Market Quality: The joint impact of Algorithmic Trading and Fragmentation

AND GLADLY TECHE

Drew Harris

A dissertation submitted in fulfilment

of the requirements for the degree of

Doctor of Philosophy

Discipline of Finance, Macquarie Graduate School of Management

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

…………………..........

Drew Harris

Acknowledgement

My PhD has been a fantastic, life changing experience and I am happily indebted to the extensive network of individuals who supported me throughout the journey.

To my supervisor, Andrew Lepone, I feel incredibly lucky to have worked with you. Thank you for your unwavering patience and constant support. To my advisors Mike Aitken and Rick Harris, I am indebted to the time and resources you gave. Your experiences and knowledge were invaluable in the development of my research. The financial support provided by the Capital Markets CRC Limited, specifically through Professor Michael Aitken, is gratefully acknowledged.

Thank you to NASDAQ for sponsoring throughout my thesis. The research experience and access to information provided is gratefully acknowledged. Special thanks to Jeffrey Smith of NASDAQ for always having time to share his unparalleled wealth of information on markets.

To my family, Mum, Dad, thank you for the love and support. Auntie Sue and Uncle Tony, thanks for giving a second home to two new PhD students, the security you provided us was invaluable! Finally, I would like to dedicate this PhD to my wife Hannah. Thank you for being my best friend, my partner in love and adventure, my constant support, and my inspiration. Without you, there would be no PhD. PS, I win…

Abstract

This thesis examines the combined effect of algorithmic trading and market fragmentation on market quality. Three distinct but inter-related research studies are conducted and the ultimate findings of the thesis are three fold. First, exchange listed companies can use stock splits to manage their tick size and influence the level of algorithmic market making in their security, which can subsequently impact the company's liquidity. Stock splits alter a security's relative tick size. In some cases, this change in relative tick size increases the quoted spread captured by market makers. This extra incentive improves liquidity and reduces transaction costs. Companies that undertake stock splits while already tick constrained increase the profit of market makers at the cost of liquidity takers. Second, the research shows that dark trading contributes very little to the price discovery of a market. Further, regulation that reduces the level of dark trading in a market does not impact the relative competitiveness in price discovery for cross listed assets. Third, the thesis examines the joint impact of fragmentation and algorithmic trading. Findings show that on exchange fragmentation increases market competition and reduced transaction costs, with two side effects: the joint growth of dark fragmentation and algorithmic trading. Dark trading reduces integrity by adding an alternate venue with lesser price impact, while algorithmic trading increases both market efficiency and integrity.

Acronyms and Abbreviations

2SLS – Two-stage Least Squares

3SLS – Three-stage Least Squares

AMEX – American Stock Exchange

ASX – Australian Securities Exchange

AT – Algorithmic Trading

ATSs – Alternative Trading Systems

BATS – BATS Global Markets Exchange

CESR – Committee of European Securities Regulators

CESR – Committee of European Securities Regulators

CFS – Common Factor Share

CRSP – Centre for Research in Security Prices

CTR – Cancel to Trade Ratio

ELP – Electronic Liquidity Provider

ELPs – Electronic Liquidity Providers

FX – Foreign Exchange

HFT – High Frequency Trading

ILS – Information Leadership Share

IOSCO – International Organisation of Securities Commissions of Canada

IS – Information Share

LOB – Limit Order Book

LSE – London Stock Exchange

MiFID – Markets in Financial Instruments Directive

NASDAQ – Nasdaq Stock Market

NBBO – National Best Bid and Offer

NMS – National Market System

NYSE Euronext – New York Stock Exchange/Euronext

OTR – Order to Trade Ratio

PDE – Price Discovery Efficiency

PII – Permanent Information Impounding

SIP – Securities Information Processor

SIRCA – Securities Industry Research Centre of Asia-Pacific

TRF – Trade Reporting Facility

TRTH – Thompson Reuters Tick History

UK – United Kingdom

US – United States

VAR – Vector Auto Regression

VECM – Vector Error Correction Model

VWAP – Volume Weighted Average Price

1. Table of Contents

List of Tables

List of Figures

1. Introduction

The aim of this dissertation is to examine the effect of algorithmic trading and market fragmentation on market quality. The literature review in chapter two explores current research on market quality, as the study of both market integrity and efficiency. The existing research around two budding areas of market microstructure research: algorithmic trading and market fragmentation, are reviewed. Research into both of these areas has provided significant findings relating to market efficiency, however, there is an overall lack of evidence regarding the impact of algorithmic trading and fragmentation on market integrity.

Initial studies on High Frequency Trading (HFT) and market integrity indicate a positive relationship. HFT are a subset of algorithmic trading firms that operate in an ultra low latency environment. This thesis extends on this research by jointly estimating the growth in Algorithmic Trading and Fragmentation. This thesis demonstrates the highly correlated growth in Algorithmic Trading and Fragmentation over the past decade. It is postulated that these two new developments in financial markets are co-joint and any study on one feature alone risks mis-specifying the significance of the other. The sections of this chapter below summarise the structure of this thesis.

1.1. Tick Size, Electronic Liquidity Providers and Market Quality

Following the literature review in chapter two, chapter three presents a unique data set of the daily percentage of trading undertaken by HFT and a subset of HFT (which are labelled as Electronic Liquidity Providers (ELP)). This data set is used to illustrate how changes in relative tick sizes can alter trading behaviour. It is established that liquid securities can increase their liquidity provision by widening their spreads; and furthermore, less liquid securities can also increase market-making activity in their stocks simply by widening the relative tick size. Message traffic has previously been associated with nefarious trading strategies and HFT strategies. The study in chapter three finds that firms across all liquidity types can decrease message traffic by splitting their stocks and widening the relative tick size. The study in chapter three finds that, in addition to liquid securities being able to increase their liquidity provision by widening spreads, low liquidity securities can increase market-making activity in their stocks simply by widening their relative tick size.

The study shows that, for liquid securities, this improvement in trading behaviour may come at the cost of higher spreads as the quoted spread becomes 'pushed open'. In the case of unconstrained stocks, a higher relative tick size results in a tightening of spreads (quoted, effective and realised). This appears to create a win-win scenario for less liquid securities where they can simultaneously increase the quality of the trading behaviour in their stock while decreasing transactions costs. The story is not so simple for liquid securities that are already tick constrained. However, changing relative tick size does offer one avenue for managers to reduce message traffic in their company, short of regulatory changes.

The findings of the study conducted in chapter three contributes to the past literature by providing empirical evidence of the previous theories on tick sizes put forward by Harris (1993), Angel (1997) and Huang and Stoll (1994). The study finds direct causal evidence that increasing the relative tick size improves transaction costs by lowering spreads, a common measure of transaction costs.

1.2. Price Discovery and Dark Trading

Chapter four presents the second study for this dissertation and analyses both the factors which lead to informative dark trading, and the effect of IIROC's price improvement rule on permanent information impounding and price discovery efficiency in cross-listed securities. This rule was implemented on 15 October 2012 and the study in chapter four suggests that it had the effect of pushing price discovery back into the lit market in Canada. Further, the study finds no evidence that price discovery shifts from the Canadian market to the cross-listed US market.

The research methodology used in chapter four controls for three new measures of order book quality, in addition to liquidity variables and time-series metrics of information efficiency. It finds that these measures contribute important price discovery insights, consistent with Jain, Jain and McInish (2012).

Dark trading in Canada contributes very little information to the market. Although the information leadership share of dark trades declines after the introduction of the price improvement rule, there are few serious ramifications given the low information content of dark trades before the ruling. Further, the price improvement rule is found not to increase the informational content of the Canadian market relative to the US market.

The study in chapter four finds that, following IIROC notice 12-0130, there is a 19.4% reduction in the information content of dark trades after controlling for order book quality metrics, informational asymmetry, transactional efficiency, and stock-specific effects. These results indicate that very little information content remains attributable to Canadian dark trades. On average, only a 7.1% Information

Leadership Share is contributed through the dark pools. Surprisingly, Canadian-US cross-listed securities during this same period show no significant change in the impounding of new information as a result of the rule change in Canada. However, price discovery efficiency in Canada is significantly reduced by the price improvement rule.

This rule change is likely to shift price discovery further into the lit markets and out of dark pools. However, it is anticipated that Canada may have decreases in price discovery relative to foreign markets, as traders are forced to either place orders more subtly (slowing the price discovery process), or chew through the lit order book, which could create further noise in the price discovery process.

1.3. Joint impact of Fragmentation and Algorithmic Trading on Market Quality

Chapter five presents the final study for the thesis, and provides research showing that in the post-Reg NMS institutional environment, fragmentation of the lit market order flow and the ensuing increase in competition, especially from HFT/ATs and alternative trading systems, is overwhelmingly positive for both aspects of market quality. The research shows that effective spreads and end-of-day manipulation have both been reduced. A doubling of the cancellation-to-trade proxy for HFT/AT 2004-2013 has lowered effective spreads by 12 basis points. In this sense, the lit fragmentation facilitated by Reg NMS has clearly benefited transaction cost. The net effect of off-exchange fragmentation, however, is quite the opposite.

Fragmentation of trading into the dark has detracted from market fairness by increasing closing price manipulation. Additionally, there has been a 2-14% increase in Trade Reporting Facility (TRF) dark share volume between 2004 and

2013 which has resulted in an 8 basis point increase in effective spreads. The negative impact of increased dark trading on spreads must be traded off against the gains from the enhanced competition for lit order flow that accompanies Reg NMS. This may warrant a different policy stance regarding fragmentation into the dark.

In addition to manipulation at the close, if trading ahead of price-sensitive announcements and front running have increased with fragmentation into the dark, then efficiency gains must be traded-off against these deleterious effects on market quality. The study in chapter five demonstrates that such market fairness violations triggered by trading in the dark increase effective spreads by an order of magnitude similar to the decreases attributable to lit market fragmentation.

While these questions are important, there are causal links between dark trading, algorithmic trading and transactions costs. These are handled in this research by utilising a two stage least squares methodology.

1.4. Summary

To summarise, this dissertation is comprised of three primary research projects that work towards a unifying approach to analysing market quality. The first two components, chapters three and four, advance research in specific areas: dark trading and algorithmic trading, respectively. These areas are not fully developed in existing literature. Chapter three examines the causal impact of a shock to HFT by utilising stock splits as a change in relative tick size. This work provides further insight into the effect of HFT on the market by combining a proprietary data set that can more accurately specify liquidity providing HFT with a causal research design. Chapter four examines the impact of price improvement regulation as a shock to dark trading levels to price discovery. This study furthers the literature by using dynamic lag estimation in the vector error correction framework first developed by Hasbrouck (1995) and Gonzalo and Granger (1995). This offers a first look at the impact of regulation on dark trading and its effect on price discovery. Chapter five represents the culmination of this thesis, utilising a structural equations model to jointly model the impact of fragmentation and algorithmic trading on the US equities market. This is the first attempt in academic research to undertake such a study. Having documented the findings of all three studies, chapter six provides a summary of the findings and insights provided by the dissertation as a whole.

2. Literature Review

The primary objective of this dissertation is to examine the effect of algorithmic trading and market fragmentation on market quality. Market quality is defined as the extent to which markets are fair (of high integrity), efficient, and have adequate price discovery. The first section of this literature review concentrates on the literature surrounding the measurement and definitions of market quality. Section 2.2 reviews the current literature on High Frequency and Algorithmic Trading. Section 2.3 reviews the literature on Fragmentation and Dark Trading. Section 2.4 gives a brief overview of the literature on tick sizes that is utilised as a driver of algorithmic trading in subsequent chapters. Section 2.5 develops the theories and hypotheses that are tested in this dissertation, using the literature reviewed in the preceding sections. Section 2.6 summarises and concludes this chapter, setting the stage for the first study documented in chapter three.

2.1. Market Quality

This thesis builds on the work of several key academic players, to create a generalised framework for analysing changes in market dynamics by assessing impacts to market quality. Relevant works include Cumming, Zhan and Aitken (2013b); Aitken, Aspris, Foley and Harris (2014); Cumming, Zhan and Aitken (2013a); Harris, Aitken, and Ji (2014); Siow and Aitken (2004). This literature approaches market quality as the analysis of both market efficiency and market integrity. Broadly speaking, market efficiency encompasses the realms of transaction costs, liquidity, and price discovery. Market integrity refers to violations of market rules and regulations such as price manipulation, insider trading, and broker-client conflicts.

While the majority of literature focusses on the transaction costs side of market quality, recent work by researchers at the CMCRC has shown using a structural equations model that both integrity and efficiency are causally linked (Harris, Aitken and Ji, 2014; Aitken, Aspris, Foley, Harris, 2014). This implies that one cannot fully model either arm of market quality without the other. While it may be economically appealing to focus on transaction costs as it has the most easily interpretable economic impact, it is shown that incidences of market integrity violations can drive changes in transactions costs.

Sections 2.1.1 – 2.1.4 review the techniques used and definitions of various measures of market quality. In Section 2.1.1 the current literature that is undertaken to analyse market quality is reviewed; both in the form of event studies on regulatory and technology changes, as well as using comparative analysis between markets. By way of introduction, market quality can be broken down into three categories: Efficiency, Integrity and Price Discovery.

2.1.1. Market Efficiency

In the seminal paper by Eugene Fama (Fama, 1997), market efficiency is referred to as the extent to which prices in the market conform to fair value by reflection of relevant market information. In market microstructure literature, market efficiency is referred to as the ability of traders to access liquidity at a fair price. Measurement of market efficiency typically revolves around proxies for transaction costs and other liquidity metrics, which encapsulate the ability of market participants to transact volumes of significant size.

The International Monetary Fund (IMF) terms liquidity as measures to gauge 'tightness (costs), immediacy, depth, breadth and resiliency'.[1] The IMF states that 'liquid markets tend to exhibit five characteristics'.[2] These characteristics are – (i) Tightness, (ii) Immediacy, (iii) Depth, (iv) Breadth, and (v) Resiliency. Tightness refers to how low transaction costs are, for example the difference between buy and sell prices (the bid ask spread) in quote driven markets, and also implicit costs. Immediacy represents the speed at which orders can be executed and settled. Therefore, immediacy reflects the efficiency of trading, clearing and settlement systems. Depth relates to the number of orders, both above and below the current trade price, that are accessible to potential buyers or sellers. Breadth is described as meaning that 'orders are both numerous and large in volume with minimal impact on prices'. (Sarr and Lybek, 2002) Finally, resiliency is defined as 'a characteristic of markets in which new orders flow quickly to correct order imbalances which tend to move prices away from what is warranted by fundamentals.' (Sarr and Lybek, 2002).

In a variety of papers, tightness is referred to as the quoted spread. Other measures of market tightness based on spreads are effective spread and realised spread. Effective spreads (Aitken and Comerton-Forde, 2005; Aitken, Aspris, Foley and Harris, 2014; Harris, Aitken and Ji, 2014; Foley and Putniņš, 2015) aim to better capture the spread that investors pay by measuring the difference between the bid or offer and transacted prices as trades occur. This overlaps into

[1] Sarr A and Lybek T (2002) *Measuring Liquidity in Financial Markets*, IMF, p5
[2] ibid

immediacy as the effective spread captures actual transacted prices. Realised spreads attempt to further capture the price impact of trades by comparing the transacted price of trades to the bid or offer after a period of time.

2.1.2. Market Integrity

Market integrity and fairness is widely quoted as an objective for exchanges around the world. Siow and Aitken (2004) provide numerous examples, quoting from various exchanges websites:

> "Providing the highest possible market quality was our top priority, along with ensuring the liquidity and transparency that market participants have come to expect." (NYSE, 2004)
>
> "NASDAQ is among the world's most regulated stock markets, employing sophisticated surveillance systems ... to protect investors and provide a fair and competitive trading environment." (Nasdaq, 2004)
>
> "The FCA summarises its job as "To maintain efficient, orderly and clean financial markets and help retail investors achieve a fair deal..." (Financial Conduct Authority, 2013)
>
> "Euronext aims to provide a fair and orderly market with built-in safeguards for the quality of price formation. Euronext is of the opinion that market participants should have a level playing field." (Euronext, 2004)

In general, market integrity is concerned with the extent to which market activity follows legal guidelines and regulation about fair access and trading. Violations of market integrity can include: trade based manipulation; insider trading; and various forms of broker-client conflict. The primary focus of microstructure research on market integrity relates to trade based manipulation and its impact on the market (Cumming, Zhan and Aitken, 2013a; Allen and Gale, 1992; Chakraborty and Yılmaz, 2004).

2.1.3. Price Discovery

There is a growing subfield of literature that bases the notion of price discovery on the measures developed by Hasbrouck (1995) and Gonzalo and Granger (1995). Through this research, the authors developed the Information Share (IS) and Common Factor Share (CFS) models, respectively. These models use Vector Auto Regression and Vector Error Correction Models to ascertain the extent to which prices under-react or over-react to information from competing price channels. Yan and Zivot (2007), Putniņš (2013), and Harris, Aitken and Di Marco (2012) have worked in tangent to develop a subset of price discovery measures that are derivatives of the IS and CFS measures.

This methodology is used by Comerton-Forde and Putniņš (2015) to analyse the effect of dark trading on price discovery. Brogaard, Hendershott and Riordan (2014) use the initial IS model to analyse the contribution of HFT to price discovery. Additional research uses the same models to undertake comparative analysis on price discovery between markets; typically where there are cross listed securities (Harris, Aitken and Di Marco, 2012; Harris and Di Marco, 2012).

2.1.4. Studies on Market Quality

While there are numerous studies on market efficiency (Bennett and Wei, 2006; Harris and DiMarco, 2012; Foley and Putniņš, 2015; Brogaard, Brennan, Korajczyk, McDonald and Vissing-Jorgensen, 2010; O'Hara and Ye, 2011; Anand, Tanggaard and Weaver, 2009), there are fewer studies that explore market quality as the joint measurement of market efficiency and integrity.

Harris, Aitken and Ji (2014) provide the most in depth analysis of market quality by employing a three stage least squares (3SLS) model incorporating both market integrity and market efficiency. This allows the authors to jointly measure the impact of market design changes on market quality, as well as accounting for the correlated impacts of efficiency and integrity. Harris, Aitken and Ji (2014) proxy for market fairness by measuring the incidence of end-of-day manipulation and measure market efficiency as the effective spread. A key finding in this research is that both market fairness and market efficiency impact one another. This indicates that measuring either fairness or efficiency in isolation may be erroneous. Research findings suggest that an increase in the incidence of end of day manipulation leads to an increase in spreads (decline in market efficiency) in the top seven liquidity deciles. Aitken, Aspris, Foley, Harris (2014) recreate this methodology in Europe and study the impact of algorithmic trading on both efficiency and fairness. They find that algorithmic trading has a net positive effect on market quality as a whole.

2.2. High Frequency Trading and Algorithmic Trading

The following sections document the recent literature into High Frequency Trading and Algorithmic trading. The majority of this literature studies the impact of these relatively new market participants on various aspects of market quality.

2.2.1. Measuring/Identifying HFT/AT

Estimates of the impact of HFT on the market vary widely. Empirical evidence regarding the size and impact of HFT liquidity provision is relatively sparse and relies primarily on noisy proxies. Studying the LSE, Jarnecic and Snape (2010) find that from their 2009 sample, 40-64% of trades include a HFT participant on at least one side. In the LSE's 2010 response to the Committee of European Securities Regulators (CESR) call for evidence, the LSE identified that during 2010 their internal estimates of HFT participation varied between 32-33% of total UK equities trading. In a similar submission, NYSE Euronext calculated that in the overall European market there was a 5% market share (as percentage of total traded value) for HFT participants in the first quarter of 2007, increasing to 23% of market share in the first quarter of 2010.

In the Brogaard, Brennan, Korajczyk, Macdonald and Vissing-Jorgensen (2010) analysis, which focuses on US equities, the author finds that 60-80% of all NASDAQ trades involve a HFT participant as either a liquidity provider or demander. Ito and Lyden (2012) construct an undisclosed measure of HFT participation for the largest 15 stocks traded on NASDAQ, NYSE and BATS in the US and show that HFT participates in one side of trades between 87-92% of the time. Hirschey (2013) uses a unique flagged set of HFT trades from the NASDAQ stock exchange; he reports that HFT account for approximately 40% of all NASDAQ trades in 2009.

Frino, Lepone and Mistry (2012) find that from 2006 to 2009, algorithmic trading had grown to account for over 55% of dollar volume on the Australian Securities Exchange (ASX). They find that algorithmic traders tend to increase participation when volume, volatility and depth is low and spreads are wide.

Estimates of HFT participation in the market vary significantly. However, researchers agree that HFT are able to extract value from the market through their superior access to, processing of and response to information. Several papers attempt to empirically estimate these profits, with results as diverse as the estimates on trading activity.

The first paper to address this question is Kearns, Kulesza, and Nevmyvaka (2010). The authors analyse a broad cross section of trades on all US markets and construct an upper bound for the maximum profits that can be attributed to HFT participants during 2008. They find this upper bound to be approximately US$21 billion. This estimate is roughly 10 times larger than the annual US$2.8 billion computed by Brogaard (2010) using his data set of HFT flagged trades. McInish and Upson (2012) conduct an empirical analysis of inter-market arbitrage using 2008 NASDAQ data. This arbitrage is made possible within the sub-second environment by the Flicker Quote Exception rule. They estimate that over US$233 million per year is transferred from slow retail traders to fast HFT participants in the US, on the basis of this phenomenon.

Several studies, including Brogaard (2010), Jarnecic and Snape (2010), and Ito and Lyden (2012), find that HFT participants are more active in larger stocks than smaller stocks, and are comparatively more active towards the end of the day. These results are indicative of the market making nature of the HFT participants, preferring to close the day with zero inventory positions, where possible.

To date, very few event studies exist in relation to HFT participation. Kirilenko, Kyle, Samadi and Tuzun (2014) provide the most recognised study in this regard, dealing with HFT and utilising audit trail data for the E-mini S&P 500 futures contracts on the day of the "Flash Crash" (6 May 2010). This data is used to identify HFT participants, relying on trade frequency and size to determine that 16 accounts out of a total of 15,422 belong to HFT participants on that day. By analysing a variety of metrics including holding periods, inventories and trade directions, they find that HFT participants, after providing some initial liquidity to fundamental sellers, contributed to the significant selling pressure that precipitated the flash crash. While Kirilenko, Kyle, Samadi and Tuzun (2014) do not go so far as to blame this incident on HFT participants, they do determine that HFT presence in the market exacerbated the volatility during this period of extreme market stress.

The above evidence stands in contrast to an experiment using flagged HFT data conducted by Brogaard (2010). In this study, the author examines the supply of liquidity by HFT participants during the four days in September 2008, in which the news regarding the collapse of Lehman brothers became public. Brogaard (2010) finds that HFT participants did not significantly increase their demand for liquidity, but did significantly increase their liquidity supply. This analysis, and an examination of HFT participation following earnings announcements with similar findings, leads Brogaard (2010) to conclude that HFT participants do not remove liquidity from the market, even in times of severe market stress. Additionally, Hendershott and Riordan (2013) use a unique set of trades from Deutsche Boerse Xetra, which identifies automated trading, and find that around 50% of all volume in the top tier securities are automated.

