significance at the 5% (1%) level.

	Call		Put	
	Pre-event	Post-event	Pre-event	Post-event
Realised Spread (3 min)	0.8130	1.0668	0.9278	0.6383
Price Impact (3 min)	2.4888	2.7040	2.4346	2.8367
Realised Spread (10 min)	0.6852	1.0624	0.9775	0.5557
Price Impact (10 min)	2.6556	2.8849	2.5465	2.9494

We further undertake multivariate analysis for call and put options market quality variables. Table 5-10 reports the regression results for call options' realised spread and price impact measured with three-minute and ten-minute assumptions. Results suggest that the three-minute and ten-minute realised spread and price impact are less affected by the dark trading regulatory event after controlling for other market factors. This is consistent to the results for the one-minute measurements.

In addition, Table 5-11 reports the regression results for put options realised spread and price impact, measured with three-minute and ten-minute assumptions. Similar to those of call options, the three-minute and ten-minute realised spread and price impact for put options are not heavily influenced by the dark trading regulations. This indicates that the revenue to liquidity providers, and gross loss to liquidity demanders, due to adverse selection does not experience significant changes after the transition. Thus, the regression results in Section 5.5.2 are robust for alternative time interval assumptions.

Table 5 - 10
Regressions of Market Spreads of Call Options (Alternative Time Interval)

This table reports the regression results of the market spreads for call option per trade basis. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded put option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days. The unit of observation is an option contract per trading day. Regressions are estimated for 3-minute and 10-minute realised spread and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a call option series is calculated as the closing spot price divided by the strike price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Realised Spread (3 min)	9.9828**	0.2497	-0.0030**	-9.3347**	0.0757	0.0218	-0.4236**	0.0157	2,261
	(<0.0001)	(0.1606)	(0.0063)	(<0.0001)	(0.4356)	(0.1665)	(0.0042)		
Price Impact (3 min)	18.2208**	0.0844	-0.0077**	-16.7883**	0.4017**	-0.0431**	0.0811	0.0916	2,260
	(<0.0001)	(0.5903)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0003)	(0.4970)		
Realised Spread (10 min)	8.7185**	0.3212	-0.0028*	-8.1148**	0.0996	0.0185	-0.4916**	0.0120	2,268
	(<0.0001)	(0.1029)	(0.0113)	(<0.0001)	(0.3661)	(0.2440)	(0.0019)		
Price Impact (10 min)	20.2367**	0.1013	-0.0082**	-18.7891**	0.4045	-0.0414**	0.1382	0.0721	2,268
	(<0.0001)	(0.5784)	(<0.0001)	(<0.0001)	(0.0002)	(0.0044)	(0.3340)		

Table 5 - 11
Regressions of Market Spreads of Put Options (Alternative Time Interval)

This table reports the regression results of the market spreads for put option per trade basis. The new dark trading regulation took effect on 15 October 2012. *Pre period* is between 27 August 2012 and 12 October 2012. *Post period* is between 15 October 2012 and 30 November 2012. The option contracts examined for each trading day are the top three actively traded put option contracts for each underlying stock selected. There are 12 stocks in this analysis. The sample includes 64 trading days. The unit of observation is an option contract per trading day. Regressions are estimated for 3-minute and 10-minute realised spread and price impact. $Event_t$ takes the value of zero if trading day *t* belongs to the pre-event period, and one during the post-event period. *TTM* denotes the time-to-maturity for each option contract (number of days). The moneyness (*M*) of a put option series is calculated as the strike price divided by the closing spot price. Option volume *(V)* is the natural logarithm of the options trading volume for trading day *t*. Option volatility (*бo*) is the implied volatility for option i on day t. Stock volatility *(бs)* is defined as the natural logarithm of the highest stock price divided by the lowest stock price for the underlying stock of option i on trading day *t*. The *p*-values are computed based on Newey-West standard errors. To reduce the effects of extreme values, all continuous variables in the regressions are winsorised at 1% and 99% levels. * (**) denotes statistical significance at the 5% (1%) level. The *p*-values are reported in parenthesis. R^2 is the adjusted R-squared. *N* is the number of observations.