2.2.2. HFT/AT and Market Efficiency / Integrity

Cvitanic and Kirilenko (2010) suggest that the introduction of HFT participants will reduce the average trade value and move the distribution of prices closer to the mean, resulting in reduced volatility. Their theoretical model simulates an electronic limit order book in which both high-frequency market makers and low-frequency (human) traders participate. The findings indicate that the time between trades and the volume of each trade decreases in proportion to the participation of human traders. These predictions of reduced volatility, trade value and volume are empirically supported by the work of Jarnecic and Snape (2010). Using a proprietary data set from the London Stock Exchange (LSE), participants are separated into high frequency traders, investment banks, large institutions, small institutions, retail brokers, and market makers. The results of this study indicate that HFT participants supply and demand liquidity in almost even proportions, and that HFT activity is more likely to dampen than increase volatility.

Jovanovic and Menkveld (2015) do not assume a 'classical' Kyle-style market maker model in which the "middlemen" – HFT or Algorithmic Trading (AT) participants – are uninformed. Rather, they assume that HFT/AT participants are both faster and more informed than their counterparts. Under these assumptions, HFT/AT participants may increase efficiency through reduced spreads. This increased efficiency is due to HFT/AT updating their information set faster than traditional market makers (Brogaard, Hendershott and Riordan, 2014), thereby increasing their ability to avoid adverse selection. In Jovanovic and Menkveld (2015), an empirical analysis of 77 trading days for Dutch index stocks between 2007 and 2008 is conducted. HFT/AT participants in their sample are found to be better informed about news than the average trader. Jovanovic and Menkveld (2015) warn that the ability of HFT participants to update their information set faster than human traders may itself reduce the willingness of human participants to enter the market. This reduction in liquidity could widen spreads and thereby reduce efficiency.

Another potential negative effect of HFT/AT is outlined by McInish and Upson (2012) who examine the SEC's Flicker Quote Exception rule. This rule allows inter-market trade-throughs to occur, as long as the new price has been displayed for less than one second. HFT/AT participants are able to profit from their knowledge of the true state of the market by "picking off" orders from slower human liquidity demanders in the sub-second environment at prices inferior to the national best bid and offer (NBBO).

Hendershott, Jones and Menkveld (2011) use the volume of message traffic, normalised by the number of trades, as a proxy for the level of HFT/AT participation. Their 5-year sample period straddles the staggered introduction of the automation of quote dissemination on the NYSE in 2003. Their findings indicate that algorithmic trading significantly reduces both quoted and effective spreads as a result of a decline in adverse selection and an increase in the price discovery associated with the trades. Consistent with the results of McInish and Upson (2012), Hendershott, Jones and Menkveld (2011) find that the introduction of algorithmic trading increases profits for liquidity providers by increasing the realised spread.

Evidence gleaned directly from HFT/AT firms supports different conclusions about the effect of secular growth in HFT/AT. Brogaard (2010) uses a data set provided by NASDAQ that directly identifies 26 HFT traders over various periods during 2008, 2009 and 2010. Each trading day in his sample period is divided into 15-minute segments, allowing the author to separately analyse periods of both high and low volatility. The study finds that when prices fluctuate more than normal, HFT participants supply more liquidity and demand less liquidity, compared to the average participant. Brogaard (2010) concludes that average HFT participants are unlikely to exacerbate volatility.

Hasbrouck and Saar (2013) analyse the trading activity on the NASDAQ for one month each during both 2007 and 2008, which unlike studies such as Groth (2011) and Jarnecic and Snape (2010), allows them to analyse HFT participation during a period of high market stress. Their findings indicate that in 10-minute intervals, increased HFT participation increases quoted depth, reduces quoted spreads, and reduces volatility. They apply a two-stage simultaneous equation model for each liquidity metric, allowing for a potentially endogenous relationship between HFT participation and volatility, depth and spreads.

Cumming, Zhan and Aitken (2013) look at the measure of end-of-day dislocation, as a proxy for market manipulation, in conjunction with variations in HFT trading across several markets. They utilise measures of HFT from order- and cancel-to-trade ratios coupled with the introduction of co-location across markets to estimate the effect of HFT on market integrity. They find that HFT is a strong estimator of the incidence of end-of day manipulation; HFT can significantly decrease the incidence by as much as 70%. Frino and Lepone (2012) find similar results when looking at the LSE and Euronext Paris; they find that HFT significantly reduces the incidence of end of day dislocation.

2.2.3. HFT/AT and Price Discovery

Brogaard (2010) and Brogaard, Hendershott, and Riordan (2014) report that the price discovery contribution of HFT participants is greater than that of the non-HFT participants. HFT marketable limit orders trade in the direction of permanent stochastic trends and against transitory pricing errors, on both average trading days and in periods of market stress. By looking at the depth and time spent by each participant type at the NBBO, HFT participants spend more time at the NBBO but provide less depth than their non-HFT counterparts. Brogaard (2010) additionally finds that HFT participants are better able to avoid trading with insiders than are non-HFT participants, consistent with the theoretical findings of Jovanovic and Menkveld (2015).

Brogaard, Hendershott, and Riordan (2014) find that HFT liquidity supply with non-marketable limit orders is positively correlated with transitory pricing errors, echoing the hypothesis that end-of-day manipulation increases with increased HFT-based fragmentation into the dark. This is consistent with the findings of Hendershott and Riordan (2013) who find that flagged automated trades on Deutsche Boerse Xetra drive prices towards efficiency, with no evidence that they exacerbate volatility. Chaboud, Chiquoine, Hjalmarsson and Vega (2014) use similarly flagged data for the Foreign Exchange (FX) market. They find that automated trades increase liquidity provision and drive prices towards efficiency.

O'Hara and Ye (2011) look at odd-lot trading from the NASDAQ flagged HGT data used by Hendershott and Riordan (2013). They find that odd-lots account for 40% of price discovery, and that HFT are more likely than other participants to trade in odd-lots. Gerig (2015) uses the flagged NASDAQ data to show that HFT can be attributed with creating more efficient prices by improving price synchronisation which reduces arbitrage opportunities. Hagströmer and Nordén (2013) utilise flagged HFT strategy data from NASDAQ OMX Stokholm. They find that both liquidity providing and opportunistic HFT decrease intraday volatility.

2.2.4. HFT/AT as Liquidity Providers

Literature on market makers in the US begins with the New York Stock Exchange (NYSE) "specialists" who made markets on the floor of the NYSE. NYSE specialists were offered a unique information advantage by having access to the state of the limit order book and order flow, allowing them to control inventory in anticipation of trading and having superior information to help predict price movements. In return, specialists were required to maintain 'acceptable' bid-ask spread in times of stress. This informational advantage is attributed as the primary source of NYSE specialist's profits by Hasbrouck and Sofianos (1993). Madhavan and Smidt (1993) utilise a proprietary data set to show that specialists operate in more than simply a market making role, and hold long-term positions in stocks as an active investor. To complement profits made by enhanced access to information, Anand, Tanggaard and Weaver (2009) show that designated market makers are compensated based on contractual obligations outlined in a liquidity agreement with the listed firm.

In comparison to the previous definitions of HFT and the literature surrounding specialists (and designated market makers), there are numerous parallels. Both utilise a combination of market making strategies and anticipatory trading strategies. Critics have argued that HFT trade using unfair advantages in order book information, which is akin to a specialist view of the order book. However, the HFT informational advantage is available to all participants if they choose to purchase and process the information, while a specialist is given monopolistic access to a more complete view of the order book, compared to that available to HFT.

Groth (2011) analyses trading in German stocks on the Deutsche Boerse Xetra. Due to a rebate scheme applied to algorithmic traders, a flag is applied to every trade arising from a human or algorithmic source. He uses four trading days during 2007 to analyse the conduct of HFT participants in times of high and low volatility during 5- minute intraday intervals. His findings indicate that HFT participants do not change their trading behaviour conditional on the volatility in the market, and that they are as active in periods of high liquidity as they are in periods of low liquidity. Groth (2011) also finds that there is no evidence of market withdrawal by HFT participants during periods of increased volatility.

One of the more unique proxies for HFT used in the literature is described by Hasbrouck and Saar (2013). The authors use trade and quote data in the millisecond environment to identify strategic runs of trades, observing interactions between traders separated by as little as 3-5 milliseconds. These strategic runs are used to create a proxy for the level of HFT participation.

2.3. Fragmentation

The following sections document the recent literature into fragmentation; a key concern of which is its impact on market quality. There is a trade off between fragmentation's costs in terms of market efficiency, and its believed impact on market transparency.. The fragmentation of trading between marketplaces is a central concern of US equity market design and regulatory focus (Colby and Sirri, 2010). Today in the US, stock investors can trade on approximately 300 different venues, including thirteen registered exchanges, 40 plus Alternative Trading Systems (ATSs), and numerous broker-dealer internalisation platforms. This fragmentation encourages a diversity of different market structures and trading mechanisms designed to appeal to the specific trading needs of different segments of market participants. The recent proliferation of venues partially outside of the requirements of the National Market System (NMS) in the US, and the Markets in Financial Instruments Directive (MiFID) in Europe, invites an examination of the effects of this trend on market quality.

There are three main differentiating features separating fully participating US market centres, which are referred to as lit markets, and those partially exempt from the NMS requirements, which are referred to as dark venues. First, dark venues are currently not subject to fair access requirements and thus can prohibit or limit access to their services (see Reg ATS Rule 301(b)(5)). Second, dark venues provide limited or no pre-trade transparency in that they are not required to distribute their best-priced bids and offers through the NMS consolidated quotation data. Finally, executions by dark venues occur at finer price increments than lit markets. Since dark venues are also not required to disclose their market structures to the public (see Reg ATS Rule 301(b)(6), SEC Rule 3a1-1, and SEC Concept Release 2010), few details are known about how the operations of specific dark venues differ.

2.3.1. Fragmentation and Market Efficiency / Integrity

When assessing the relationship between dark fragmentation and market quality, it is especially important to recognise the impact of adverse selection risk on trading behaviour. Previous studies demonstrate that the trading of diversely informed traders discourages discretionary uninformed traders (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990; Wang, 1994). The arrival of new information generates more informed trading on the market, temporarily increasing stock price volatility and raising effective spreads. Intuitively, investors and traders who do not possess this new information, or only trade for liquidity reasons, will strategically avoid trading in such periods. Because there is a higher concentration of uninformed traders on dark venues relative to lit markets, the level of adverse selection risk decreases with the proportion of trades executed in the dark. Thus, the negative relationship between dark trading and spreads reported in earlier studies, including O'Hara and Ye (2011), may be due to reductions in the dark venue adverse selection risk relative to the same underlying security traded in lit markets.

Given the importance and rapid growth of dark pools as an alternative trading system, there is a growing body of literature that examines the relationship between dark pools and market quality and efficiency. For example, Ye (2011) uses an extension of Kyle's 1985 model to analyse the strategic decisions of a single informed trader who splits trading interest between a dealer market and a dark pool. As the information advantage increases, the insider optimally submits a smaller order in the lit market and a larger order in the dark pool. This is in conflict with the model by Zhu (2013) which relies on the intuition that informed traders will likely indicate trading interest in the same direction and therefore have a lower execution probability in the dark. Zhu's model therefore predicts impatient informed traders would seek execution in the lit market.

Weaver (2014) estimates the relationship between the bid-ask spread quoted for NYSE stocks and the portion of trading executed off-market. Higher off-market trading raises the spread. This finding supports the fragmentation hypothesis for US markets and implies that trading in off-market venues such as dark pools impairs the liquidity of lit markets. Degryse, Achter and Wuyts (2008) also find that dark fragmentation widens quoted and effective spreads, as well as increasing price impact.

Boulatov and George (2013) find that informed traders choose to post liquidity in the dark, arguing that they choose not to submit aggressive lit limit orders that would reveal their information. These results are consistent with Bloomfield, O'Hara and Saar (2015) who find less depth in the lit market, but an overall increase in depth for both markets combined. Further, empirical evidence from Buti, Rindi and Werner (2011) and Foley and Putniņš (2015) find that dark trading reduces both the cost of trading and volatility, and increases depth.

Nimalendran and Ray (2014) investigate a unique sample of trades from a Dark Crossing Network. This allows them to look closely at the information content of trades in the dark, but concentrate on short term returns (maximum 2 hours) which is on a similar scale to intra-day price discovery. They find that crossing network trades are informative as evidenced by positive returns in conjunction with a subsequent widening of bid-ask spreads. Nimalendran and Ray (2014) hypothesise that informed traders utilise both crossing networks and lit venues to capture the value of fleeting technical information.

Exemption from the fair access requirement allows dark venues to segment order flow, and without the requirement to display firm quotations, dark venues can price discriminate by selectively improving the price shown on lit markets. Hatheway, Kwan and Zheng (2014) show that dark venues successfully "peel-off" uninformed order flow from the lit markets by offering sub-penny price improvement to particular customers and types of orders. This leaves lit market liquidity providers with an adversely selected order flow, and therefore a need for higher spreads to protect against picking off risk. Hatheway, Kwan and Zheng (2014) find that adverse selection risk on dark venues is 60% to 80% less than that on lit markets, while the average realised spreads for liquidity providers on lit markets is estimated as only 40% of those on dark venues. Similar cream-skimming has been documented previously for regional exchanges in their competition with the primary markets (Easley, Kiefer and O'Hara, 1996; Bessembinder and Kaufman, 1997).

Sometimes dark venues operate in parallel to traditional upstairs markets as both feature limited pre-trade transparency, uncertainty surrounding trade execution, and customer screening based on the likelihood of information (Seppi, 1990; Madhavan and Cheng, 1997; Smith, Turnbull and White, 2001; Booth, Lin, Martikainen and Tse, 2002). However, a significant difference is that traditional upstairs markets mainly execute block trades, while the average trade size on dark venues is now less than 250 shares (Hatheway, Kwan and Zheng, 2014). Hence, all subsequent analysis is considered to address non-block trades.

Madhavan (1995) models the pricing behaviour of downstairs markets with heterogeneous information, and shows that information fragmentation leads to higher volatility, wider spreads and less efficient mid-quote prices. Bolton, Santos and Scheinkman (2016) model the impact of informed dealers cream-skimming the transparent markets and predict that in equilibrium, cream-skimming will undermine the lit exchanges and result in transaction cost inefficiencies (i.e., higher effective spreads).

In addition, dark venues offer price improvement to serve as a partial payment to brokers for routing uninformed liquidity to these markets. Chung, Chuwonganant and McCormick (2006) find that, in general, internalisation can be used to reduce the price impact to dealers. Chung, Chuwonganant and McCormick (2006) find that dealers still suffer the same market price impact through internalisation, but at reduced size. Since market markers use quotations to compete for liquidity (Bessembinder 2003), the practice of order preferencing creates disincentives for posting competitive quotes (Huang and Stoll, 2001). Hence, dark venue order preferencing also increases effective spreads.

2.3.2. Fragmentation and Market Price Discovery

Many regulators and stock exchanges have expressed concern that the migration of trading volume to venues with little or no pre-trade transparency may harm price discovery. For example, in October 2009, NASDAQ's Chief Economist Frank Hatheway stated in a congressional testimony that dark pools "undermine public price discovery by shifting liquidity away from the lit markets".

The International Organisation of Securities Commissions of Canada (IOSCO), in a 2011 report, also stated that "the development of dark pools and use of dark orders could inhibit price discovery if orders that otherwise might have been publicly displayed become dark". Consequently, on 13 April 2012, IOSCO announced new "price improvement rules" that require (i) priority be given to displayed orders over non-displayed orders on the same venue; (ii) dark trades for

5,000 shares or less must give the active participant at least one tick price improvement (one-half tick if the spread is one tick); and (iii) a minimum trade size on passive dark orders may be imposed if deemed necessary.

Eun and Sabherwal (2003) study the price discovery process of Canadian securities cross-listed on the US market and find that they are highly co-integrated. They find that the Canadian share of price discovery ranges from 0.2% to 98.2%, averaging 38.1%. In controlling for the origin of price discovery, they find the share of trading and the ratio of informative trades increase price discovery, while bid-ask spreads are inversely proportional to price discovery.

Comerton-Forde and Putniņš (2015) study price discovery in dark trading on the Australian stock exchange. They look at the effect of dark trading on the informational efficiency of prices in the lit market, as well as the changes in price discovery in response to a greater share of volume being executed in the dark. Their study finds that informational efficiency is negatively related to the share of volume executed in the dark, suggesting that dark trading harms aggregate price discovery.

2.4. Tick Sizes

Previous research examines the possibility of managing stock prices through stock splits to achieve a beneficial tick size. Angel (1997) suggests that non-US companies can strategically manage their relative spread through stock splits, when tick size is based on a price grid. In this manner, an optimal tick size must trade-off both the incentive that a larger relative tick size provides for market makers and the cost transferred to investors. While tick size sets the binding spread constraint, it also influences the speed of the trading process and the cost of negotiation (Harris, 1993; Angel, 1997); having less possible tick increments will reduce this cost.

Perhaps more pertinent to the current market structure dominated by algorithmic trading is the time priority constraint given by discrete tick sizes. Huang and Stoll (1994) believe that a discrete tick size gives meaning to time priority so that traders cannot free ride on market maker quotes by jumping ahead with non-meaningful price improvement. This is reinforced by Harris (1996) who finds that the minimum tick size affects order exposure. He explains that traders who display orders face step-ahead risk (the risk of being front run). A wider tick size increases the cost of stepping ahead and may reduce the risk of being front-run for displayed orders. His study uses transaction data from the Paris Bourse and the Toronto Stock Exchange to compare order exposure across different tick sizes. He finds that traders display more size when the tick is large and when intraday volatility is small.

O'Hara and Ye (2011) show that tick size is endogenous in explaining market quality across different exchanges. They find that a minimum tick size is required to enforce time priority such that an order cannot 'cheaply' step ahead of another limit order or the dealer quote.

The introduction of decimalisation greatly reduced spreads (both effective and quoted) (Chakravarty, Harris and Wood ,2001; Bacidore, Battalio and Jennings, 2003; Bessembinder, 2003). Bessembinder (2003) separates his study into small, middle and large capitalisation stocks with a matched sample, before and after decimalisation. He finds significant and robust changes across market capitalisation, except in the smallest capitalisation group. Further, these studies find that the decline in effective spreads is greater for smaller trades. Chakravarty, Harris and Wood (2001) focus on institutional trading and do not find a significant decline in effective spreads for large trades. However, Chakravarty, Panchapagesan,and Wood (2005), and Werner (2003), find that institutional transaction costs decline. This is not entirely surprising as studies that examine depth around decimalisation find that the best quoted prices decline in size available (Chakravary, Harris and Wood, 2001; Bessembinder, 2003). Coughenour and Harris (2004)find that NYSE specialists participate more after decimalisation, but Ronen and Weaver (2001) find that on the American Stock Exchange (AMEX) specialists do not experience any change in profitability.

In terms of stocks splits, similar conclusions are drawn surrounding the price behaviour of such events in the microstructure literature. In many markets where the tick size is consistent across price levels, a stock split is similar to a change in tick size. As the stock price of a company changes the relative tick size (tick size per unit price) will fluctuate. In terms of stocks splits, similar conclusions have been drawn surrounding the price behavior of such events in the microstructure literature. Stock splits are corporate events initiated by listed companies that have the effect of increasing the number of shares on issue without changing a firm's market capitalization - but reducing its price level. Angel (1997) points out that such an action increases the relative tick size, inflating the floor value of the bid-ask spread. Higher spreads give liquidity providers an incentive to make markets, and leads to higher depth for the stock. Schultz (2000) and Kadapakkam, Krishnamurthy, and Tse (2005) also observe an increase in small buy orders after stock splits and an increase in transaction costs following stock splits. One hypothesis is that brokers more actively promote stocks after split event. Desai et al. (1998) finds a significant increase in volatility and number of trades following stock splits. One hypothesis is that brokers more actively promote stocks after the split event. Desai, Nimalendran and Venkataraman (1998) find a significant increase in volatility and number of trades following stock splits.

2.4.1. Effect of Tick Size Changes around the World

Below is a summary of various papers that examine tick size changes in different markets throughout the world. Each paper includes a brief summary of the findings.

- Ahn, Cao and Choe (1998) studies decimalisation on the Toronto Stock Exchange that are cross listed on the AMEX, NASDAQ and NYSE markets. They find that a reduction in tick reduces the spread on TSX. For NASDAQ this effect is mirrored to a lesser extent; but on AMEX and NYSE they found no change.
- Ahn, Cai, Chan and Hamao (2007) studies a reduction of tick size in some stocks on the Tokyo Stock Exchange. They find a decrease in quoted spreads and an increase in order competitiveness.
- Lau and McInish (1995) study a reduction of tick size in some stocks on the Singapore Stock Exchange. They find a decrease in transaction costs measured as bid-ask spreads.
- Goldstein and Kavajecz (2000) study the move from eights to sixteenths on the New York Stock Exchange. They find a reduction in transaction costs measured as bid-ask spread. They also find a reduction in limit order depth.

- Aitken and Comerton-Forde (2005) study a reduction in tick size for low priced stocks on the Australian Stock Exchange. They find that lower tick sizes improve liquidity, but it is localised to high trading volume.
- Anderson and Peng (2013) study a reduction in a small sample of dual listed securities on the New Zealand Stock Exchange. Similar to Aitken and Comerton-Forde (2005), they find improvements in liquidity that are concentrated in liquid securities.

Prior research on tick sizes shows strong and unanimous evidence that smaller tick sizes improve liquidity. However, there is some evidence that the effect is localised to already liquid securities and that it comes at the cost of limit order depth.

2.4.2. Stock Splits

In terms of stocks splits, similar conclusions have been drawn surrounding the price behavior of such events in the microstructure literature. Stock splits are corporate events initiated by listed companies that have the effect of increasing the number of shares on issue without changing a firm's market capitalisation - but reducing its price level. Angel (1997) points out that such an action increases the relative tick size, inflating the floor value of the bid-ask spread. Higher spreads give liquidity providers an incentive to make markets and leads to higher depth for the stock. Schultz (2000) and Kadapakkam, Krishnamurthy, and Tse (2005) who also observes an increase in small buy orders after stock splits and an increase in transaction costs following stock splits. One hypothesis is that brokers more actively promote stocks after split event. Desai et al. (1998) finds a significant increase in volatility and number of trades following stock splits.

2.5. Hypothesis Development

This section uses the literature reviewed in the previous three sections to develop several hypotheses that are tested in this dissertation. The hypotheses are discussed in the order that they are explored in the thesis.

2.5.1. Tick Size, Electronic Liquidity Providers and Market Quality

Several papers have researched the effect of tick sizes on transaction costs (Goldstein and Kavajecz, 2000; Lau and McInish, 1995; Ahn, Cai, Chan and Hamao, 2007; Angel 1997; Huang and Stoll, 2001; Aitken and Comerton-Forde, 2005). However, each of these papers pools together securities without separating them by proximity to the tick constraint. While tick sizes can change the minimum quoted size, there becomes a limit where the tick size may force the quoted spread to become wider. The hypothesis formulated below addresses these issues by separating tick sizes into three categories where firms either become over constrained (quoted spread forced wider by tick change), become constrained (are moved to the constraint limit) or non-constrained (are not near or at the limit).

Hypothesis $_{3,1}$: Firms that become over constrained have increased transaction costs

The next hypothesis relates more to simple market mechanics than to a specific theory. If the quoted spread is already at the minimum tick size allowed, then a split will cause the minimum relative tick size to increase (since relative tick = tick size / price; and price is being reduced). This will increase the quoted spread. This is also likely to increase the effective and realised spreads. It is possible that the effective and realised spreads do not change; for this to happen there would have to be an increase in the mid-point to offset the increase in spread. The study conducted in chapter three finds some increase in midpoint activity, but not enough to completely negate the widening spread. Realised spreads could potentially stay the same, but this would require a significant decrease in volatility that is not demonstrated by the research.

Similarly, depth at the inside will increase as firms become over-constrained. This can happen for several reasons; the mechanical reason is that the depth at or near the inside (for example the depth within 1of the midpoint) is spread over fewer price levels. It could also be the case that, since the price level moves less often, traders must compete more for price priority and queue position.

In stocks that are already tick constrained pre-split, no prediction is made about the level of Electronic Liquidity Providers (ELP) in the market. While an increase in relative tick size offers a greater pay-off, the fact that the spread is already tick constrained may mean that the stock has already reached saturation of ELP. That is to say, that ELP are already being provided high enough returns for their service.

> **Hypothesis$_{3,2}$** : Firms that split into the proximity of tick constrained regimes will see improvements in transaction costs and increased competition at the NBBO, as well as more ELP.

The principal hypothesis is that by widening the relative tick size, firms can increase the liquidity provision in their stock. This is achieved by increasing the dollar amount required to step ahead of displayed liquidity. Huang and Stoll (1994) document this effect, and suggest that wider tick sizes reduce non-meaningful price improvement. By reducing the ability of traders to free-ride on market maker quotes, it is assumed that they will more actively participate in liquidity provision. Harris (1996) reinforces this hypothesis, finding that minimum tick sizes dictate order exposure by reducing step-ahead risk. This is because minimum tick sizes increase the cost of stepping ahead, the quote has a higher execution probability and thus it becomes more worthwhile for market makers to participate.

It is anticipated that the largest effect on market quality and increase in ELP will be seen in firms that split their stock such that the quoted spread approaches the minimum tick constraint. By doing so, price precedence is established to the maximum extent possible, particularly when the quoted spread meets the tick constraint.[3] This leads to the final hypothesis for the study in chapter three:

> **Hypothesis$_{3,3}$** : Firms that split and are not in proximity of tick constrained regimes will see improvements in transaction costs and ELP trading which is proportional to the relative increase in size of distance between quotable price levels

---

[3] It is still possible for off-exchange venues to trade at sub-penny increments, and to trade at the midpoint

2.5.2. Price Discovery and Dark Trading

Prior research into the information content of dark trades shows that, in the case of the Australian market, dark trades provide little in the way of price discovery (Comerton-Forde and Putniņš, 2015). Chapter four of this dissertation establishes whether this is also the case in the Canadian market, or whether there is a significantly different trend. Following past literature, it is hypothesised that this Canadian study will yield similar results.

Hypothesis$_{4,1}$: Dark Trading provides significantly less information that lit trading in Canadian equity markets.

To date there are no studies into the effect of regulation of dark trading on price discovery. Nimalendran and Ray (2014) find that informed traders utilise dark crossing networks to capture the value of fleeting technical information. By increasing the cost of dark trading or limiting the ability of informed traders to utilise dark pools, the overall information in the dark will be reduced.

Hypothesis$_{4,2}$: Regulation which reduces dark trading will reduce the information content of trading in the dark.

Jain, Jain and McInish (2012) study the effect of order book quality measures, which contribute to price discovery in Japan's equity market. Often, market microstructure research focuses on measures such as spreads, which capture the liquidity at the top of the order book. While these measures are found to adequately represent costs to small orders as round trip transactions, they do not take into account how a large marketable order would impact the order book, potentially at multiple price levels. Increased values in any of the following measures indicate a greater resiliency in response to order book shocks. This leads to the following hypothesis:

Hypothesis$_{4,3}$: Controlling for depth of order book measures will significantly alter event study results

2.5.3. Joint impact of Fragmentation and Algorithmic Trading on Market Quality

For the final study conducted in chapter five of this thesis, the first hypothesis is that dark trading increases the incidence of successful manipulation events by removing liquidity from the lit market, making it easier to move prices and then profit by closing positions at lower price impact in the dark. This mechanism is laid out by Klock, Schied and Sun (2011), who show in an Almgren-Chriss model that dark trading's differences in cross-venue impact create the opportunity for trade-based manipulation. It is suggested that fragmentation in lit venues will cause a similar degradation of market quality because of varying levels of price impact. However, it is also anticipated that the added transparency in lit markets will largely mitigate this effect.

Hypothesis$_{5,1}$: Dark Trading will reduce market integrity

Prior literature shows that algorithmic trading reduces the cost of trading for other participants by reducing the bid ask spread. Hirschey (2013) shows that HFT can accurately predict future buying and selling pressure, while Brogaard, Hendershott and Riordan (2014) find that HFT have significantly better price information. These findings indicate that HFT are able to better predict future price movements than other participants. Trade based manipulation is in essence trading behaviour that pushes prices away from their accurate valuation. This leads to the final hypothesis:

> **Hypothesis$_{5,2}$** : Algorithmic Trading will improve market integrity and efficiency

This hypothesis reflects in part the research by Aitken, Harris, Aspris and Foley (2014) who hypothesise that HFT/AT modelling of the 'state of the market' information renders trade-based manipulation less profitable, even when manipulators execute against uninformed counterparties. While these hypotheses appear distinct, the prior linkages to transaction costs for both algorithmic trading and fragmentation are causally entangled. By utilizing a 2SLS design these hypotheses can be jointly assessed.

2.6. Summary

This chapter reviews the literature on market quality as well as recent studies on algorithmic trading and fragmentation. It develops several hypotheses that are tested in the following chapters. Chapter Three examines the effect of regulation on dark trading, and the overall level of dark trading to the relative price discovery of a market. Chapter Four examines the effect of a change in tick size to the liquidity provided by HFT and ELP, as well as its impact on market efficiency. Chapter Five examines the joint impact of algorithmic trading and fragmentation on market quality. The findings of these three studies are then summarised in Chapter Six.

3. Tick Size, Electronic Liquidity Providers and Market Quality

3.1. Introduction

This chapter examines the effect that changes in relative tick sizes can have on trading behaviour. This examination allows for the undertaking of a causal research study on the effect of High Frequency Traders (HFT; and a subset of market making HFT: Electronic Liquidity Providers (ELP)). Message traffic has previously been associated with nefarious trading strategies and HFT strategies (Cumming, Zhan, and Aitken, 2013b). The findings of this paper demonstrate that firms across the spectrum of market capitalisation can decrease message traffic by splitting their shares and widening the relative tick size.

As noted at the outset of this thesis, the improvement in trading behaviour that results from a stock split may come at the cost of higher spreads in the case of liquid securities, as the quoted spread is 'pushed open'. For unconstrained stocks, a higher relative tick size results in a tightening of spreads (quoted, effective and realised). This appears to be of substantial benefit to less liquid securities, allowing for a simultaneous increase in the quality of the trading behaviour in that stock, while decreasing transaction costs. This is not the case for liquid securities that are already tick constrained. However, stock splits do offer one avenue for managers to reduce message traffic in their company, without the need for regulatory intervention.

The Securities and Exchange Commission (SEC) has been discussing, researching and regulating tick sizes since the early 1990s. This topic has been of interest to the SEC since before the implementation of decimalisation in April 2001. Prior to decimalisation, the US market traded in fractional increments. In

1992 the American Stock Exchange reduced the tick size from 1/8th to 1/16th for stocks between $0.25 and $5. This was expanded to all stocks above $0.25 in 1997; subsequently NASDAQ and NYSE followed that year. These changes catalysed discussion on, and introduction of, a bill to the US House of Representatives, supporting a move towards decimal pricing. The result of this bill was a phase-in plan beginning in September 2000 and completed in April 2001. Decimalisation was followed by a widely reported drop in quoted spreads (Bacidore, Battalio and Jennings, 2003; Bessembinder, 2003; Chakravarty, Harris and Wood, 2001). However, given the contemporaneous increases in market competition and new technology, it is unclear whether the drop was a direct result of decimalisation. In 2014, the SEC proposed a step backward from decimalisation and is considering widening the tick size in small cap stocks.

Furthermore, this research will extend the work of Chordia, Roll and Subrahamyan (2008) who use NYSE trading from 1993 to 2002 who measure the changes in measures of informational efficiency across tick sizes. While the following research is primarily interested with market efficiency as a measure of cost; the measure of realised spread translates to their measures of return predictability in the sense of measuring it as price impact. They find that variance ratios increased but autocorrelations declined (particularly for smaller firms) as the minimum tick size decreased. They report that the change increase in price autocorrellation impacts the market makers ability to quote by increasing their predicatbilty and ability to accommodate order imbalances. While this studiy does not measure return predictability , I find a similar effect related to the tick size as a measure of market makers ability to be compensated for adverse selection. As the tick size increases there is greater dollar depth quoted; reflecting an increase in larger order imbalances that can be absorbed by a market maker.

3.2. Methodology

3.2.1. Defining Electronic Liquidity Providers

For the purposes of this study, Electronic Liquidity Providers (ELPs) are defined as a subset of HFT who concentrate their activity in the provision of liquidity through utilising advanced algorithmic trading strategies. To begin, the characteristics of HFTs stated in the SEC Concept Release on Equity Market Structure are outlined:[4]

- Proprietary trading firms/professional traders acting in a proprietary capacity that generate a large number of trades on a daily basis
- Use of extraordinarily high speed and sophisticated programs for generating, routing and executing orders
- Use of co-location services and individual data feeds offered by exchanges and others to minimise network and other latencies
- Very short time-frames for establishing and liquidating positions
- Submission of numerous orders that are cancelled shortly after submission
- Ending the trading day in as close to a flat position as possible

To extend these characteristics to the liquidity providing subset, it is suggested that ELPs must:

[4] Securities Exchange Act Release No. 34-61358, 75 FR 3594, 3606 (January 21, 2010)

- Be a liquidity provider for the majority of executions (i.e., capture the liquidity rebate)
- Must be co-located, and primarily execute trades through co-located order types (i.e., orders that directly emanate from co-located ports, not a combination of routable and port driven orders)
- Must be consistently competing to set or join the National Best Bid and Offer (NBBO) to provide liquidity

The SEC outlines four broad types of short-term trading strategies:

- Passive market making
- Arbitrage
- Structural
- Directional

This chapter focuses on the first strategy type listed above, passive market making, but cannot rule out the likely scenario where the flagged firms are also participating in arbitrage, structural and directional strategies concurrently. Due to the fragmented market structure in the US, several of these indicators are intractable without access to the complete market order book (which would comprise of the limit order book of 13 exchanges, if off-exchange venues are ignored). One of the strongest indicators of short-term strategies is to close the trading day flat (or with limited exposure to overnight movements). This is a weak indicator when viewing a single venue as it is impossible to know what a participant's strategy and position is on other markets. A participant who ends the day with a seemingly large position may have offloaded this inventory on another marketplace. This extends to the SEC characteristic of very short time-frames for establishing and liquidating positions; some participants may be seen to be reversing their positions in short intervals, yet others may look to be building positions which are in fact being off-set on another venue.

This situation makes it technically difficult to isolate arbitrage, structural and directional strategies. For this study the primary interest is liquidity provision where liquidity/rebate flags can be utilised as a primary indicator of passive market making. Below is a revised list of characteristics used to isolate ELPs:

- Proprietary trading firms/professional traders acting in a proprietary capacity that generate a large number of trades on a daily basis (often stated by the firm in promotional material, or company mission statement; otherwise established through industry knowledge).
- Use of extraordinarily high speed and sophisticated programs for generating, routing and executing orders (evidenced by order submission through co-located servers and consistent short duration to execution peaks).
- Use of co-location services and individual data feeds offered by exchanges and others to minimise network and other latencies (evidenced by utilising order types which require detailed information on national state of the market i.e., Inter-market Sweep Orders).
- Submission of numerous orders that are cancelled shortly after submission (evidenced by high order to trade ratios).

- Liquidity provider status for the majority of executions (evidenced by a majority of trades capturing a rebate on execution).[5]
- Competitively setting and/or joining the NBBO (evidenced by percentage of orders submitted at or improving the current NBBO).

3.2.2. Measures of Liquidity

The quoted, effective and realised spreads are calculated from the consolidated best bid and offer and measured in basis points relative to the mid-quote. Quoted spreads are measured as the time-weighted average of quoted spreads throughout the day — a daily average round trip transaction cost of immediately reversing a trade.

$$Quoted\ Spread = [(Ask - Bid)/m] * 10^4 \tag{3-1}$$

Effective and realised spreads take into account the cost of trading of individual trades benchmarked to the midpoint. Effective spreads measure the transaction cost of a marketable order relative to the current midpoint, while realised spreads measure the profit of the liquidity provider relative to the prevailing midquote at *t+x* minutes.

$$Effective\ Spread = 2q[(p_t - m_t)/m_t] * 10^4 \tag{3-2}$$

[5] This sample does not require a 100% liquidity provision as market makers are likely to trade aggressively if they have a requirement to off-load inventory

$$Realized\ Spread = 2q[(p_t - m_{t+x})/m_{t+x}] * 10^4 \tag{3-3}$$

In these equations, q indicates the direction of the trade obtained using the Lee and Ready (1991) algorithm (+1 for buyer initiated, and -1 for seller initiated). The price p_t is measured at trade time, for effective spread the midpoint at the time of trade, m_t, and x minutes post trade time, m_{t+x}, for realised spreads. Both measures are weighted by the trade volume across all trades during regular hours.

The dollar depth is calculated as the time weighted dollar depth available at the best bid and offer. Intraday volatility is measured as the standard deviation and autocorrelation of the midpoint returns at various time intervals for each trading day.

$$Midpoint\ Return_t = \ln {}^{m_t}/_{m_{t-x}} \tag{3-4}$$

$$Intraday\ Volatiltiy = stdev(Midpoint\ Returns) \tag{3-5}$$

$$Autocorrelation = \left|Corr(r_{k,t}, r_{k,t-1})\right| \tag{3-6}$$

3.2.3. Data

This paper utilises two unique data sets on Electronic Liquidity Providers (ELPs) as a subset of High Frequency Traders. The selection criteria are similar to Brogaard, Hendershott and Riordan (2013). The approach differs, however, in one major criteria; this paper requires that the majority of ELP's trades be liquidity providing (as specified from the NASDAQ CORE feed), and that 80% of trades are liquidity providing. This allows for the isolation of HFT that are market making, while previous data sets have not distinguished between HFT strategies.

This data set is separated into two samples. The first takes a random sample of 400 securities listed on both NASDAQ and NYSE, stratified by Market

Capitalisation (MCAP) and price for the month of March[6] in 2010, 2011, 2012 and 2013. This establishes a relationship between ELP liquidity provision and price in the absence of stock split events. The second sample is collected for 852 securities for 2010, 2011, 2012 and 2013; representing all securities that underwent stock splits (together with a matched pair sample). The method uses stock matching on price, industry and market capitalisation. Since the study focuses on the relationship between liquidity provision and price, it is required that stock prices must be within 5%.[7] A second matched pair sample is at the binding tick constraint. The purpose of this is to better address the effects of a change in relative tick size dependent on a securities proximity to the binding constraint.

The measures of Spreads, Depth and Resilience are calculated from the consolidated feeds from the Securities Information Processor (SIP). Stock specific accounting data is collected from the FactSet database and Centre for Research in Security Prices (CRSP). Stock splits are collected from the NASDAQ stock maintenance database. Those stock splits that have repeated split events and/or secondary offerings within the event window are filtered out (from both the stock split sample and the matched sample).

3.3. Descriptive Statistics

3.3.1. Stratified Sample

The first sample set aims to provide evidence that the relationships between tick size and HFT activity are prevalent across all stocks and are not

[6] March is of no specific importance, this was dictated by access to data
[7] Where this is not possible this assumption is relaxed by 5% until an adequate match is found

unique to stocks undertaking splits, or to those stocks which fall into the sample during the period because of their decision to split at this time. A balanced cross sectional sample of firms across the windows 2010-2013 as a one-month snap shot per year (March) is created. By sampling across 2010-2013 it is possible to establish whether or not there have been significant changes to the level of ELP in the market place, or changes in the relationships between ELP trading and the variables of interest. Firms are required to be listed on either the NASDAQ or NYSE, and must trade during each of the sample months and close at a price greater than $5. Next, this group is separated into four quartiles based on market capitalisation; within each quartile, securities are split into price deciles. From each decile, 10 firms are randomly selected to produce a sample of firms across a range of prices and firm size. Summary statistics are presented in Table 3-1.

The price ranges in the 400 stock sample vary from $4.38 to $528.82, which in relative tick terms is 2 bps to 0.18bps per dollar volume traded. The average trade size for Electronic Liquidity Providers was 106.39 compared to 117.03 for all other trades. While this does indicate the Electronic Liquidity Providers are trading in smaller sizes, it is barely significant.

TABLE 3-1: DESCRIPTIVE STATISTICS OF 400 STOCK SAMPLE

Descriptive statistics for 400 stock sample for the month of March in each year for 2010-2013. Stock Monthly values are created by taking the monthly dollar volume weighted average for each stock month, resulting in 1600 observations. Data and measurements only consider trades between 9:30am and 4:00pm EST.

	min	mean	median	max	sd
Volume Weighted Average Price	4.38	38.04	29.35	528.82	37.79
Market Capitalisation ($USD Millions)	39	11013	2535	243034	25608
Average Daily Dollar Volume ($USD Millions)	0.01	12.36	2.67	290.92	24.82
Average Daily Share Volume (Thousands)	1.68	653	171	13499	1275
Average Daily Trade Count	15	4805	1668	73347	7443
Average % of Liquidity Supply by ELP	2.82	20.74	19.4	81.94	8.14
Average ELP Trade Size	40.59	106.39	96.97	549.52	43.02
Average non-ELP Trade Size	34.1	117.03	104.44	622.26	49.29
Variance Ratio (midquote 10s-60s)	0.71	0.85	0.85	0.99	0.02
Realised Spread (60s bps)	1.01	12.36	6.1	2000.29	51.38
Effective Spread (bps)	1.08	12.74	6.12	1999.8	51.42
Quoted Spread (bps)	1.15	15.69	8.53	114.87	18.18
Median time between NBBO updates (milliseconds)	1.1	144.97	60.59	7451.79	335.92
Consolidated Dollar Depth	26.31	685.6	287.14	11192.96	1107.47
Order to Trade Ratio	4.57	40.22	21.35	2176.32	97.08

Figure 3-1 indicates that ELPs tend to supply more liquidity in lower price stocks; similarly, Figure 3-2 shows the same trend for all HFT liquidity provision. The relationship appears to be consistent between years, with slight deviations in the level of ELP activity.

FIGURE 3-1 LIQUIDITY PROVISION BY ELECTRONIC LIQUIDITY PROVIDERS BY YEAR 2010 – 2013

ELP Liquidity is measured as the total dollar volume of trades where ELP provided liquidity on the passive side of the trade. Each point represents the average percentage of ELP Liquidity for each stock in the 400 stock sample for the month of March in each year for 2010-2013. ELP Liquidity is plotted against the log of each stocks monthly volume weighted traded price. Data only considers trades between 9:30am and 4:00pm EST.

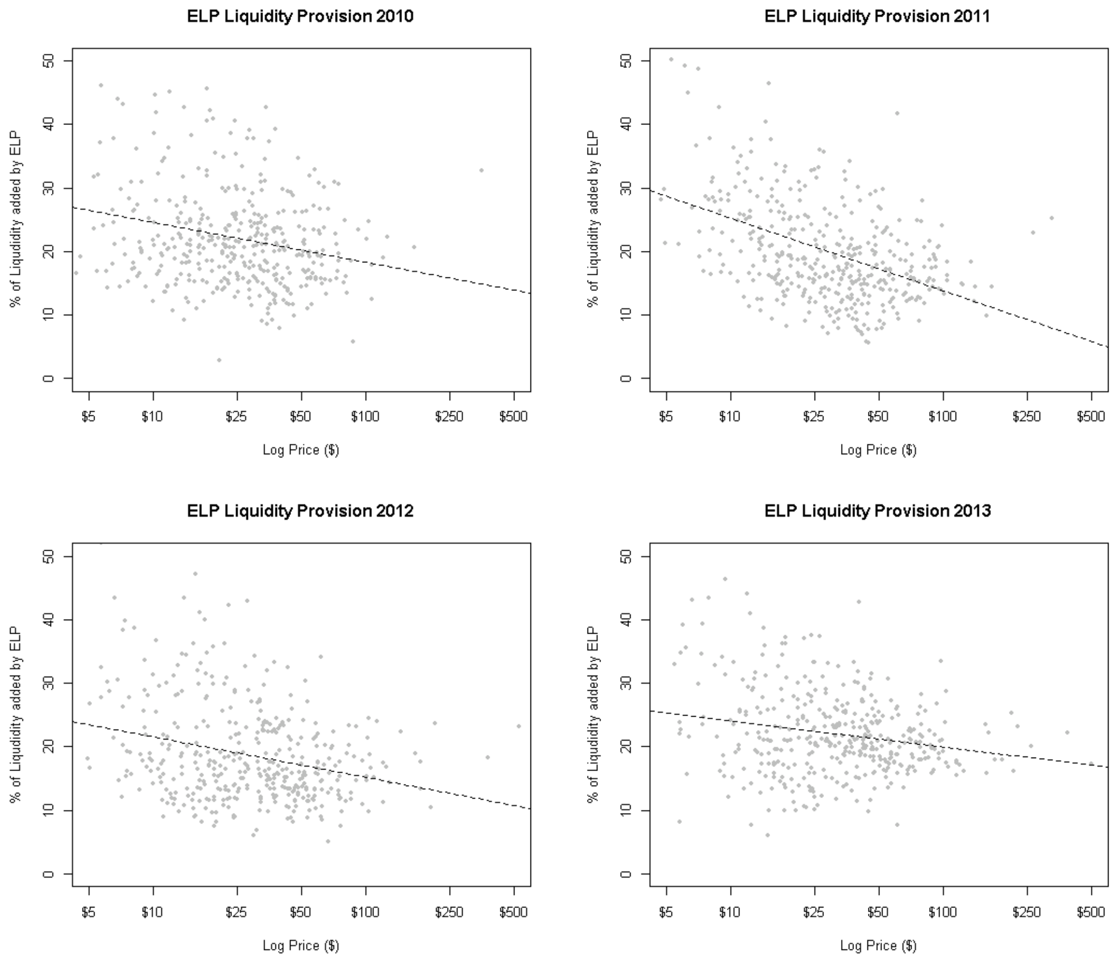
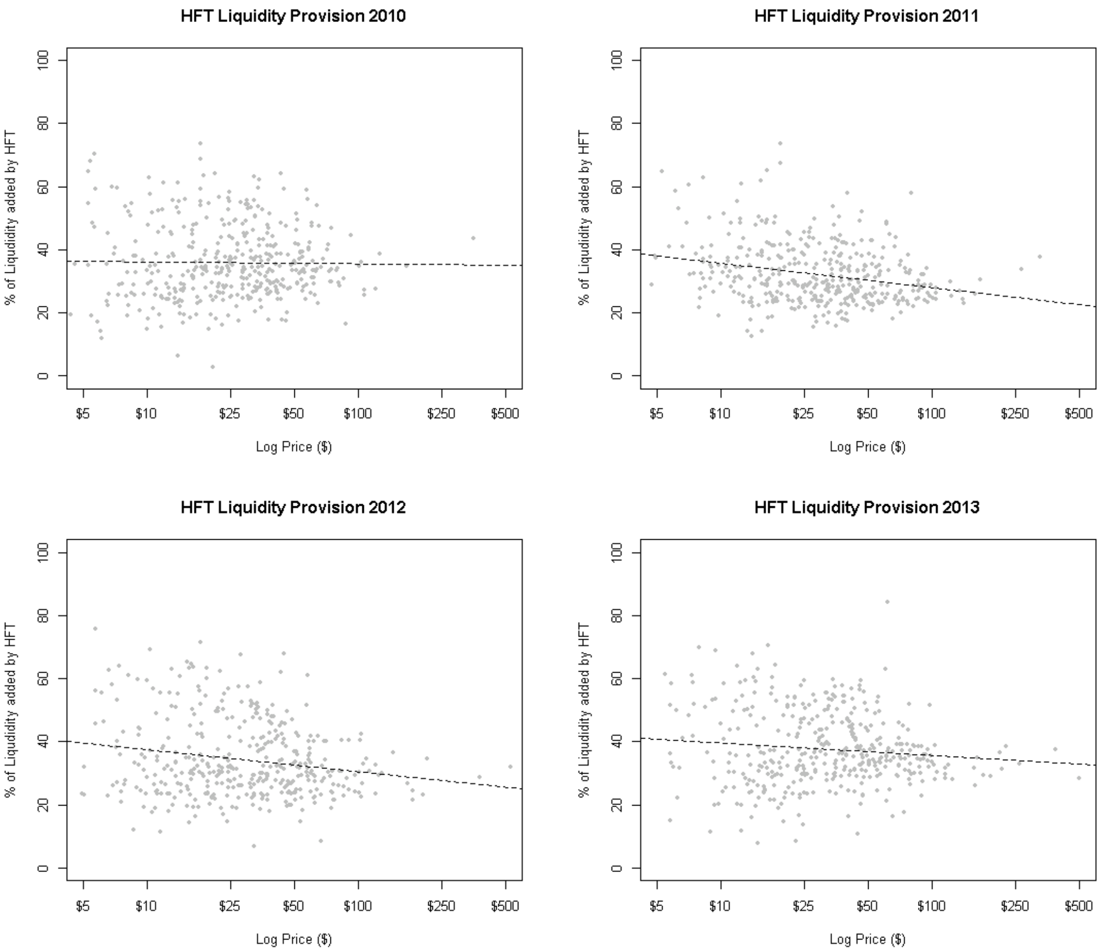


FIGURE 3-2: LIQUIDITY PROVISION BY HIGH FREQUENCY TRADERS BY YEAR 2010 - 2013

HFT Liquidity is measured as the total dollar volume of trades where HFT provided liquidity on the passive side of the trade. Each point represents the average percentage of HFT Liquidity for each stock in the 400 stock sample for the month of March in each year for 2010-2013. HFT Liquidity is plotted against log of each stocks monthly volume weighted traded price. Data only considers trades between 9:30am and 4:00pm EST.