	Constant	*Event*	*TTM*	*M*	*V*	*бo*	*бs*	R^2	*N*
Realised Spread (3 min)	11.6048**	-0.0895	-0.0030**	-8.7873**	-0.4872**	0.0184	-0.2716*	0.0356	2,234
	(<0.0001)	(0.6466)	(<0.0001)	(<0.0001)	(<0.0001)	(0.1837)	(0.0335)		
Price Impact (3 min)	13.2066**	0.2888	-0.0061**	-12.4956**	0.5932**	-0.0241	-0.1108	0.0852	2,233
	(<0.0001)	(0.0901)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0533)	(0.3522)		
Realised Spread (10 min)	8.9920**	-0.1596	-0.0032**	-5.9310**	-0.4630**	0.0260	-0.5226**	0.0224	2,243
	(<0.0001)	(0.4795)	(<0.0001)	(0.0006)	(0.0006)	(0.1130)	(0.0007)		
Price Impact (10 min)	16.0303**	0.3621	-0.0063**	-15.6512**	0.6097**	-0.0293	0.1216	0.0720	2,242
	(<0.0001)	(0.0796)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0696)	(0.4443)		

5.7 Conclusions

This chapter investigates the relationship between individual equity options market liquidity and restrictive dark trading regulations in Canada. On 15 October 2012, the new dark trading regulation took effect for Canadian stocks. Under the new rule, dark orders are required to provide at least one full tick size of price improvement relative to the prevailing best bid and ask price in the lit market. This essay discusses the impact of this new rule on the behaviour of options market makers, through examining the options market spreads around this regulatory change.

This chapter provides empirical evidence that with a decreasing level of dark trading, both call and put option markets are less liquid in terms of relative bid-ask spreads. Market depth at the best prevailing bid and ask quotes improves for both call and put options. Further, it is observed that traders in a call options market suffer larger execution costs after the regulatory change, whereas the execution costs of traders in put options are less affected. Given put options' lower level of trading activity relative to call options, options market makers may have more flexibility in hedging put options positions in the underlying stock market. This could explain why options market makers do not alter effective spreads significantly in response to the event. Decomposing the effective spread into realised spread and price impact, we find no evidence that the revenue of liquidity providers, or the cost of liquidity demanders, are substantially influenced by the new dark trading regulation.

Appendix 5.1

Table 5 - 12
List of Stocks Selected as the Underlying Assets of Options

This list presents the underlying stocks selected in this analysis. Those stocks are inter-listed on both domestic and foreign exchanges.

Stock Code	*Company Name*	*Exchange Listed*	*Sector*
ABX	Barrick Gold Corporation	TSX-NYSE	Mining
AEM	Agnico Eagle Mines Limited	TSX-NYSE	Mining
BMO	Bank of Montreal	TSX-NYSE	Financial Services
BNS	The Bank of Nova Scotia	TSX-NYSE	Financial Services
CM	Canadian Imperial Bank of Commerce	TSX-NYSE	Financial Services
CNQ	Canadian Natural Resources Limited	TSX-NYSE	Oil & Gas
G	Goldcorp Inc.	TSX-NYSE	Mining
MFC	Manulife Financial Corporation	TSX-NYSE-HK Ex	Financial Services
RY	Royal Bank of Canada	TSX-NYSE	Financial Services
SU	Suncor Energy Inc.	TSX-NYSE	Oil & Gas
TCKb	Teck Resources Ltd	TSX-NYSE	Mining
TD	The Toronto-Dominion Bank	TSX-NYSE	Financial Services

Chapter 6 – Conclusions

Market regulation and supervision play an essential role in the stability of the financial system worldwide. Regulations and policies are commonly introduced and amended to ensure the efficiency, integrity, and fairness of capital markets. An efficient market consists of informed and uninformed traders. Informed traders acquire costly information and they trade on their views about the fundamental value of securities; then, market prices can reflect all publicly available information. Uninformed traders provide liquidity to the market and improve trade execution. To keep both types of traders participating in the market, regulators are obliged to maintain a “level playing field” through regulation and supervision; otherwise, investors may cease quoting and migrate their trades to other jurisdictions.

The effectiveness of regulatory changes is carefully monitored by regulatory authorities. The literature review, as presented in Chapter 2 of this dissertation, documents a large number of previous studies that discuss various issues in equities market microstructure and examine the implications of relevant market regulations. The findings of these studies are diverse due to different market structures, time periods, and methods of variables measurement. This dissertation builds on the existing literature and further evaluates the impact of various contemporary regulatory events on derivatives markets. Specifically, the policies and rules in this dissertation are the short sales restrictions in China; the message traffic restrictions in Australia, Canada, Italy, and France; and the dark trading regulation in Canada. The results contribute to a greater understanding of potential effects of those regulations, which can assist the future decision making process of policy-makers.