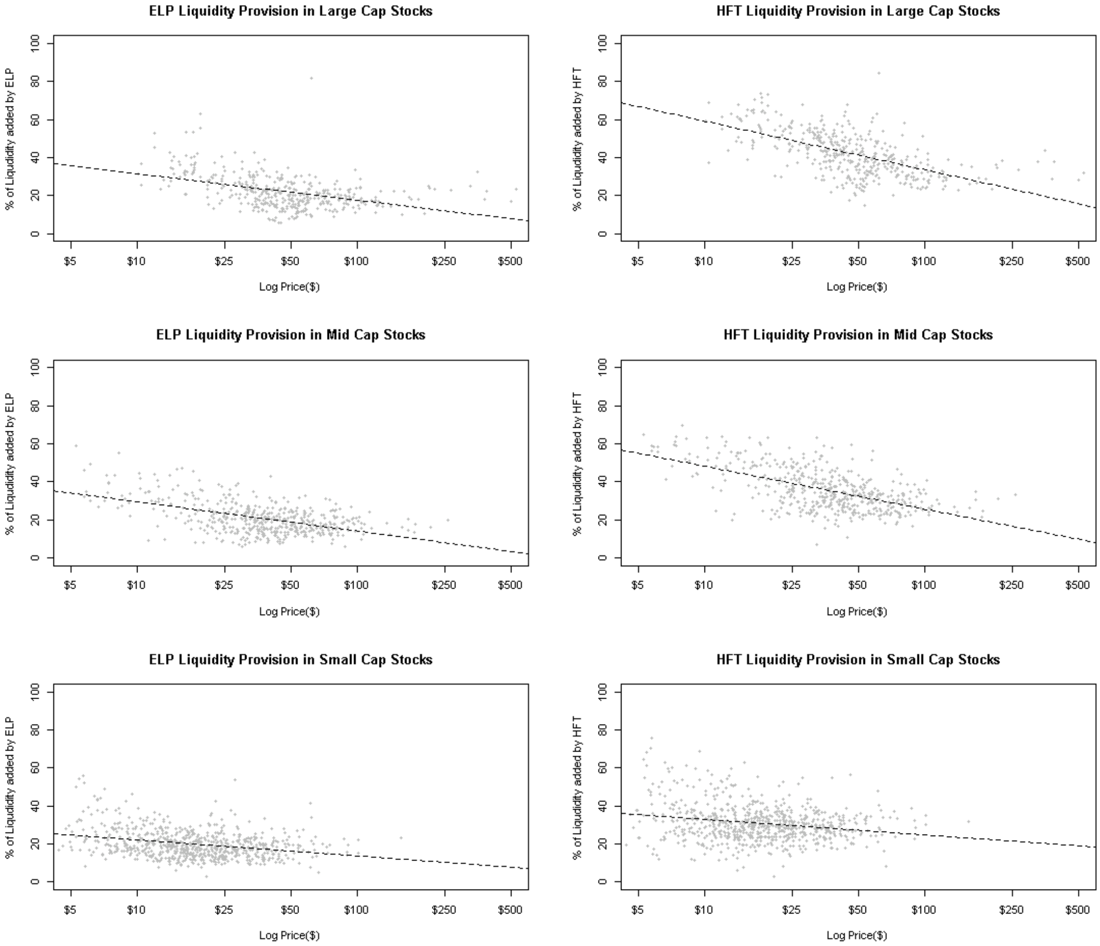
Separating the stocks into market capitalisation groups, it is evident that the relationship between price and ELP activity is strongest in the large capitalisation stocks (see Figure 3-3). As anticipated, there is a higher level of ELP liquidity in large- and mid-capitalisation stocks than in small-capitalisation stocks. It is often noted that ELPs only supply liquidity in highly active large capitalisation stocks. However, the results provide evidence that ELPs provide a significant amount of liquidity in small capitalisation stocks as well. For the month of March in the years 2010 – 2013, results indicate that ELP provide on average 19.9% of the liquidity.[8] In contrast, ELP provide 22.1% of the liquidity in large-capitalisation stocks, and 21.4% in mid-capitalisation stocks.[9] Within the sample, the price is relatively stable across the three tiers; averaging at $59.42, $44.22 and $21.73 for large-, mid- and small-capitalisation stocks, respectively.

[8] Measured as the monthly percentage of dollar volume of passive side liquidity by stock month for the sample of 400 stocks over 2010-2013; simple average for stocks under $2 Billion Market Capitalisation.

[9] As above, for firms with Large Capitalisation (Market Capitalisation over $10 Billion) and Mid Capitalisation (Market Capitalisation between $2 and $10 Billion)

FIGURE 3-3: LIQUIDITY PROVISION BY ELP/HFT BY MCAP TIER

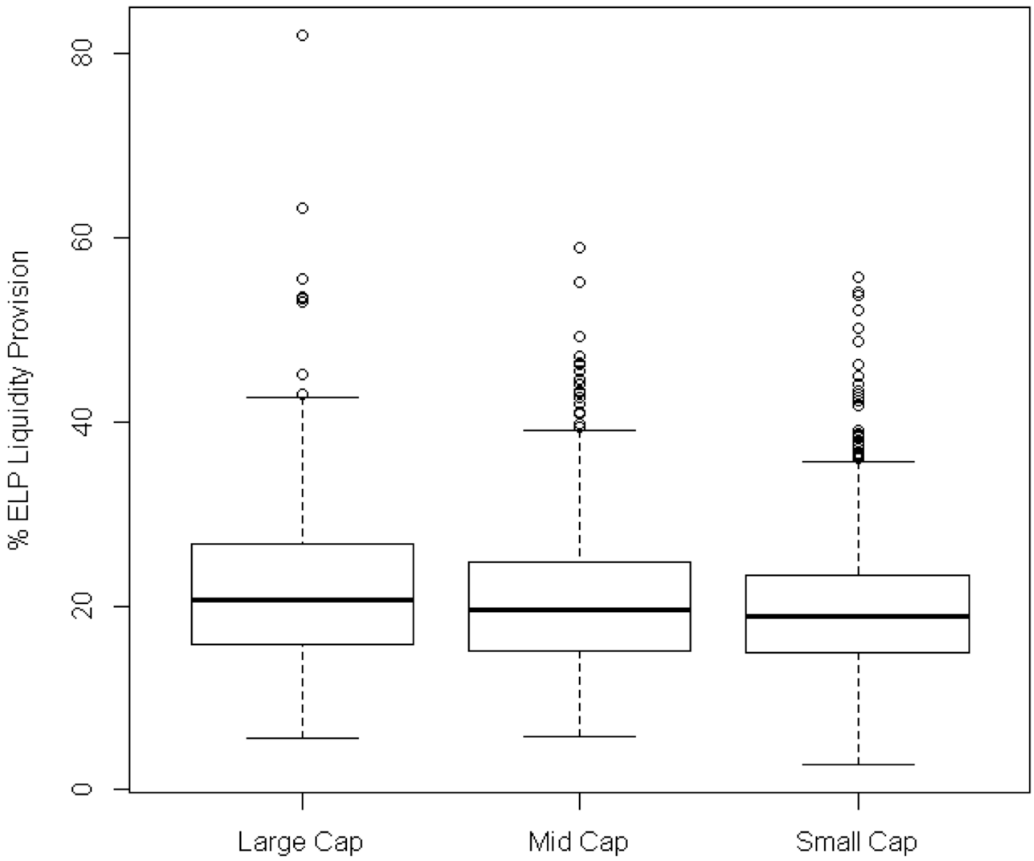
In the left hand side, ELP Liquidity is measured as the total dollar volume of trades where ELP provided liquidity on the passive side of the trade. On the right hand side, HFT Liquidity is measured as the total dollar volume of trades where HFT provided liquidity on the passive side of the trade. Each point represents the average percentage of Liquidity supplied for each stock month of the 400 stock sample for the month of March in each year for 2010-2013 plotted against the log Volume Weighted Average Price for that month. Data only considers trades between 9:30am and 4:00pm EST.



However, the distribution of liquidity provision within each of the tiers differs. Large-capitalisation stocks are skewed higher, with several firms having much greater liquidity supply by ELP, while small- capitalisation stocks are clustered tightly and have a slightly lower distribution. This is illustrated in Figure 3-4.

FIGURE 3-4: BOX PLOTS OF LIQUIDITY PROVISION BY MCAP TIER

ELP Liquidity is measured as the total dollar volume of trades where ELP provided liquidity on the passive side of the trade. Box plots are constructed by Market Capitalisation tier (x >$10 Billion, $10 Billion> x > $2 Billion, x < $2 Billion for Large, Mid and Small capitalisation respectively). Box plots are constructed for the ELP percentage of Liquidity supplied for each stock month of the 400 stock sample for the month of March in each year for 2010-2013. Data only considers trades between 9:30am and 4:00pm EST.



While the relationship between ELP liquidity provision and price is interesting, there is clear evidence that market capitalisation and trading volume are major drivers of ELP and HFT trading (which has previously been documented by Brogaard, Hendershott and Riordan (2014)). This is also illustrated in Figure 3-4. This creates a problem for any linear modelling due to the high correlation between market capitalisation and price. This creates a tri-directional co-linearity problem. ELP trading is associated with lower price levels and higher market capitalisations; but higher market capitalisation is also associated with higher prices. Figure 3-5 illustrates the relationship between ELP liquidity, price and market capitalisation. The ramifications of this relationship are that the any decrease in ELP related to an increase in stock price will be dampened by the increased market capitalisation associated with the higher price. Table 3-2 illustrates that these relationships are not only significant in size, as measured by correlation, but that they are also statistically significant.

FIGURE 3-5: ELP LIQUIDITY, PRICE AND MARKET CAPITALISATION

Top - ELP Liquidity is measured as the total dollar volume of trades where ELP provided liquidity on the passive side of the trade plotted against the stock-month Market Capitalisation log transformation. Middle - ELP Liquidity plotted against the stock-month volume weighted average price log transformation. Bottom - stock-month volume weighted average price log transformation plotted against the stock-month Market Capitalisation log transformation. Each data point is a stock month from the 400 stock sample during March of 2010-2013. Data only considers trades between 9:30am and 4:00pm EST.

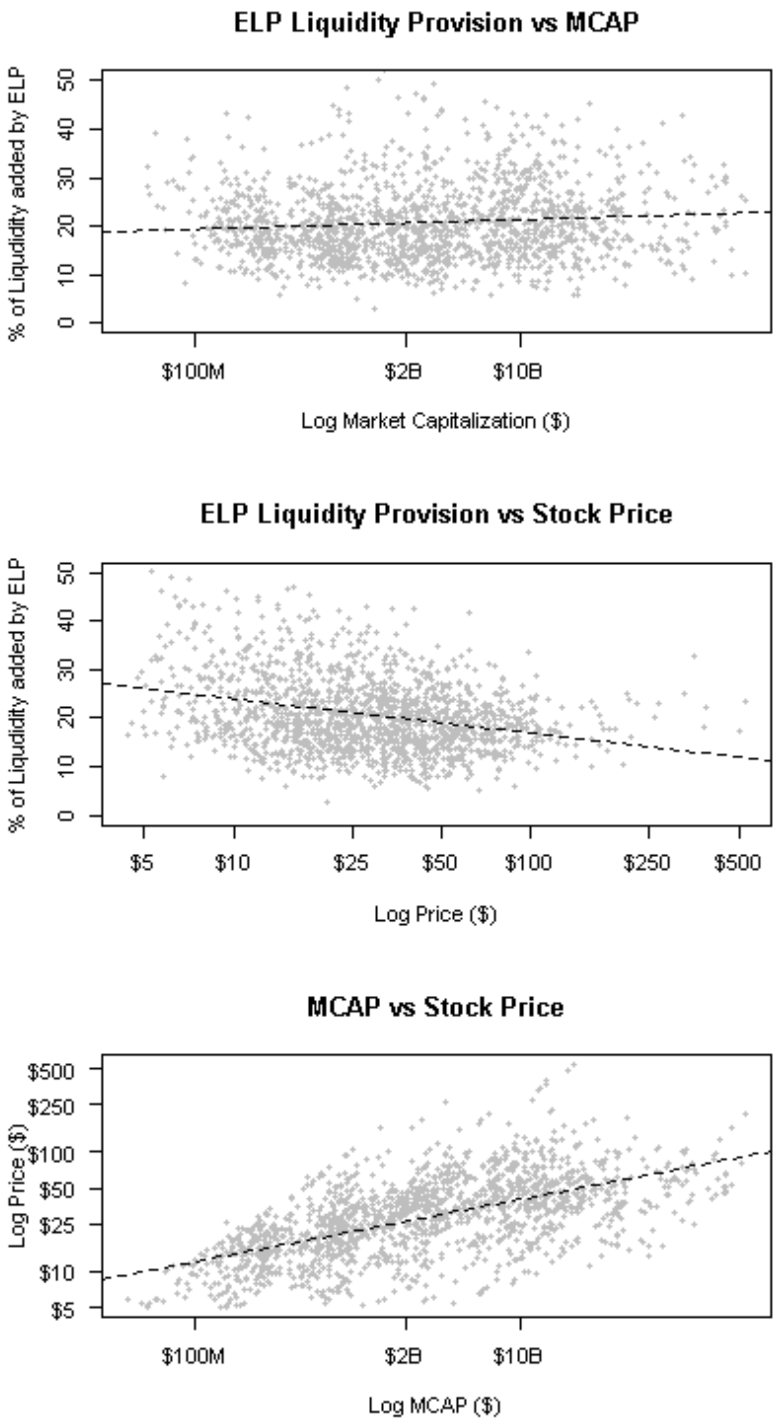


TABLE 3-2: CORRELATIONS BETWEEN ELP, PRICE AND MARKET CAPITALISATION

Correlations are generated for the 400 stock sample for the month of March in each year for 2010-2013. Values on the upper right of the diagonal represent the correlations between each variable. Values on the lower left of the diagonal represent p-values for the spearman correlation test statistics. Stock Monthly values are created by taking the monthly dollar volume weighted average for each stock month, resulting in 1600 observations. Data and measurements only consider trades between 9:30am and 4:00pm EST.

	ELP Liquidity	Price	MCAP
ELP Liquidity	*****	-0.244	0.093
Price	<0.001	*****	0.623
MCAP	<0.001	<0.001	*****

3.3.2. Stock Split Sample

Between January 2010 and December 2013, there are 528 stock split and reverse stock split events. For the purpose of this analysis, only stock splits with a stock split factor greater than 1.5 or less than 2/3 are considered. Any events for which there are not 120 trading days of data pre- and post-event are also removed (for example a stock split that occurs on 1 January 2010 falls outside of the data set). Any stock split which has a repeated stock split or reverse split within the event window, or a secondary offering, is also removed.[10] After applying these rules, the sample contains 325 stock split events; 207 stock splits and 118 reverse stock splits.

Table 3-3 separates the events by market capitalisation tier and event type. The stock splits are distributed across the market capitalisation tiers with roughly half the stock split events in the mid- capitalisation range and a quarter in each of

[10] Secondary Offering dates are retrieved from Thomson One

the large- capitalisation and small- capitalisation tiers. The majority of reverse stock split events are in the micro-cap range. There is a clear divide between the market capitalisation of firms that underwent stock splits and those which underwent reverse stock splits. For the purpose of this study the sample for stock splits is divided to only include large-, mid- and small- capitalisation companies, resulting in 192 events.

TABLE 3-3: DISTRIBUTION OF STOCK SPLIT AND REVERSE STOCK SPLITS BY MARKET CAPITALISATION TIERS

Number of Stock Split and Reverse Stock split events in sample. After removing repeated events and secondary offerings within a 120-day event window, and splits with a stock split factor between 0.67 and 1.5, split events are broken down by market capitalisation tier.

		R	S
Large Cap	(over $USD 10B)	1	48
Mid Cap	($USD2B to $USD 10B)	4	89
Small Cap	($USD 300M to $USD 2B)	8	55
Micro Cap	(less than $USD 300M)	105	15

3.4. Methodology

Causal links between tick sizes, market quality and trading behaviour are established through a matched pair difference-in-difference analysis. Inferences around the effect of relative tick sizes are made by developing a combination of dummy variables and continuous treatment effects for various levels of relative tick and jumps in relative tick size.

To examine the causal effect of tick sizes on market quality, it is necessary to have an exogenous shock, a treatment group, and a control group. Firms undertaking stock splits offer both an exogenous shock, and the treatment group.

To construct a control group the matched sample methodology is used (SEC, 2001; Bennett and Wei, 2006; O'Hara and Ye, 2011). Matching is completed on three criteria; price, market capitalisation and average daily dollar volume traded. Next, a score is generated:

$$S_{ij} = \left|\frac{Price_i}{Price_j} - 1\right| + \left|\frac{MCAP_i}{MCAP_j} - 1\right| + \left|\frac{ADV_i}{ADV_j} - 1\right| \tag{3-7}$$

The closest matched pair that has the smallest match score possible is then selected. Two additional criteria are required. Only securities from within the same GICS industry are selected; it is also required that the stock price must match within 5%, which can be subsequently relaxed in 5% increments until a match is found. A second set of matches is created that additionally includes the percentage of time spent at the binding tick constraint.

$$S_{ij} = \left|\frac{Price_i}{Price_j} - 1\right| + \left|\frac{MCAP_i}{MCAP_j} - 1\right| + \left|\frac{ADV_i}{ADV_j} - 1\right| + \left|\frac{\%TickConstrained_i}{\%TickConstrained_j} - 1\right| \tag{3-8}$$

To analyse the effect of a change in relative tick size, a Difference-in-Differences methodology is used. Stock splits are used as a treatment effect on the price of a relative tick size of the stock by causing an exogenous shock to the stock's price, while not affecting the tick size.[11] The models can be separated into

[11] The U.S markets only have one change in tick sizes which occurs below one dollar. This is only seen in the reverse stock split sample.

two broad categories: trading behaviour and transaction cost models. Equation 3-9, below, specifies the trading behaviour model

$$Y_{it} = \alpha + B_1 PostSplit_t + B_2 \, SplitFirm_i + B_3(PostSplit_t * SplitFirm_i) + \gamma_{it} + \varepsilon_{it} \quad (3\text{-}9)$$

where Y_{it} represents the measure of trading behaviour. $PostSplit_t$ is a 0,1 dummy variable equalling 1 on and after the stock split date, 0 otherwise. SplitFirm is a 0,1 dummy variable equal to 1 for firms which undertake a stock split, and 0 for matched firms. This model is estimated for 5 variants of the independent variable:

- Message Traffic - The log of the total orders and cancelations/trades
- HFT Liquidity Rate – The % of total liquidity provided by HFT
- HFT Trading Rate – The % of total liquidity removed by HFT
- ELP Liquidity Rate – The % of total liquidity provided by ELP
- NO. NBBO Quote Updates – The log of the total number of NBBO updates

The γ_{it} are control variables: quoted spread; intraday volatility; daily dollar volume traded; and ELP liquidity rate.

Similarly, the transaction cost model is specified as below in Equation 3-10.

$$TC_{it} = \alpha + B_1 PostSplit_t + B_2 \, SplitFirm_i + B_3(PostSplit_t * SplitFirm_i) + \gamma_{it} + \varepsilon_{it} \quad (3\text{-}10)$$

TC_{it} represents the transaction cost dependent variable. $PostSplit_t$ is a 0,1 dummy variable equalling 1 on and after the stock split date, 0 otherwise. SplitFirm is a 0,1 dummy variable equal to 1 for firms which undertake a stock split, and 0 for matched firms. This model is run for 7 variants of the TC variable:

- Dollar Depth at the NBBO
- Quoted Spread
- Effective Spread
- Realised Spread - at 1, 30, 60 and 300 second intervals

Again, the γ_{it} are control variables; for the above variations, the return autocorrelation, intraday volatility and daily dollar volume traded.

Both of the above models are estimated on a pooled sample of all stock splits based on the primary matching criteria. To directly address the three Hypotheses on the effect of tick sizes, the sample is separated into three groups, and the models are re-estimated. The three categories are labelled over-constrained, becoming constrained and unconstrained.

The first hypothesis addresses the effects of tick size changes on firms which are over constrained; that is, that the current quoted spread is less than the minimum quoted spread possible after a stock split. To do this, it is assumed that the quoted spread is the same pre- and post-split. Next, the absolute dollar quoted spread is calculated as it would be based on the new stock price. If this is less than $0.01, it is deemed over-constrained as this spread is no longer possible.

To address hypothesis two, the sample is sub-setted to only include firms which have a TWQS greater than $0.03 on average in the period leading up to the split, and that are expected to be at or near tick constrained post-split. To determine whether a firm is likely to be tick constrained post-split, the average TWQS pre-split is multiplied by the stock split factor. Cases are only included where the anticipated post-split TWQS is less than \$0.03.

Hypothesis three aims to address the proportional change in market quality with respect to the relative change in tick size. To achieve this goal a continuous treatment effect Difference-in-Differences model is used. Within the sample, stock split factors range from 1.5 to 10. This allows for the use of a continuous Difference-in-Differences method as discussed in Abadie (2005). The stock split factor is the treatment variable. Higher stock split factors essentially apply a higher dosage of relative tick size increases.

The models are equivalent to Equations 3 and 4; with the SplitFirm variable substituted for the SplitFactor. This is a continuous variable equaling (1 – StockSplitFactor) of the underlying stock.[12] The matched control firms have a split factor of 0 as they have no alteration in shares.

I anticipate that, for liquid securities, the improvement in trading behaviour may come at the cost of higher spreads. The expected results of equation 3-10 regressions will be a significant increase in the level of both ELP and HFT liquidity, and a decline in the level of message traffic. In equation 3-10, this will result in a significant and negative B_3 coefficient (the DID term). Conversely, I expect to see a large increase in the dollar depth, indicated by B_3 coefficient (the DID term).

[12] This is done so that a firm doing a 3:2 split will have a split factor of 0.5, not 1.5. This corresponds with the 50% increase in the relative tick size.

3.5. Specification

3.5.1. Stock Matching

To give consistent estimates, it is necessary that the stock and reverse stock split samples (treatment group) are adequately matched to the peers (control group). The pair wise t-tests for the difference in means between the treatment and control groups are calculated on the matching criteria reported in Table 3-4. The table shows that, in both the split and reverse split samples, the market capitalisation and average daily dollar volume are not statistically significantly different. In both split event groups, the price is statistically significantly different. However, the price in both groups is very close and does not constitute an economic difference (in the context of relative tick sizes).

TABLE 3-4: UNIVARIATE TESTS FOR DIFFERENCE IN MEANS BETWEEN TREATMENT AND CONTROL GROUPS

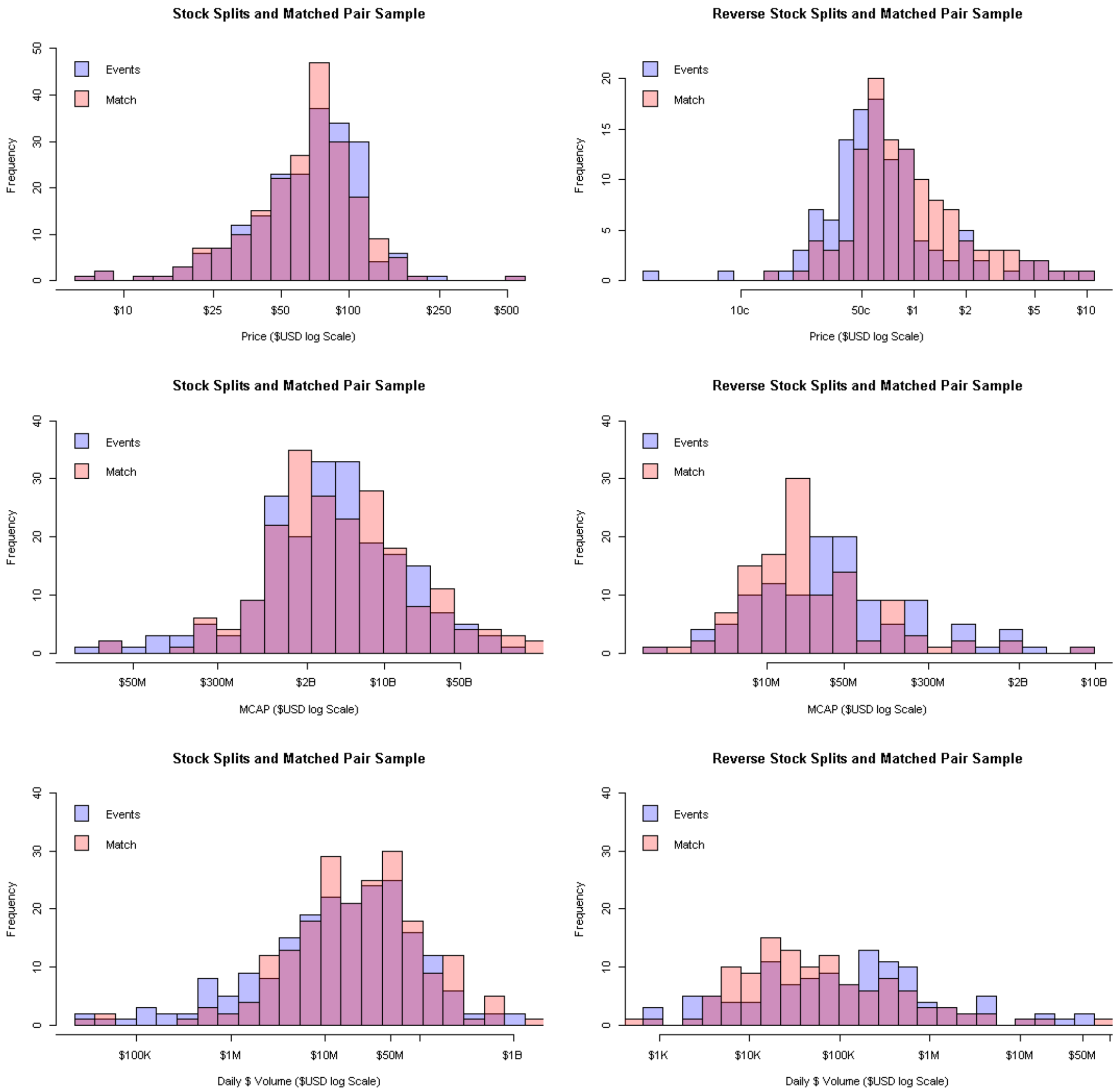
Each table compares the mean value between Price, Market Capitalisation and Average Daily Dollar Volume for stocks, which underwent a split and reverse split (treatment) and matched peer sample (control). Test statistics are generated using the students paired t-test. group Inc is removed from the Reverse Stock Split sample; as it reprressents the only ultra large cap security to undertake a reverse stock split. It can not be analysed with a large enough statistical sample.

	Stock Splits		
	Treatment	Control	p-value
Price	$75.37	$72.10	<0.001
Market Capitalisation	$9.3B	$13.2B	0.08
Average Daily Dollar Volume	$53M	$69M	0.11
	Reverse Stock Splits		
	Treatment	Control	p-value
Price	$1.03	$1.32	<0.001
Market Capitalisation	$241M	$138M	0.24
Average Daily Dollar Volume	$1.9M	$1.2M	0.26

Figure 3-6 presents the histogram of price for the stock split sample (and reverse stock split sample) overlaid with the price for the matched pair sample. Both sets of prices are well matched, consistent with the means tests above. The distributions of market capitalisation and average daily dollar volume are not as 'uniformly' distributed, but are well matched in the majority of instances.

FIGURE 3-6: COMPARISON OF MATCHING CRITERIA– MATCH 1: STOCK SPLIT SAMPLE SEPARATED EVENT TYPE

Left – Histogram of Pre-Split price, market capitalisation and dollar volume in log scale for all stock split events. Separated into stock split sample which underwent the event, and a matched peer. Overlapping points displayed by merging colour of event and matched pair groups. Right – Histogram of Pre-Split price, market capitalisation and dollar volume in log scale for all reverse stock split events. Separated into reverse stock split sample which underwent the event, and a matched peer (Citigroup 'C' has been removed from the sample). Overlapping points displayed by merging colour of event and matched pair groups.



3.5.2. Difference in Differences Analysis: Stock Split Sample

An underlying assumption of the Difference in Differences methodology is that both the treatment and control group follow the same path in the measured variable. The assumption made is that, without the treatment being applied, both groups would continue along the same path, so that the treatment and control have parallel trends. Presented in Figure 3-7 are the median price levels of the treatment and control samples for all stock splits pre- and post-event date.

FIGURE 3-7: PARALLEL PRICE TRENDS TREATMENT AND CONTROL SAMPLE (STOCK SPLITS)

X-axis represents the number of days before or after the event (stock split) where 0 is the event day. Each point represents the median of the Volume Weighted Average Price for all the securities within the sample. Blue points are from the treatment group (firms that underwent a stock split) and red points are the control group (matched pair sample).

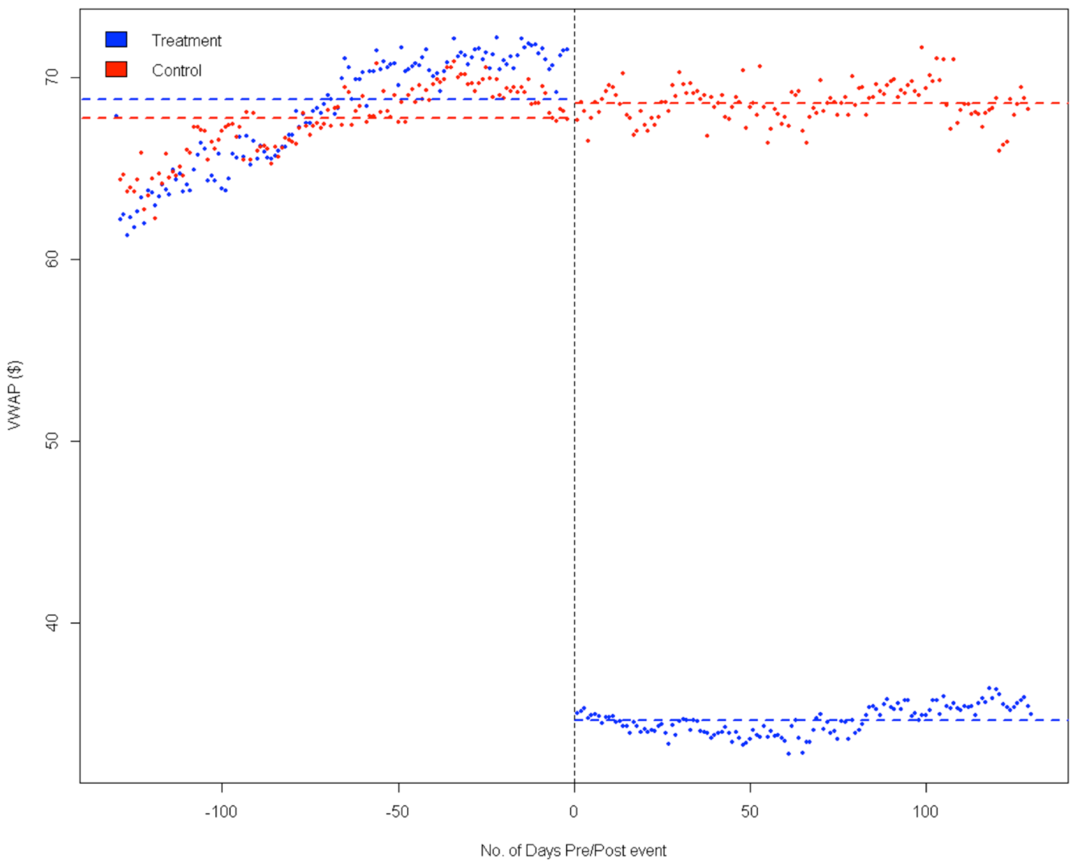
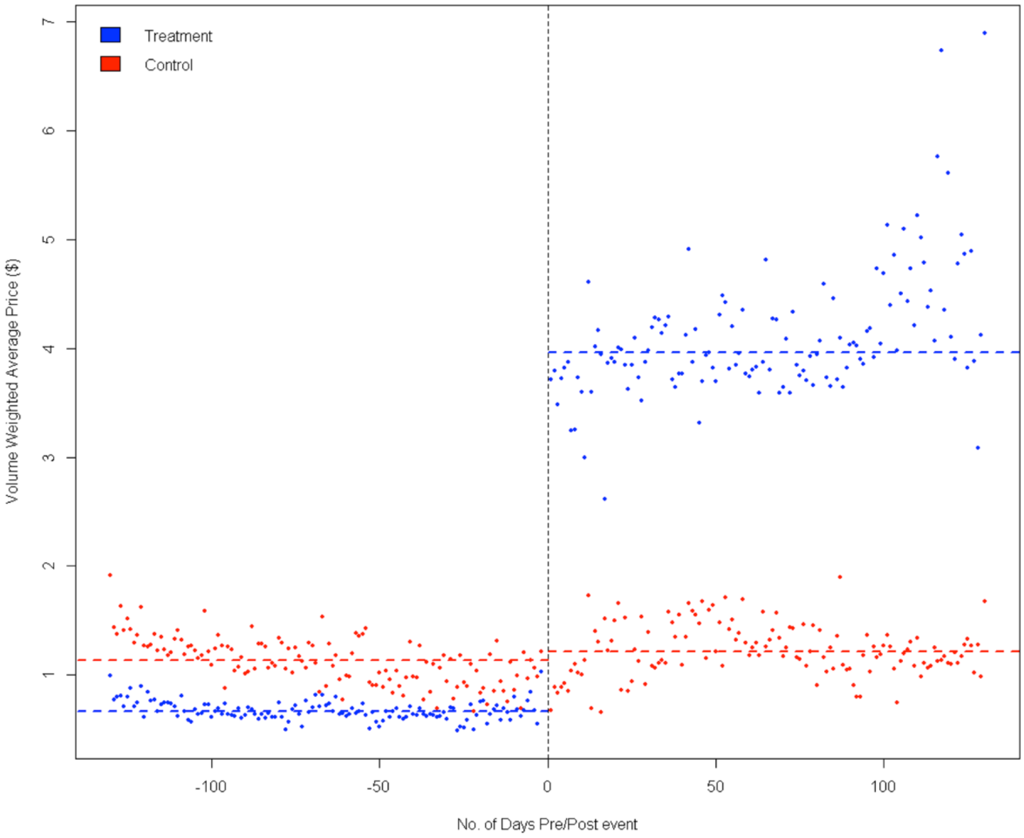


Figure 3-7 shows a strong relationship between the treatement and control samples in terms of price. After the structural break at t=0, the prices tend to follow the same path, but now at very different levels. The relationship is also strong for the reverse stock split sample. However, post-split the VWAP for the treatment group becomes more erratic, as exhibited in Figure 3-8. The post reverse split prices exhibit much greater volatility. This indicates that there may be more forces at work than the adjustment in minimum tick size due to the reverse split. The joint increase in price of both the treatment and control is an artifact of the data. However, it does help confirm the parallel trends assumption which solidifies the treatment groups validity.

FIGURE 3-8: PARALLEL PRICE TRENDS TREATMENT AND CONTROL SAMPLE (REVERSE STOCK SPLITS)

X-axis represents the number of days before or after the event (reverse stock split) where 0 is the event day. Each point represents the median of the Volume Weighted Average Price for all the securities within the sample. Blue points are from the treatment group (firms that underwent a reverse stock split) and red points are the control group (matched pair sample). Dashed lines represent the mean of each sample, calculated pre and post the event.



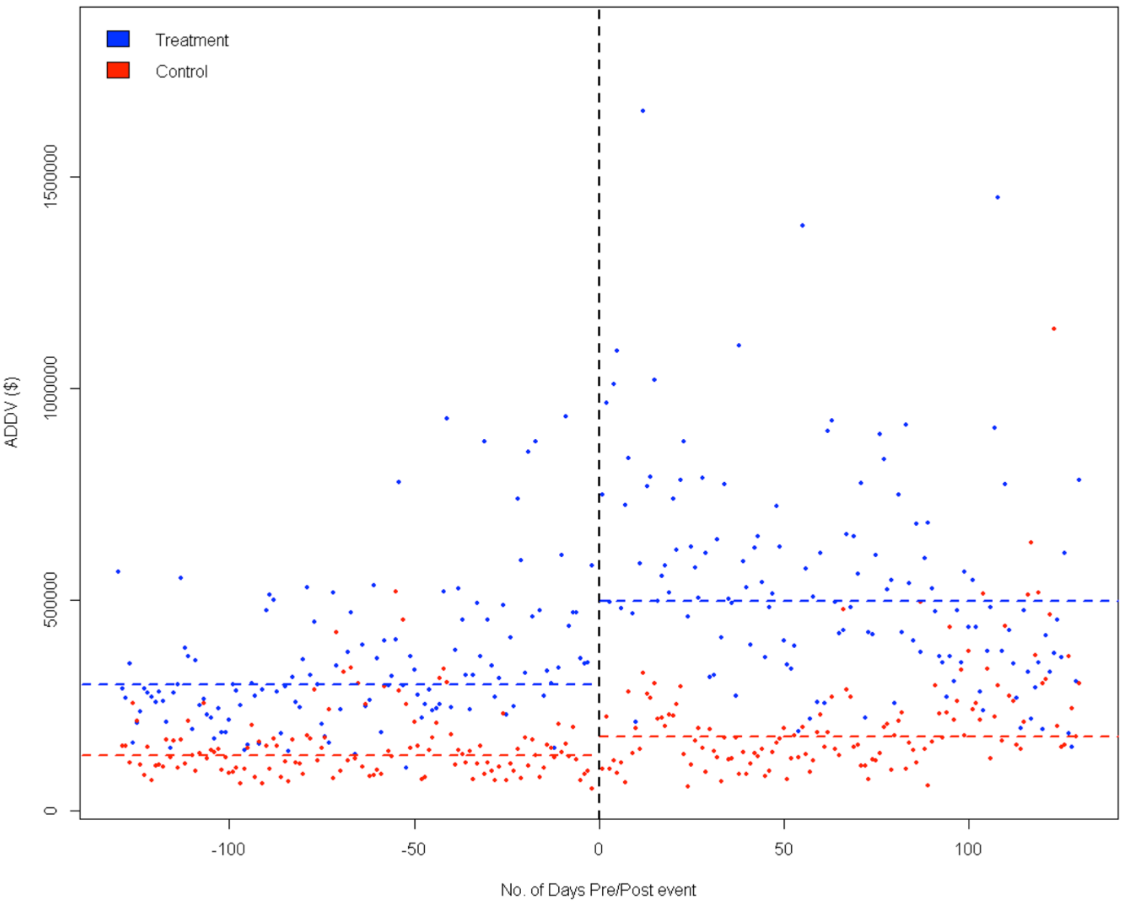
These complications likely arise from several factors:

1. Stocks trading below $1 have different tick sizes than those trading above $1; trading in $0.001 increments
2. Stocks trading below $1 have a very real threat of de-listing and may exhibit signs of financial distress
3. Micro-cap stocks are highly illiquid, which reduces the sample size, and affects the availlability of data at any given point

For these reasons we only present univariate statistics around the reverse stock split events. As demonstrated in the following section, point 1 above leads to some interesting results. The majority of reverse stock splits are from below $1 to above the $1 threshold. So the reverse split in fact widens the relative tick size and leads to greater liquidity provision. A major confounding factor for reverse splits is the increase in trading activity (measured by total daily dollar volume traded). Figure 3-9 indicates that the reverse split not only increases the price (in this case crossing over the $1 threshold and increasing the minimum tick constraint), but also greatly increases the level of trading activity.

FIGURE 3-9: DAILY TRADING ACTIVITY TRENDS TREATMENT AND CONTROL SAMPLE (REVERSE STOCK SPLITS)

X-axis represents the number of days before or after the event (reverse stock split) where 0 is the event day. Each point represents the median of the Average Daily Dollar Volume traded for all the securities within the sample. Blue points are from the treatment group (firms that underwent a reverse stock split) and red points are the control group (matched pair sample). Dashed lines represent the mean of each sample, calculated pre and post the event.



3.5.3. Univariates: Pre- and Post-Stock Splits

Stock splits in the sample have a median volume weighted average price of \$70.53 before the split, and \$36.68 after. This represents a 0.00014 (0.01/70.53) relative tick size before, and 0.00027 (0.01/36.68) relative tick size after. On average, the relative tick size doubles, and is consistent with the average split factor of 1:2 (median factor of 1:2.163). Table 3-5 presents univariate tests pre- and post-stock split for the sample. We do not see a significant impact in the liquidity provision of ELP or HFT in the aggregated sample. This is accompanied by minimal changes in market quality across the measures. This is unsurprising for two reasons. First, the sample includes stock splits where both before and after the stock split the tick sizes are not near the binding constraint. It is anticipated that ELP will increase when the relative tick size increases, regardless of being bound at the minimum tick. However, given that the median change in relative tick is only 0.00013, it may not have a major impact. Second, throughout 2010 to 2013 we see a continuous decline in the level of HFT in the market; so it is anticipated that each post-period is likely to have less ELP than the pre-period. This is unrelated to the stock split event and is controlled for with the matched sample.

TABLE 3-5: UNIVARIATE TESTS FOR DIFFERENCE IN MEANS BETWEEN PRE AND POST STOCK SPLIT

Each table compares the difference in means pre- and post-stock split. Each mean is the mean of the median value for each variable by stock. Test statistics are generated using the students paired t-test. The above table incorporates data for all firms within our stock split sample.