Chapter 3 of this dissertation explores the effect of short sale restrictions on index futures pricing efficiency in an emerging market. Previous literature fails to reach a consensus as to whether the short sale restrictions bring more benefits than costs to market quality or not. Many studies report that short sale restrictions lead to persistent futures under-pricing (or stock overvaluation). Short-term arbitrageurs are prohibited or face higher levels of execution costs to act on index futures under-pricing, which involves a short position in underlying stocks. However, some researchers argue that index futures markets are less affected by short sale restrictions if traders already own those underlying stocks. They discover that futures contracts are more frequently over-priced than under-priced. In mid-2015, the Chinese regulator imposed a restrictive policy on the securities lending scheme, aiming to curb the excess volatility of its stock market. Under the new short sales rule, investors who borrow shares for short-selling are not allowed to cover their positions within a trading day. This regulatory change severely affects the behaviour of short-term arbitrageurs, who target the price misalignments between CSI 300 index futures contract and its underlying spot index. The first essay (Chapter 3) utilises a data set of intraday futures prices and index points at one-minute intervals. The index futures price is compared with its theoretical value, based on the "cost-of-carry" model. Further, the model incorporates seven levels of pre-assumed transaction costs coping for different market participants.

Results show that futures under-pricing occurs more frequently at transaction costs levels ranging from 0 to 1.50%, while futures over-pricing occurs less frequently under transaction cost levels ranging from 0 to 0.75% after the regulatory change. This finding is consistent with previous literature that index futures mispricing is asymmetric, with more under-pricing than over-pricing. With a tighter short-selling regulation, futures under-pricing occurs more frequently after controlling for futures market price volatility and trading volume. Results also indicate that the relative size of futures mispricing increases substantially at the transaction cost levels from 0 to 0.25% after the transition. Overall, the recent implementation of short-selling restrictions in China exerts a negative impact on the pricing efficiency of its index futures market. This finding is consistent with the literature that restrictions on short sales in underlying markets are associated with an increase in both the frequency and magnitude of index futures under-pricing relative to its spot index.

The second essay in this dissertation, presented in Chapter 4, examines the impact of message traffic restrictions on the relative pricing efficiency between index futures contracts and Exchange-Traded Funds (ETFs) which track the stock index. There are debates over the effectiveness and efficiency of algorithmic trading/high frequency trading regulations, yet no consensus has been reached. In earlier years, the literature documents the positive effect of algorithmic trading/high frequency trading on market quality. Algorithmic trading is discovered to reduce market spreads, lower price volatility, and improve price discovery. More recent research suggests that high frequency trading activity can bring severe detriments to market efficiency and fairness. Specifically, high frequency trading can increase price volatility and reduce liquidity when the market is in stress. In addition, it is observed that high frequency traders earn significant amounts of profit at the expense of low speed market participants, such as institutional and retail investors. A typical type of high frequency trading regulation is a financial transaction tax, which is designed to lower the market volatility as well as collecting revenue for governments. However, it is argued that financial transaction taxes can generate negative externalities to market quality. Some previous research reports that financial transaction taxes are associated with wider market spreads, higher price volatility, larger price impact, and lower trading volume.

Based on the literature, on the one hand, the message traffic restrictions exert a negative impact on high frequency trading, thus decreasing the relative pricing consistency between index futures and index ETFs. On the other hand, the restrictive regulations mitigate the competition among high frequency traders and also reduce noise orders in the market. Consequently, the relative pricing efficiency can increase after the transition.

Chapter 4 adopts an order level data set to examine the impact of the message traffic regulatory change on index futures pricing efficiency. As an extension of Chapter 3, we specifically investigate the return correlation between index futures contracts and index ETFs, which are frequently utilised by index arbitrageurs. The return correlation in Chapter 4 is computed on a daily basis at one-second time intervals. The sample includes four markets, with two types of message traffic regulations. In Australia and Canada, regulators recover their market surveillance costs based on number of trades and quotes of each participant. In France and Italy, the financial transaction tax is levied on the value of quotes modified and cancelled by high frequency traders over a certain level.

Results suggest that price volatility and trading volume of the financial instruments do not show a consistent change after the implementation of the message traffic restrictions. Specifically, the market volatility and trading volume for ETFs in Australia and France decrease, whereas the price volatility of ETFs in Canada and Italy are less affected. In addition, the ETF trading volume in Canada experiences a substantial drop after the transition, while the ETF trading volume in Italy is observed to increase during the sample period.