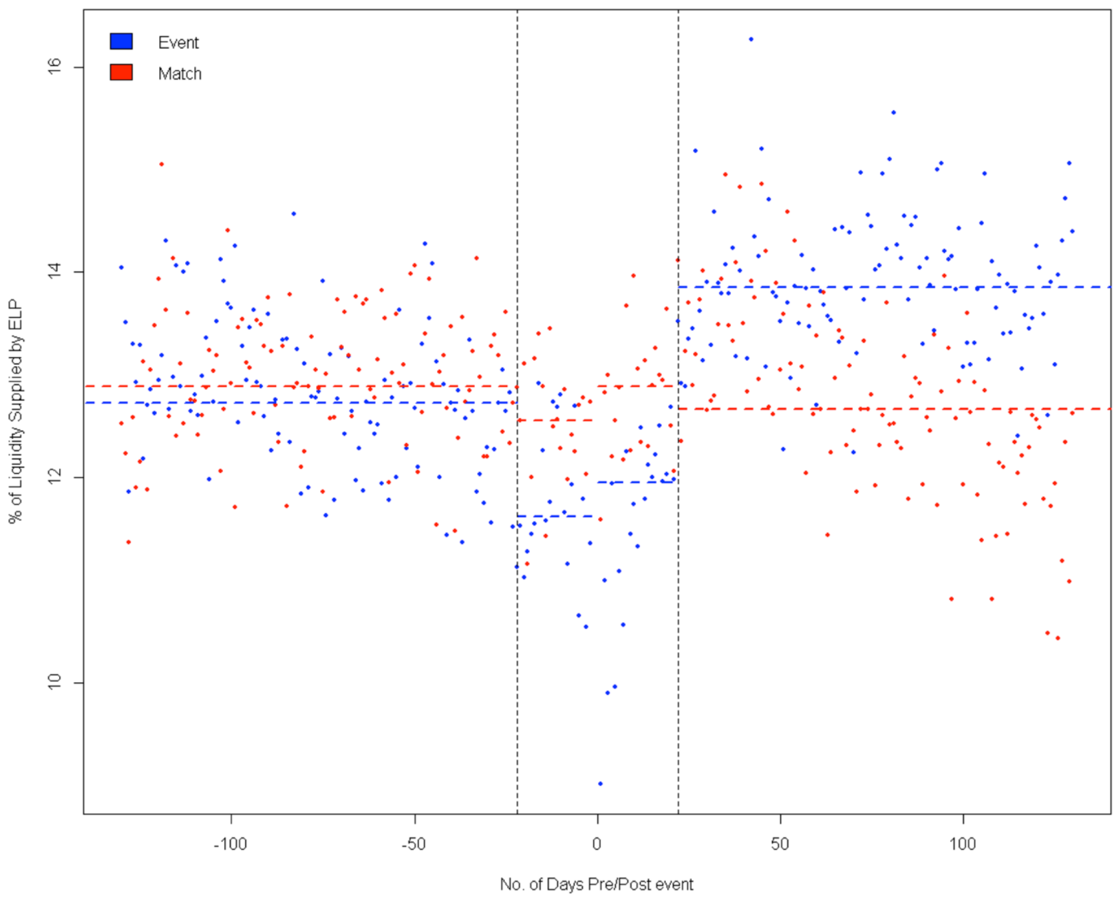
		Mean of Medians		Change		
		PRE	POST	Absolute	%	p-value
Activity	VWAP	$ 70.53	$ 36.68	-$33.84	-48.0%	0.000
	Average Daily Trades	4,050	7,391	3,341	82.5%	0.000
	Average Daily Volume (Shares)	657,312	1,345,100	687,788	104.6%	0.000
	Average Daily Dollar Volume ($)	$ 55,990,271	$ 57,856,331	1,866,060	3.3%	0.367
ELP	ELP Liquidity	15.2%	15.3%	0.09%	0.6%	0.819
	HFT Liquidity	23.0%	23.2%	0.29%	1.3%	0.533
Trading Costs	Quoted Spread ($)	$ 0.148	$ 0.080	-$0.07	-45.5%	0.000
	Relative Quoted Spread (bps)	30.8	27.7	-3.12	-10.1%	0.270
	Relative Effective Spread (bps)	19.0	14.6	-4.42	-23.3%	0.007
	Relative Realised Spread 1 seconds (bps)	18.0	14.0	-4.03	-22.4%	0.015
	Relative Realised Spread 30 seconds (bps)	18.0	14.1	-3.87	-21.6%	0.021
	Relative Realised Spread 5 minutes (bps)	17.9	14.5	-3.38	-18.8%	0.059
Stability	Quoted Depth at NBBO ($)	$ 35,071	$ 30,825	-$4,246.24	-12.1%	0.003
	Number of NBBO Updates	20,245	22,926	2681	13.2%	0.004
	Variance Ratio (1 to 10 seconds)	9.02	8.93	(0.084)	-0.9%	0.591
	Variance Ratio (10 to 60 seconds)	14.36	14.17	(0.194)	-1.4%	0.318
	Variance Ratio (60 seconds to 5 minutes)	16.32	15.98	(0.345)	-2.1%	0.103
Price Efficiency	Return Auto-correlation (1 second)	5.31	4.75	-0.562	-10.6%	0.000
	Return Auto-correlation (10 seconds)	7.82	6.59	-1.229	-15.7%	0.000
	Return Auto-correlation (1 minute)	9.48	8.95	-0.533	-5.6%	0.009
	Intraday Return Volatility (1 second)	1.62	1.62	-0.006	-0.4%	0.953
	Intraday Return Volatility (10 seconds)	4.55	4.87	0.314	6.9%	0.102
	Intraday Return Volatility (1 minute)	10.43	11.57	1.146	11.0%	0.000

3.5.4. Univariates: Pre- and Post-Reverse Stock Splits

The sample of reverse stock splits has a median volume weighted average price of $0.84 before the reverse split, and $4.70 after. The majority of stocks in the reverse split sample are in fact widening the minimum tick size by crossing the $1 level and moving to decimal tick sizes. This represents a 0.00012 (0.0001/0.84) relative tick size before, and 0.0021 (0.01/4.7) relative tick size after. This factor of 20 increases in relative tick size is associated with a significant increase in liquidity supplied by ELPs; this is illustrated in Figure 3-10.

FIGURE 3-10: LIQUIDITY PROVISION OF ELP IN STOCKS PRE AND POST STOCK SPLIT

X-axis represents the number of days before or after the event (stock split) where 0 is the event day. Each point represents the median of the percentage of passive trading volume by Electronic Liquidity Providers for all the securities within the sample. Blue points are from the treatment group (firms that underwent a stock split) and red points are the control group (matched pair sample). Dashed lines represent the mean of each sample, calculated pre and post the event. A separate window is calculated for the trading month immediately before and after the stock split date, to account for the behaviour surrounding the split event (bounded by vertical dashed lines).



Due to the low level of trading and increase in volume surrounding reverse stock splits, the study does not utilise Difference-in-Differences models. Instead, various univariates around the reverse stock split date are presented, which still reveal some interesting relationships around tick sizes, ELP and market quality in micro-cap stocks. Results are summarised in Table 3-6.

TABLE 3-6: UNIVARIATE TESTS FOR DIFFERENCE IN MEANS BETWEEN PRE AND POST REVERSE STOCK SPLIT

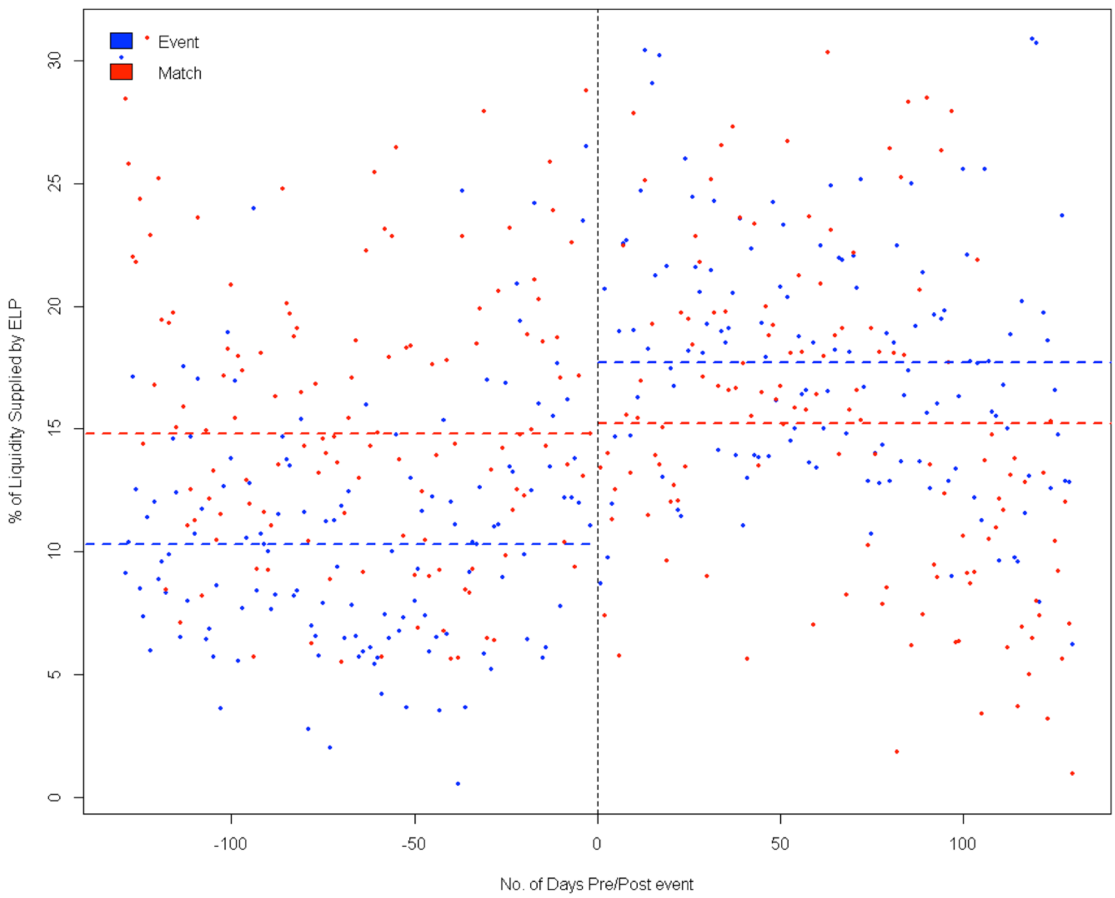
Each table compares the difference in means pre and post reverse stock split. Each mean is the mean of the median value for each variable by stock. Test statistics are generated using the students paired t-test.

		Mean of Medians		Change		
		PRE	POST	Absolute	%	p-value
Activity	VWAP	$ 1.10	$ 6.14	$ 5.03	457.0%	0.000
	Average Daily Trades	1,357	1,014	-343	-25.2%	0.095
	Average Daily Volume (Shares)	743,120	293,682	-449,437	-60.5%	0.001
	Average Daily Dollar Volume ($)	$ 1,580,518	$ 2,477,999	$ 897,481.05	56.8%	0.113
ELP	ELP Liquidity	16%	20%	4.3%	27.1%	0.049
	HFT Liquidity	22%	27%	5.2%	24.0%	0.021
Trading Costs	Quoted Spread ($)	$ 0.015	$ 0.064	$ 0.05	320.2%	0.000
	Relative Quoted Spread (bps)	226.44	172.31	-54.14	-23.9%	0.014
	Relative Effective Spread (bps)	191.57	139.92	-51.64	-27.0%	0.002
	Relative Realised Spread 1 seconds (bps)	179.29	136.15	-43.14	-24.1%	0.002
	Relative Realised Spread 30 seconds (bps)	186.58	141.86	-44.72	-24.0%	0.003
	Relative Realised Spread 5 minutes (bps)	198.68	151.71	-46.98	-23.6%	0.005
Stability	Quoted Depth at NBBO ($)	$10,291	$8,779	-$1,512	-14.7%	0.462
	Number of NBBO Updates	2,231	2,780	549	24.6%	0.089
	Variance Ratio (1 to 10 seconds)	6.97	6.28	-0.69	-9.9%	0.071
	Variance Ratio (10 to 60 seconds)	13.06	11.42	-1.65	-12.6%	0.024
	Variance Ratio (60 seconds to 5 minutes)	14.45	14.20	-0.25	-1.7%	0.821
Price Efficiency	Return Auto-correlation (1 second)	2.82	3.46	0.64	22.7%	0.167
	Return Auto-correlation (10 seconds)	5.38	5.07	-0.30	-5.7%	0.521
	Return Auto-correlation (1 minute)	6.84	6.29	-0.55	-8.0%	0.224
	Intraday Return Volatility (1 second)	6.13	5.44	-0.69	-11.2%	0.156
	Intraday Return Volatility (10 seconds)	18.42	15.81	-2.60	-14.1%	0.048
	Intraday Return Volatility (1 minute)	41.33	36.42	-4.90	-11.9%	0.110

Several variables of interest stand out. First, the liquidity supplied by ELPs increased by 27% after the stock splits (significant at the 5% level). This is associated with an across the board decline in every measure of trading costs. There is also a decline in the dollar depth available at the NBBO; which is reassuring as tighter spreads can coincide with reduced depth, indicating no net benefit. There appears to be no significant change in mid-quote stability or efficiency (as measured by NBBO updates, Variance Ratios, Auto-Correlation and Return Volatility). Although the sample does not allow conclusions to be drawn about causality, the results are encouraging. The sharp increase in relative tick size results in across the board improvements in liquidity at the same time as liquidity supply by ELPs increases. Figure 3-11 charts the change in ELP in reverse splits and their matched peer sample. A visual check indicates that a Difference-in-Differences approach would probably find a significant increase in ELP.

FIGURE 3-11: LIQUIDITY PROVISION OF ELP IN MICROCAPS UNDERTAKING REVERSE STOCK SPLITS

X-axis represents the number of days before or after the event (reverse stock split) where 0 is the event day. Each point represents the median of the percentage of passive trading volume by Electronic Liquidity Providers for all the securities within the sample. Blue points are from the treatment group (firms that underwent a reverse stock split) and red points are the control group (matched pair sample). Dashed lines represent the mean of each sample, calculated pre and post the event.



3.5.5. Univariate: Second Matched Sample with Tick Constraint Match

The second matched sample includes a fourth matching criteria; the percentage of time that the quoted spread is at the binding tick constraint. Figure

3-12 compares the distribution of the matching criteria for the treatement and control samples based on the new matching criteria. The figure shows that, in the majority of cases, the distributions match. This confirms that a match has been created where it can be reasonably assumed that the treatment and control groups could have been drawn from the same distribution. The inclusion of a fourth matching criteria appears to limit the impact on the quality of the match of the other variables. As with the first matched stock split sample, there is a strong co-trend both on price and ELP between treatment and control groups. Again there is a discrepancy in the month surounding the split, which is removed from the sample.

FIGURE 3-12: COMPARISON OF MATCHING CRITERIA– MATCH 2

Histogram of Pre-Split price, market capitalisation and dollar volume in log scale and the percentage of time at the binding tick constraint for all stock split events. Separated into stock split sample which underwent the event, and a matched peer. Overlapping points displayed by merging colour of event and matched pair groups.

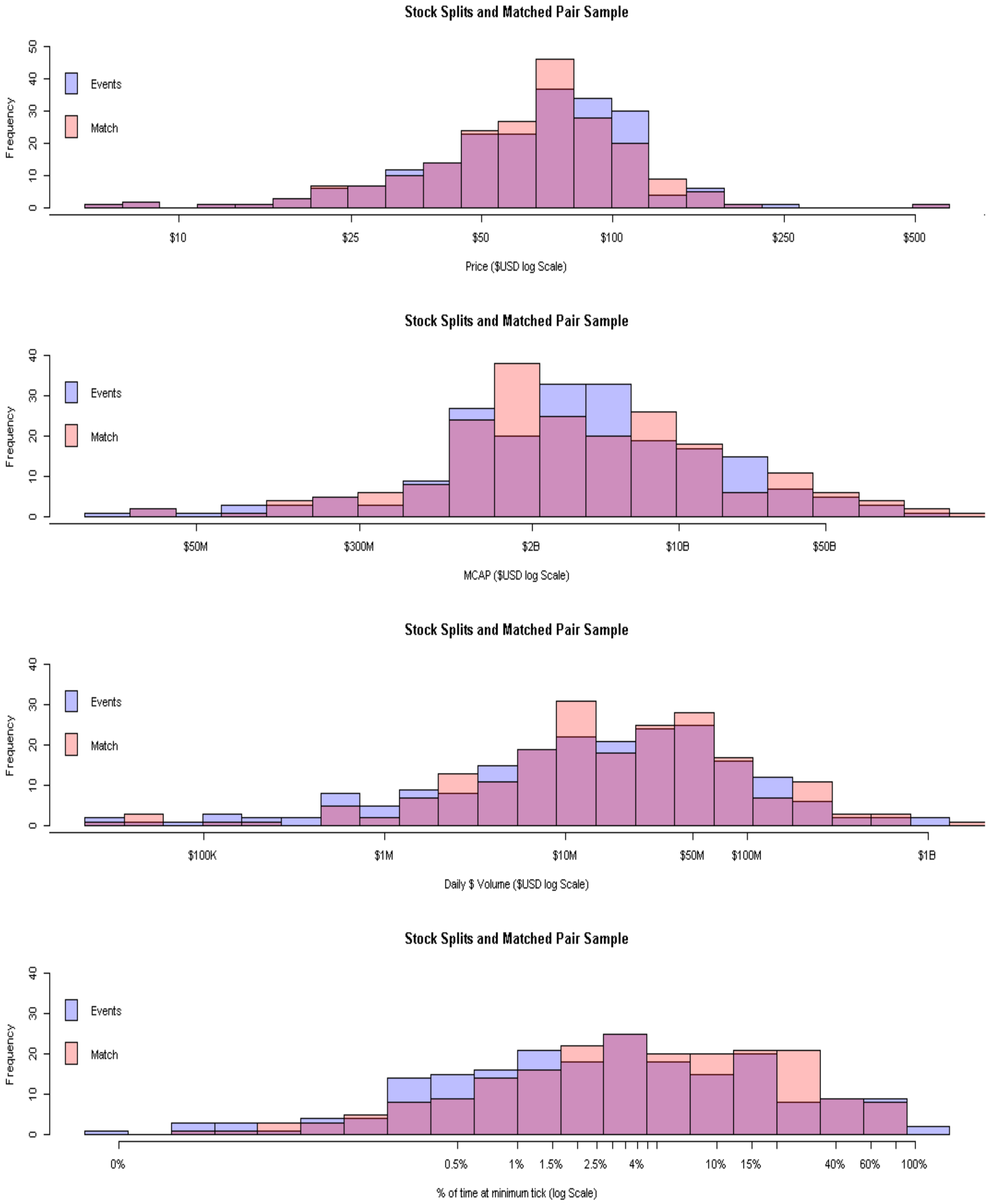


FIGURE 3-13: PARALLEL PRICE TRENDS TREATMENT AND CONTROL SAMPLE (STOCK SPLITS: MATCH 2)

X-axis represents the number of days before or after the event (stock split) where 0 is the event day. Each point represents the median of the Volume Weighted Average Price for all the securities within the sample. Blue points are from the treatment group (firms that underwent a stock split) and red points are the control group (matched pair sample).

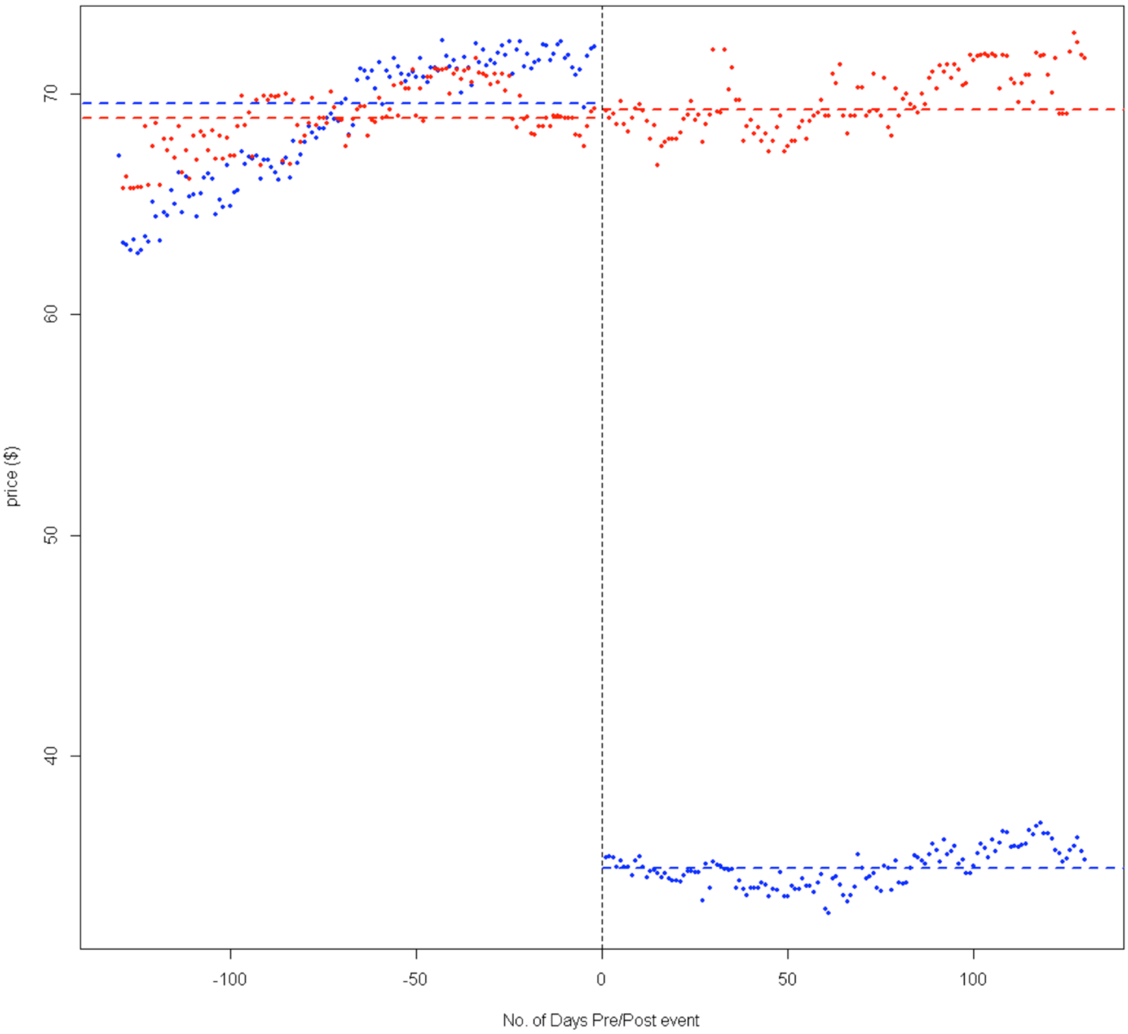
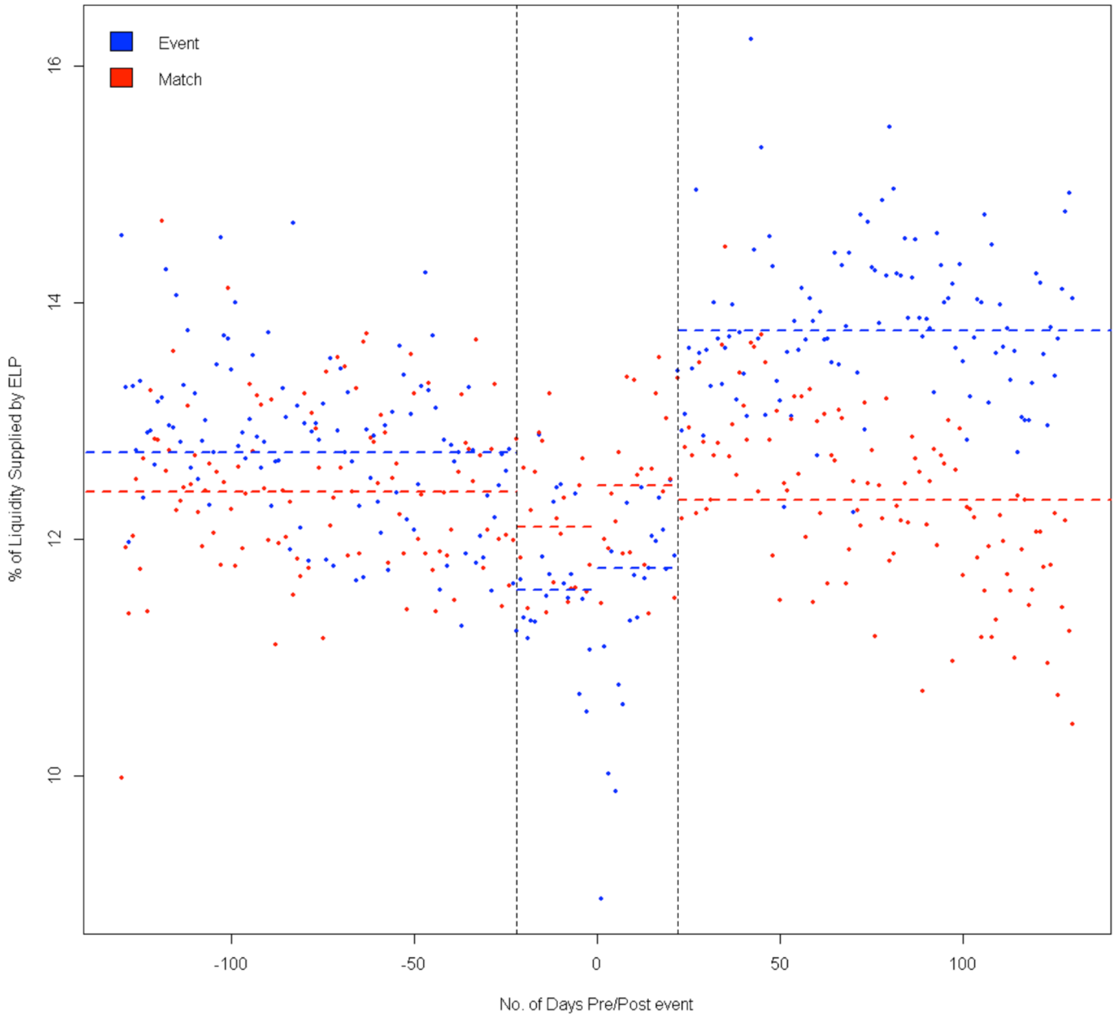


FIGURE 3-14: LIQUIDITY PROVISION OF ELP IN STOCKS PRE AND POST STOCK SPLIT (MATCH 2)

X-axis represents the number of days before or after the event (stock split) where 0 is the event day. Each point represents the median of the % of passive trading volume by Electronic Liquidity Providers for all the securities within the sample. Blue points are from the treatment group (firms that underwent a stock split) and red points are the control group (matched pair sample). Dashed lines represent the mean of each sample, calculated pre and post the event. A separate window is calculated for the trading month immediately before and after the stock split date, to account for the behaviour surrounding the split event (bounded by vertical dashed lines).



3.6. Results

3.6.1. Difference in Differences Analysis: Pooled Stock Split Sample

The initial model utilises the pooled sample of all stock splits and a matched peer sample based on price, market capitalisation and average daily dollar volume traded. The difference-in-differences estimates on trading behaviour yield some interesting new results. These results appear to be consistent across each sample. Previous studies have used measures such as the order/cancel to trade ratio or message traffic to measure HFT. However, there is a statistically significant decline in message traffic coupled with an increase in both ELP liquidity and the liquidity provided by all HFT (after controlling for increases in ELP).

There is also a statistically significant decrease in the amount of liquidity taking by HFT. This finding indicates that HFT switch strategies from removing liquidity to liquidity provision. This could have two interpretations; it might simply indicate that message traffic is a weak indicator of HFT. Alternatively, it may indicate that increases in relative tick size can effectively reduce the negative behaviour associated with high message traffic while simultaneously increasing the positive market making trading by HFT.

These findings occur in conjunction with across the board decreases in the transaction costs as measured by effective and realised spreads. Across the pooled sample there is no statistically significant change in the quoted spread; there is a decline in the dollar depth quoted at the NBBO. These findings appear to suggest that, in general, stock splits have a large positive impact on trading by reducing several measures of transaction costs. Additionally, HFT strategies move towards pure market making strategies coupled with a reduction in message traffic. These findings provide evidence that supports $Hypothesis_{3,1}$.

TABLE 3-7: DIFFERENCE IN DIFFERENCES MODEL OF TRADING BEHAVIOUR FOR POOLED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre- and post-stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre- and post-stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a dummy variable, equal to 1 if the stock is in the treatment sample which underwent a stock split, 0 otherwise. D2 is a dummy variable, equal to 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects are used in this regression.

	Dependent variable:				
	Message Traffic (log)	HFT Liquidity Rate	HFT Trading Rate	ELP Liquidity Rate	No. NBBO Quote Updates (log)
ELP Liquidity Rate	0.001 ***	0.797 ***	0.004 ***		0.003 ***
	(-0.0002)	-0.002	-0.0003		-0.002
Quoted Spread (bps)	-0.030 ***	-0.168 ***	-0.005 ***	-0.504 ***	-0.089 ***
	-0.004	-0.057	-0.001	-0.087	-0.004
Intraday Volatility (60sec log)	0.200 ***	0.719 ***	0.022 ***	1.325 ***	0.350***
	-0.004	-0.054	-0.001	-0.083	-0.004
Daily Dollar Volume (log)	-0.516 ***	-0.442 ***	-0.012 ***	-2.533***	0.203***
	-0.003	-0.039	-0.0005	-0.059	-0.003
D1: Treatment	-0.117 ***	1.977 ***	-0.053 ***	-8.596 ***	-0.285***
	-0.034	-0.503	-0.006	-0.766	-0.036
D2: Pre/Post	0.082 ***	-0.684 ***	0.003 ***	-0.603 ***	0.031***
	-0.004	-0.063	-0.001	-0.096	-0.005
Interaction: D1 xD2	-0.485 ***	1.038 ***	-0.021 ***	1.035 ***	-0.002***
	-0.006	-0.089	-0.001	-0.135	-0.006
Constant	12.904 ***	21.065 ***	0.638 ***	63.032 ***	8.526***
	-0.063	-0.916	-0.011	-1.376	-0.066
Observations	69,960	70,618	70,618	70,618	69,191
R2	0.755	0.744	0.552	0.263	0.769
Adjusted R2	0.753	0.743	0.55	0.259	0.768
Residual Std. Error	0.391 (df = 69609)	5.773 (df = 70267)	0.067 (df = 70267)	8.801 (df = 70268)	0.414 (df = 68840)
F Statistic	611.643 *** (df = 350; 69609)	582.905 *** (df = 350; 70267)	247.824*** (df = 350; 70267)	71.774 (df = 349; 70268)	655.528 *** (df = 350; 68840)

*p<0.1; **p<0.05; ***p<0.01

TABLE 3-8: DIFFERENCE IN DIFFERENCES MODEL OF TRANSACTION COSTS FOR POOLED STOCK SPLIT SAMPLE

This table reports the results of a Difference in Differences regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre- and post-stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre- and post-stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a dummy variable, equal to 1 if the stock is in the treatment sample which underwent a stock split, 0 otherwise. D2 is a dummy variable, equal to 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

	Dependent variable:						
	NBBO Dollar Depth	Quoted Spread (bps)	Effective Spread (bps)	1 second	30 seconds	1 minute	5 minutes
Daily Dollar Volume (log)	3,179.913 ***	-7.496 ***	-1.243***	-0.983***	-0.498***	-0.394***	-0.128
	-154,722	-0.295	-0.058	-0.06	-0.072	-0.073	-0.082
Return Autocorrelation (1min)	56.587***	-0.163***	0.009**	0.003	-0.004	-0.012**	-0.015***
	-10.964	-0.021	-0.004	-0.004	-0.005	-0.005	-0.006
Intraday Volatility (1min stdev)	-1,303,828.000***	11,138.620***	1,015.038***	944.543***	739.373***	751.337***	770.834***
	-97,525.15	-186.154	-36.437	-37.819	-45.285	-45.749	-51.425
D1: Treatment	1,783.60	19.359***	19.483***	18.108***	17.613***	17.314***	17.643***
	-2,059.90	-3.932	-0.77	-0.799	-0.956	-0.966	-1.086
D2: Pre/Post	-1,090.187***	-0.499	-0.013	-0.021	-0.029	-0.038	-0.05
	-257.876	-0.492	-0.096	-0.1	-0.12	-0.121	-0.136
Interaction: D1 xD2	-1,951.376***	-0.967	-2.249***	-2.073***	-1.969***	-1.940***	-1.475***
	-360.94	-0.697	-0.136	-0.142	-0.169	-0.171	-0.192
Constant	-31,395.510***	109.381***	18.504***	14.553***	7.214***	5.654***	1.516
	-2,920.57	-5.575	-1.091	-1.133	-1.356	-1.37	-1.54
Observations	70,618	70,618	70,618	70,618	70,618	70,618	70,618
R2	0.605	0.225	0.717	0.678	0.597	0.591	0.529
Adjusted R2	0.604	0.221	0.716	0.676	0.595	0.589	0.527
Residual Std. Error (df = 70268)	23,782.21	45.395	8.885	9.223	11.043	11.156	12.54
F Statistic (df = 349; 70268)	308.982***	58.402***	51.276***	423.070***	298.725***	290.403***	226.484***

*p<0.1; **p<0.05; ***p<0.01

3.6.2. Difference in Differences Analysis: Stock Splits Separated by Constraint

To separate out the Difference-in-Differences models by tick constraint proximity, a second set of matches is created, which also includes the percentage of time at the minimum tick constraint. Tables 3-9, 3-10 and 3-11 give the regression output for the trading behaviour models for over-constrained, becoming constrained and unconstrained stock splits respectively. The results are summarised in Figure 3-15 which presents the beta for the DID estimators in each regression. Each are found to be significant at the 1% level.

The first group are over constrained; that is, that the current relative quoted spread is less than the minimum relative quoted spread possible after a stock split. To construct this group, it is assumed that the relative quoted spread would be the same pre and post split. I next calculate what the absolute dollar quoted spread would be based on the new stock price. If this is less than $0.01 it is deemed over constrained, as this spread is no longer possible.

The second subset in the sample only includes firms which had a TWQS greater than $0.03 on average in the period leading up to the split, and that are expected to be at or near tick constrained post-split. This only includes cases where the anticipated post-split TWQS is less than $0.03.

Remaining securities are in the final group of unconstrained securities.

TABLE 3-9: DIFFERENCE IN DIFFERENCES MODEL OF TRADING BEHAVIOUR FOR OVER CONSTRAINED STOCK SPLIT SAMPLE

This table above reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample which underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

			Dependent variable:		
	Message Traffic (log)	HFT Liquidity Rate	HFT Trading Rate	ELP Liquidity Rate	No. NBBO Quote Updates (log)
ELP Liquidity Rate	-0.001	0.702***	0.003***		0.001**
	-0.001	-0.012	-0.001		-0.001
Quoted Spread (bps)	-0.055	-7.001**	-0.073**	-0.069	-0.653***
	-0.172	-3.44	-0.033	-4.886	-0.182
Intraday Volatility (60sec log)	0.377***	2.375***	0.061***	1.197**	0.602***
	-0.017	-0.331	-0.003	-0.469	-0.018
Daily Dollar Volume (log)	-0.526***	-1.867***	-0.028***	-1.695***	0.149***
	-0.012	-0.224	-0.002	-0.317	-0.012
D1: Treatment	0.834***	9.509***	0.168***	5.234***	1.252***
	-0.053	-1.032	-0.01	-1.464	-0.055
D2: Pre/Post	0.059***	-1.550***	-0.006**	-2.601	0.085***
	-0.014	-0.282	-0.003	-0.398	-0.015
Interaction: D1 xD2	-0.437***	1.563***	-0.015***	5.848***	-0.008
	-0.02	-0.404	-0.004	-0.566	-0.022
Constant	14.787***	60.086***	1.215***	45.839***	11.464***
	-0.258	-4.945	-0.047	-6.984	-0.265
Observations	3,634	3,720	3,720	3,720	3,632
R2	0.804	0.763	0.54	0.394	0.858
Adjusted R2	0.803	0.762	0.537	0.391	0.857
Residual Std. Error	0.298 (df = 3611)	5.984 (df = 3697)	0.057 (df = 3697)	8.500 (df = 3698)	0.316 (df = 3609)
F Statistic	674.716*** (df = 22; 3611)	540.922*** (df = 22; 3697)	197.225*** (22; 3697)	114.512*** (df = 21; 3698)	993.732*** (df = 22; 3609)

*p<0.1; **p<0.05; ***p<0.01

TABLE 3-10: DIFFERENCE IN DIFFERENCES MODEL OF TRADING BEHAVIOUR FOR BECOMING CONSTRAINED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days that fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample that underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

	Dependent variable:				
	Message Traffic (log)	HFT Liquidity Rate	HTF Trading Rate	ELP Liquidity Rate	No. NBBO Quoted Updates (log)
ELP Liquidity Rate	0.001***	0.762***	0.004***		0.003***
	-0.0002	-0.004	-0.00004		-0.0003
Quoted Spread (bps)	0.028**	-0.014	-0.004*	-0.565**	0.005
	-0.012	-0.204	-0.002	-0.283	-0.012
Intraday Volatility (60sec log)	0.212***	0.626***	0.033***	1.343***	0.374***
	-0.005	-0.091	-0.001	-0.125	-0.006
Daily Dollar Volume (log)	-0.489***	-0.545***	-0.017***	-2.105***	0.240***
	-0.004	-0.068	-0.001	-0.093	-0.004
D1: Treatment	1.275***	2.610***	0.122***	-1.393*	1.047***
	-0.033	-0.584	-0.006	-0.806	-0.035
D2: Pre/Post	0.070***	-0.410***	0.006***	-0.554***	0.057***
	-0.005	-0.095	-0.001	-0.131	-0.006
Interaction: D1 xD2	-0.425***	1.251***	-0.023***	1.257***	0.114***
	-0.008	-0.134	-0.001	-0.185	-0.008
Constant	12.590***	22.311***	0.796***	56.505***	8.113***
	-0.086	-1.5	-0.016	-2.047	-0.091
Observations	30,523	30,914	30,914	30,914	30,209
R2	0.768	0.705	0.512	0.237	0.802
Adjusted R2	0.766	0.703	0.51	0.234	0.801
Residual Std. Error	0.329 (df = 30377)	5.845 (df = 30768)	0.062(df = 30768)	8.077 (df = 30769)	0.352 (df = 30063)
F Statistic	691.631*** (df = 145; 30377)	505.920*** (df = 145; 30768)	223.051*** (df = 144; 30768)	66.398*** (df = 144; 30769)	840.109*** (df = 145; 30063)

*p<0.1; **p<0.05; ***p<0.01

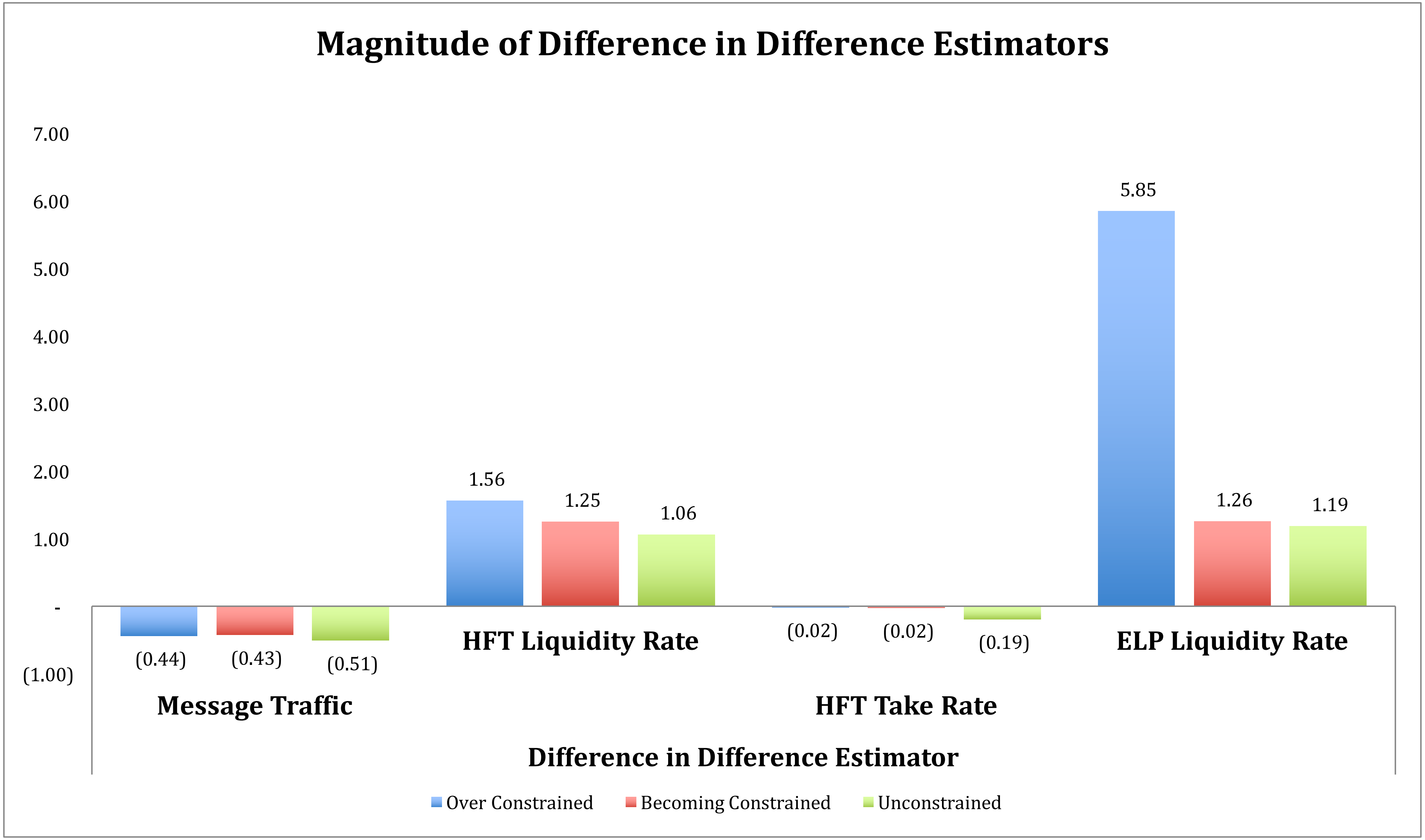
TABLE 3-11: DIFFERENCE IN DIFFERENCES MODEL OF TRADING BEHAVIOUR FOR UNCONSTRAINED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days that fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample that underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

	Dependent variable:				
	Message Traffic (log)	HFT Liquidity Rate	HTF Trading Rate	ELP Liquidity Rate	No. NBBO Quoted Updates (log)
ELP Liquidity Rate	0.001***	0.821***	0.004***		0.004***
	-0.0002	-0.003	-0.00004		-0.0002
Quoted Spread (bps)	0.028**	0.137	0.001	-0.485**	-0.015*
	-0.008	-0.108	-0.001	-0.179	-0.009
Intraday Volatility (60sec log)	0.209***	0.702***	0.018***	1.426***	0.364***
	-0.005	-0.068	-0.001	-0.111	-0.005
Daily Dollar Volume (log)	-0.548***	0.448***	-0.013***	-3.047***	0.154***
	-0.004	-0.049	-0.001	-0.079	-0.004
D1: Treatment	-0.875***	3.266***	0.125***	-9.561*	-0.812***
	-0.032	-0.417	-0.005	-0.686	-0.033
D2: Pre/Post	0.050***	-1.112***	-0.001***	-0.835***	-0.029***
	-0.006	-0.081	-0.001	-0.134	-0.007
Interaction: D1 xD2	-0.506***	1.0163***	-0.019***	1.186***	-0.045***
	-0.009	-0.116	-0.001	-0.191	-0.009
Constant	14.167***	19.596***	0.687***	71.751***	9.858***
	-0.081	-1.037	-0.013	-1.674	-0.082
Observations	40,856	41,282	41,282	41,282	40,497
R2	0.719	0.76	0.572	0.261	0.732
Adjusted R2	0.717	0.759	0.569	0.257	0.73
Residual Std. Error	0.438 (df = 40628)	5.720 (df = 41054)	0.072(df = 41054)	9.493 (df = 41054)	0.452 (df = 40269)
F Statistic	457.345*** (df = 227; 40628)	574.214*** (df = 227; 41054)	241.512*** (df = 227; 41054)	64.296*** (df = 226; 41055)	483.830 *** (df = 227; 40269)

*p<0.1; **p<0.05; ***p<0.01

FIGURE 3-15: MAGNITUDE OF DID ESTIMATES BY CONSTRAINT TYPE FOR TRADING BEHAVIOUR



The relationships with the separation are consistent with those for the pooled sample. However, there is a significant increase in the level of HFT moving to ELP strategies in the over constrained securities. This is intuitive given that profits from market making are now essentially buffered. If it is assumed that the pre-split spread was the equilibrium risk-reward trade-off, then in a post-split world the minimum reward allowed (by the tick constraint) is much larger than the equilibrium. This is mirrored in an increased HFT liquidity rate and a reduction in aggressive HFT liquidity taking strategies.

The increase in ELP liquidity is similar, but smaller in magnitude, for both the becoming constrained and unconstrained samples. This is direct evidence of the benefit of larger tick sizes; there is no direct intervention on the rewards given to ELP. In this situation, the only real change is the size of the price jump required to post ahead of the current quote. Across all three samples, the message traffic decreases, potentially illustrating a reduction in strategies that rely on excessive quoting.

In the Difference-in-Differences models for transaction costs, for over constrained stocks, all measures of spreads increase. This is being partnered with a large and statistically significant increase in the dollar depth quoted at the NBBO. A similar result is found for the set of stock splits that are becoming constrained. Both the effective and realised spreads increase. The increases are statistically significant, but of much smaller magnitude than for the over constrained securities.

Potentially the most interesting results is in the unconstrained sample. Within this sample there is no mechanical change to the quoted spreads. However, there remains a decrease in transaction costs across the board. A statistically significant decline in the quoted spread is found. This tightening of the displayed quote provides evidence that there may be some benefit to increasing tick sizes in small capitalisation stocks. These findings provide evidence that support $\text{Hypothesis}_{3,3}$.