Multivariate analysis reveals that the message traffic regulations exert a significant impact on the relative pricing efficiency between index futures contracts and index ETFs after controlling for the effects of futures market volatility and trading volume. However, the direction of change differs across markets. In Australia and Canada, the return correlation increases. In contrast, the pricing consistency of these two financial instruments declines in Italian markets. In France, the return correlation is less affected. This is because the French financial transaction tax does not impose a direct levy on either index futures contracts or index ETFs. This finding demonstrates that the message traffic regulations exert a mixed effect on market quality.

In the past decade, dark trading has experienced a tremendous growth in market share, which raises significant concerns among academics and regulators. Dark trading regulations have been implemented in some jurisdictions. In response to the public consultations organised by some regulators, the impact of dark trading on market quality is discussed from both theoretical and empirical perspectives. Yet, there is little consensus as to whether the overall effect of dark trading is positive or negative. Some researchers find that dark trading can attract more order flow, thus improving market liquidity. However, a stream of literature suggests that market fragmentation can drive the segregation of traders, which increases the adverse selection risk in the lit exchange. In addition, as derivatives, the options market liquidity is highly related to that of its underlying asset market. Options market makers need to frequently hedge their inventory positions as well as the adverse selection risk they face by trading in the underlying stock market. The trading costs arising from those hedging activities are reflected in the options market spreads.

Based on previous literature, the options market liquidity is positively associated with stock market liquidity. A high level of dark trading increases the adverse selection risk in the lit market, thus harming the options market liquidity. However, dark trading reduces the amount of information in aggregate. With a higher level of dark trading, the options market makers face lower levels of adverse selection risk. Hence, a restrictive dark trading regulation can increase the options market spreads.

In late 2012, the market regulator in Canada introduced the minimum price improvement rule, which requires dark orders to provide a minimum price improvement over the National Best Bid and Offer (NBBO). Consequently, dark trading activity reduced substantially, both in absolute terms and as a proportion of total market turnover. Chapter 5 utilises an order level data set to bridge the gap between the literature of dark trading regulations and the option market's liquidity. Five liquidity measures are tested before and after the regulatory event, which are the percentage bid-ask spread, quoted depth, effective spread, realised spread, and price impact. Further, to isolate the impact of the regulatory change, we control the effects of five market factors that are relevant to the options market spreads. Referring to the previous literature, those factors incorporated in the analysis are options' time-to-maturity, moneyness, trading volume, options market implied volatility, and stock market volatility.

The multivariate analysis shows a mixed impact of dark trading regulations on the options market liquidity. For call options, the percentage bid-ask spread increases after the transition, as does the best quoted depth. The percentage effective spread is higher under the restrictive dark trading regulations. This illustrates that traders of call options experience larger execution costs when dark trading activities are low in the stock market. Similarly, for put options, the percentage bid-ask spread and quoted depth increase after the regulatory event. However, the effective spread is less affected by the new regulation. In addition, we find no evidence showing that the realised spread and price impact change during the sample period for both call and put options. These results are robust for different time interval assumptions.

Overall, this dissertation demonstrates that some recent regulatory changes in equities markets exert significant impacts on derivatives markets. These restrictive policies impose complex implications on derivatives market quality. It is essential for regulatory authorities to utilise empirical evidence to develop a more comprehensive understanding of the market impact before new regulations are introduced or amended.

Several potential future research directions lead from the work in this dissertation. The findings in Chapter 3 suggest that short sale restrictions are associated with large futures mispricing against its spot index. Since the stock index itself is not tradable, the impact of the new short-selling regulations on arbitrage trading is not examined in this study. Future research could utilise order level data to examine the futures mispricing against the ETFs which track the stock index. The results in Chapter 4 provide empirical evidence of the mixed effects that the message traffic restrictions exert on the return correlation between index futures contracts and index ETFs. Future research could further measure the size of actual index arbitrage profits throughout the regulatory changes, taking into account the execution costs for trading strategy implementation. Chapter 5 illustrates the impact of dark trading regulations on the options market liquidity. This study is conducted based on a small sample of securities (i.e., option contracts on 12 underlying stocks) compared to the entire market, since there was another market regulation implemented during the sample period. Hence, the results may not be generalisable to a broad market. Future research could focus on the impact of the dark trading regulations in a different jurisdiction that does not have any confounding events. These research avenues are left for future work.

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