TABLE 3-12: DIFFERENCE IN DIFFERENCES MODEL OF TRANSACTION COSTS FOR OVER CONSTRAINED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample which underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

	Dependent variable:						
	NBBO Dollar Depth	Quoted Spread (bps)	Effective Spread (bps)	1 second	30 seconds	1 minute	5 minutes
Daily Dollar Volume (log)	5,713.946 ***	-0.190***	-0.005***	0.002	0.066***	0.105 ***	0.228***
	-1,177.24	-0.046	-0.021	-0.02	-0.024	-0.027	-0.045
Return Autocorrelation (1min)	129.865	0.001	-0.001	-0.001	0.001	-0.002	-0.001
	-79.367	-0.003	-0.001	-0.001	-0.002	-0.002	-0.003
Intraday Volatility (1min stdev)	-13,588,185. 000***	429.206***	318.287***	339.121***	272.509***	253.598***	315.780***
	-1,589,224.00	-62.037	-27.948	-27.615	-32.727	-36.208	-61.269
D1: Treatment	-721.438	3.323***	2.086***	2.249***	1.944***	1.819***	1.624***
	-5,542.35	-0.216	-0.097	-0.096	-0.114	-0.126	-0.214
D2: Pre/Post	-2,904.262*	-0.008	-0.021	-0.023	-0.024	-0.026	-0.043
	-257.876	-0.492	-0.096	-0.1	-0.12	-0.036	-0.061
Interaction: D1 xD2	37,521.280***	1.101***	1.189***	0.781***	0.870***	0.921***	0.995***
	-2,231.57	-0.087	-0.039	-0.039	-0.046	-0.051	-0.086
Constant	-47,305.090***	2.415***	-0.141	-0.265	-1.164***	-1.710***	-3.498***
	-16,794.19	-0.656	-0.295	-0.292	-0.346	-0.383	-0.647
Observations	3,720	3,720	3,720	3,720	3,720	3,720	3,720
R2	0.789	0.688	0.89	0.876	0.833	0.804	0.645
Adjusted R2	0.787	0.686	0.89	0.876	0.832	0.803	0.643
Residual Std. Error (df = 70268)	33,811.94	1.32	0.595	0.588	0.696	0.77	1.304
F Statistic (df = 349; 70268)	656.831***	388.485***	1,428.648***	1,247.342***	876.801***	722.216***	320.172***

*p<0.1; **p<0.05; ***p<0.01

TABLE 3-13: DIFFERENCE IN DIFFERENCES MODEL OF TRANSACTION COSTS FOR BECOMING CONSTRAINED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample which underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

	Dependent variable:						
	NBBO Dollar Depth	Quoted Spread (bps)	Effective Spread (bps)	1 second	30 seconds	1 minute	5 minutes
Daily Dollar Volume (log)	4,937.917 ***	-1.492***	-0.318***	-0.248 ***	0.004	0.090 ***	0.243***
	-312.616	-0.177	-0.018	-0.02	-0.027	-0.025	-0.034
Return Autocorrelation (1min)	93.866***	-0.073***	-0.005***	-0.010***	0.001	-0.002	-0.007***
	-21.63	-0.012	-0.001	-0.001	-0.002	-0.002	-0.002
Intraday Volatility (1min stdev)	-3,341,250.000***	3483.644***	981.821***	917.696***	509.481***	368.385***	493.312***
	-236,972.50	-133.911	-13.561	-15.092	-20.679	-19.228	-25.51
D1: Treatment	29,576.450***	6.852***	4.258***	4.151***	3.562***	3.247***	2.753***
	-2,846.96	-1.609	-0.163	-0.181	-0.248	-0.231	-0.306
D2: Pre/Post	632.024	-0.074	-0.004	-0.012	-0.003	-0.008	-0.02
	-461.928	-0.261	-0.026	-0.029	-0.04	-0.037	-0.05
Interaction: D1 xD2	4,064.619***	-0.301	0.298***	0.146***	0.352***	0.388***	0.576***
	-652.33	-0.369	-0.037	-0.042	-0.057	-0.053	-0.07
Constant	-58,381.020***	21.066***	4.218***	3.211***	-0.479	-1.684***	-4.124***
	-5,241.07	-2.962	-0.3	-0.334	-0.457	-0.425	-0.564
Observations	30,914	30,914	30,914	30,914	30,914	30,914	30,914
R2	0.542	0.121	0.832	0.795	0.697	0.719	0.615
Adjusted R2	0.54	0.117	0.831	0.794	0.696	0.718	0.613
Residual Std. Error (df = 30769)	28,557.69	16.138	1.634	1.819	2.492	2.317	2.074
F Statistic (df = 144; 30769)	253.106***	29.476***	1,058.800***	827.056***	491.620***	547.620***	340.657***

*p<0.1; **p<0.05; ***p<0.01

TABLE 3-14: DIFFERENCE IN DIFFERENCES MODEL OF TRANSACTION COSTS FOR BECOMING CONSTRAINED STOCK SPLIT SAMPLE

This table reports the results of difference-in-difference regression to determine the effect of changes in relative tick size on Market Quality. The sample incorporates all firms with stock splits between 2010-2013, which were tick constrained both pre and post the stock split, as a treatment sample and a matched pair sample (matched on price, average daily traded value, market capitalisation and industry). Each observation is one stock day; comprised of each trading day 180 days pre and post each stock split (using the same sample for the matched pair). Trading days which fall within one month of the stock split are removed from the sample. D1 is a 0,1 dummy indicating a 1 if the stock is in the treatment sample which underwent a stock split. D2 is a 0,1 dummy indicating 1 if the trading day is after the stock split date (or stock split date of matched pair). The interaction D1xD2 measures the treatment effect, as the interaction of D1 and D2. Stock Fixed effects where used in this regression.

			Dependent variable:				
	NBBO Dollar Depth	Quoted Spread (bps)	Effective Spread (bps)	1 second	30 seconds	1 minute	5 minutes
Daily Dollar Volume (log)	3,830.611 ***	-3.422***	-1.584***	-1.405 ***	-0.494**	-0.327	-0.270**
	-177.657	-0.232	-0.093	-0.113	-0.193	-0.221	-0.137
Return Autocorrelation (1min)	50.631***	-0.019	0.013*	-0.001	0.02	-0.093***	-0.018*
	-12.545	-0.016	-0.007	-0.008	-0.014	-0.016	-0.01
Intraday Volatility (1min stdev)	-893,879.800***	2,418.504***	1,025.832***	2,182.213***	1,907.036***	887.743***	1,234.713***
	-98,320.52	-128.544	-51.532	-62.361	-106.693	-122.558	-75.761
D1: Treatment	-2,387.58	32.598***	20.290***	17.668***	17.685***	18.062***	17.893***
	-1,572.09	-2.055	-0.824	-0.997	-1.706	-1.96	-1.211
D2: Pre/Post	667.870**	-0.163	-0.65	-0.142	-0.12	-0.039	-0.084
	-309.091	-0.404	-0.162	-0.196	-0.335	-0.385	-0.238
Interaction: D1 xD2	-10,772.120***	-6.633***	-4.177***	-3.805***	-3.676***	-3.735***	-2.995***
	-437,910	-0.573	-0.23	-0.278	-0.475	-0.546	-0.337
Constant	-33,156.280***	50.660***	23.316***	19.810***	5.888*	3.442	3.343
	-2,925.00	-3.824	-1.533	-1.855	-3.174	-3.646	-2.254
Observations	41,282	41,282	41,282	41,282	41,282	41,282	41,282
R2	0.554	0.455	0.701	0.591	0.329	0.27	0.484
Adjusted R2	0.55	0.452	0.7	0.589	0.325	0.266	0.481
Residual Std. Error (df = 41055)	21,797.09	28.497	11.424	13.825	23.653	27.17	16.796
F Statistic (df = 226; 41055)	226.026***	151.609***	426.363***	262.440***	88.883***	67.079***	170.371***

*p<0.1; **p<0.05; ***p<0.01

The separation of the sample into three pools based on tick constraint illustrates some interesting dynamics that can occur in causal research. Previous research documents the correlation between HFT and transaction costs; there are two separate cases where ELP and HFT liquidity increase while transaction costs are in opposite directions in each sample. For the over constrained stocks, there is a significant increase in ELP and an increase in transaction costs; in the unconstrained stocks, there is a significant increase in ELP and a decline in transaction costs. This may call into question previous research design that relate the two directly, as there are clearly two separate mechanisms that drive the relationship in potentially opposite directions.

3.7. Summary

Utilising a unique data set of the daily percentage of trading done by HFT and a subset of HFT, which has been termed Electronic Liquidity Providers (ELP), this study illustrates how changes in relative tick sizes alter trading behaviour. Not only do the findings show that liquid securities increase their liquidity provision by widening their spreads; but less liquid securities can also increase market-making activity in their stocks by simply widening the relative tick size. Message traffic has previously been associated with nefarious trading strategies and HFT strategies. Findings from this study show that firms across all liquidity types can decrease message traffic by splitting their stocks and widening the relative tick size.

On the other hand, this study finds that, for liquid securities, the improvement in trading behaviour may come at the cost of higher spreads. In contrast, for unconstrained stocks, findings illustrate a higher relative tick size results in a tightening of spreads (quoted, effective and realised). This appears to illustrate a unique opportunity for less liquid securities, where they can simultaneously increase the quality of the trading behaviour in their stock while decreasing transactions costs. Further, while the reality is more complex in the case of liquid securities that are already tick constrained, stock splits present one possibility for reducing message traffic, without the need to rely on regulatory change.

The findings of this study also contribute to the past literature by providing empirical evidence of the previous theories on tick sizes put forward by Harris (1993), Angel (1997) and Huang and Stoll (1994). This research provides direct causal evidence that increasing the relative tick size improves transaction costs by lowering spreads.

To summarise, the findings of this study illustrate that the optimal price and tick size falls on a razors edge. If the tick size is too wide and the quoted spread is heavily constrained, then the fastest liquidity providers will gain time priority due to their relative speed advantage. This may cause greater depth, but it will force slower traders to cross the spread more often and reduce their ability to provide liquidity passively. Pre-split, Citigroup is a perfect example. Their liquidity was in such abundance that it is entirely likely that very little or no intermediation was necessary. However, the 1-cent tick constraint allows liquidity providers who could establish time precedence to make large gains.

4. Price Discovery and Dark Trading

4.1. Introduction

This chapter furthers the research on the effect of fragmentation on market quality. The study focuses on the Canadian experience of dark pools, which represent a significant technology innovation in equity markets over the past decade. Dark pools differ from lit venue fragmentation in that there is no pre-trade transparency for limit orders. Comerton-Forde and Putniņš (2015) document the Australian experience of price discovery in dark pools, finding that they only account for a fraction of the overall price discovery. This chapter furthers this research by extending their results to the Canadian market. Further, the introduction of a regulation on dark trading is used to analyse changes in dark versus lit market price discovery in Canada, as well as US versus Canadian price discovery in cross-listed shares.

Furthermore, Furthermore, this research extends the research of Comerton-Forde and Putniņš (2015) by utilising dynamic lag estimation within the vector auto regression model. I find a significantly lower information content of dark trades ~8% compared to their estimate on the order of 20%. This may suggest that dark trading provides less than 50% of the information than previously found.

Dark trading can offer a number of potential benefits by matching large trades inside the best bid and offer, allowing institutional investors to minimise price impact and reduce information leakage. In addition, dark trading substantially reduces the explicit transaction costs of trading large volumes relative to lit exchanges. Although designed for large investors, recent studies find a trend towards dark trades being used for smaller order sizes typically executed in the lit market. The question that remains unanswered is whether dark trading deteriorates market quality. In this chapter, we address the effects of dark trading on information impounding and on price discovery efficiency.

This study is the first to examine the impact on price discovery of a dark trading regulation mandating price improvement that betters the lit market. A novel data[13] set of dark trades is utilised, collected from the four venues in Canada that trade listed securities without pre-trade transparency (MatchNow, Intraspread, Chi-X, and Alpha). The Canadian regulator IIROC's Notice 12-0130 was a market design change introduced on 15 October 2012 with the intent of limiting dark trading. Figure 4-1 shows the sharp and permanent decline in the ratio of dark to lit trades that occurs immediately. Canadian dark trading reached a high watermark of 5.9% in August 2012, but has averaged approximately only 2% of consolidated volume since the implementation of the price improvement rule.

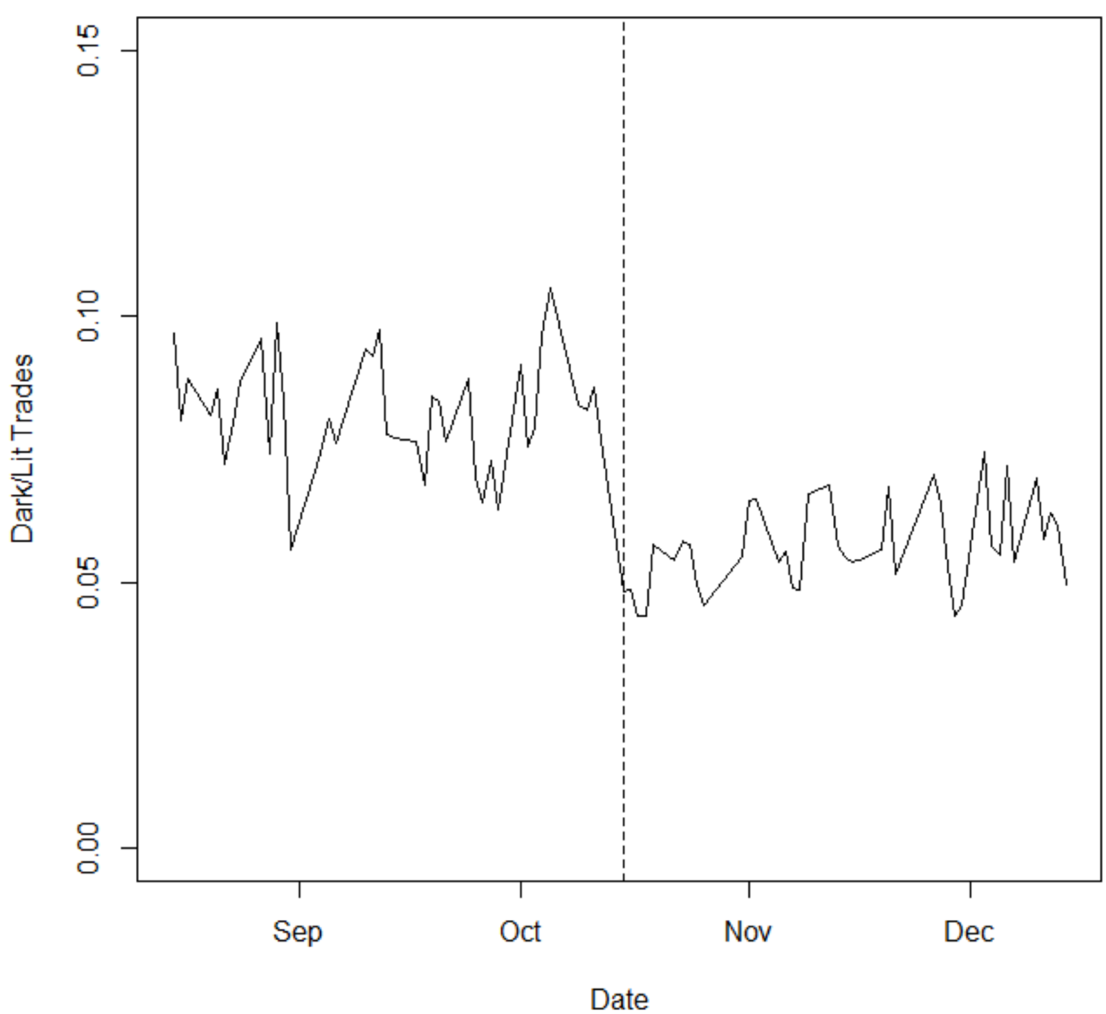
The Canadian financial market was the first to mandate a price improvement market design change for all dark trades. IIROC chose to take preventative measures to curb dark trading before it reached the levels seen in the US market which Rosenblatt Securities estimated to be 14.6% in May 2013, and 38% today. The Australian Financial Markets Regulator, ASIC, implemented price improvement regulation with the same intent on 27 May 2013. Other North American and

[13] In contrast to the work of Comerton Forde and Putnins (2015) who use on exchange dark trades, this study utilizes dark trades of alternative venues

European regulators have launched discussion of price improvement mandates for dark trading.

FIGURE 4-1: **DARK TRADING IN CANADA AS A PERCENTAGE OF CONSOLIDATED DOLLAR VOLUME.**

This figure shows daily dark trading in Canada as a fraction of total trading volume, for constituents of the TSX Composite Index chosen in this study which have greater than 390 dark trades per day, from 15 August 2012 to 15 December 2012. The vertical bar indicates the introduction of minimum price improvement requirements on 15 October 2012.



Incidental to the dark trading research, two contributions are provided by this study to the literature on price discovery. First, the methodology of price discovery is extended by utilising dynamically estimated lag structures on a stock-daily level. Second, the order book price discovery measures developed by Jain, Jain and McInish (2012) are utilised to estimate their effect on contemporary price discovery measures. It is found that their measures of order book quality are significant predictors in cross-market competitiveness of price discovery.

This chapter proceeds as follows. Section 4.2 describes the institutional details on dark trading and the impact of IIROC's price improvement regulation. Sections 4.3 and 4.4 explain the data and price discovery methods. Sections 4.5 and 4.6 specify the model and the measurement of several novel variables. Following this, Section 4.7 presents and discusses the empirical results, and Section 4.8 concludes.

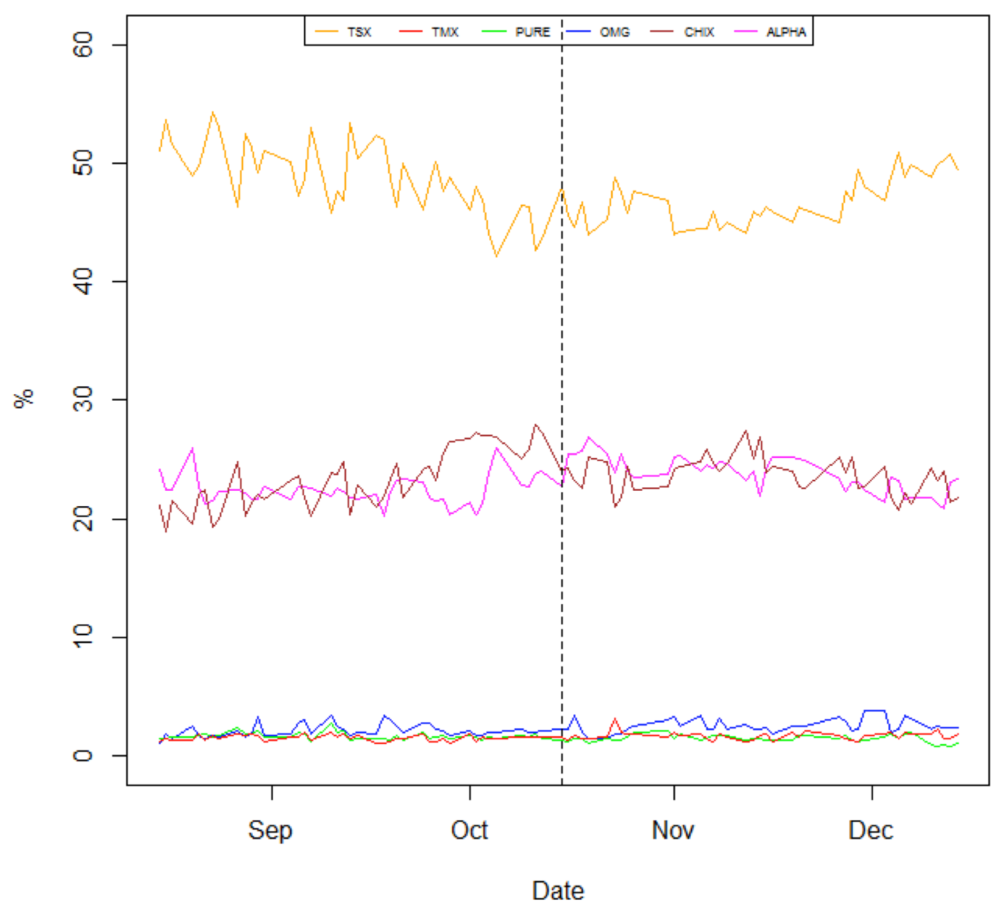
4.2. Institution Details

Canada operates under a fragmented trading landscape, consisting of the TSX and five alternative trading venues (ATS). Four venues, MatchNow, Alpha Intraspread, Chi-X and TSX allow the continuous trading of dark order types, which have no pre-trade transparency. Unlike the US system, where dark orders can trade at any increment between the best bid and ask, Canadian dark orders offered pre-determined price improvements even prior to the 15 October regulation. For example, MatchNow and Intraspread offered price improvement at the midpoint, 20% and 10%, respectively, of the national best bid and offer (NBBO). Dark orders in Canada can be submitted as either marketable orders which check for the best price in the dark and then are routed to lit venues and order flow, or as “fill or kill” orders which look for dark liquidity and are then either filled or cancelled. In addition, dark orders can be placed as passive liquidity supplying unknown counterparties.

Figure 4-2 displays the trends in trading volume as a percentage of total dollar traded value of each venue. Before the implementation of the price improvement regulation, the ATS venues as a group were taking market share from the TSX. Chi-X and Alpha were the principal benefactors. This trend reversed after the implementation of the regulation, resulting in market share growth for the TSX.

FIGURE 4-2: **PERCENTAGE OF TOTAL TRADES BY VENUE OVER THE EVENT PERIOD**

This figure shows daily trading in Canada, from 15 August 2012 to 15 December 2012. The vertical bar indicates the introduction of minimum price improvement requirements on 15 October 2012.



It is important to note that dark trades in the Canadian market must be reported upon execution to the entire market, consistent with the Canadian Universal Market Integrity Rules. As in the US, block trading in an upstairs market by large institutional investors always existed within Canada, but participation was typically non-continuous and involved only minimal trading volume. Similarly, Canada allows for broker internalisation, but unlike in the US, that trading volume has remained small because Canadian broker internalisers must offer one-tick price improvement, compared with sub-penny or zero price improvement in the US.[14]

On 13 April 2012, IOSCO notice 12-0130 announced changes to the Universal Market Integrity Rules (UMIR) effective 15 October 2012. The rule states that any dark orders less than 50 standard trading units[15] or $100,000 must price improve 1 tick, or half a tick at 1 cent spreads.[16] Foley and Putnins (2013) show that the average dark volume from the 2-months prior dropped steeply from 7.5% to 4.6% of dollar volume after October 15. They also note that in the pre-price improvement months, almost 70% of all orders were executed at less than 1 tick (or half a tick for tick-constrained spreads), so the price improvement rule mandated economically significant changes.

---

[14] Hatheway, Kwan and Zheng (2013)

[15] A standard trading unit is 100 shares for stocks priced above $1, 1000 shares for stocks priced between 10c and $1 and 10,000 shares for stocks priced below 10c.

[16] For the continuous dark pools, Intraspread and MatchNow, orders offering 10% or 20% price improvement were also disallowed.

4.3. Data

To generate meaningful price discovery measures, stock selections are restricted for both the dark trading and cross-listed analysis to the S&P/TSX60. This is important for two reasons. First, enough trades are required within each day to match the price chains in faster and slower markets, thereby limiting the need to forward-fill with misleading, stale observations. Second, to generate consistent IS estimates, it is necessary to be able to match observations at high enough frequencies to limit the covariance of the error terms across channels. Cross-listed securities are sampled at a frequency of at least 390 trades per day in both markets – this represents a 1-minute frequency.

A proprietary data set of dark trades executed on Alpha, Chi-X, Intraspread and MatchNow is used. The data are provided by the exchange venues where the trades executed; trades are stamped by stock, date, time, price and volume. This data are also reported to the consolidated tape at the time of execution. This data set constitutes approximately 74% of all dark trades (Foley and Putnins, 2013).

Trade and Quote Data, as well as depth at the top 10 price levels, are taken from the Thomson Reuters Tick History database. Trade and Quote data is available aggregated at the consolidated level for both the US[17] and Canadian markets.[18] Lit trade information contains the stock name, date, time to the millisecond, price and

[17] Consisting of NASDAQ SE, NASDAQ PSX, NASDAQ, BX, NYSE AMEX, NYSE Arca, NYSE SE, BATS Z, BATS Y, EDGE A, EDGE B, NSX, CME and the Trade Reporting Facility
[18] Consisting of Alpha, Omega, TSX, TMX Select, Pure and Chi-X

volume. The national best bid and offer is available for both markets. Depth data available to the top ten levels of the order book is utilised. For the U.S market, depth is reported by listing market, where depth is only available for NYSE stocks as depth listed on NYSE. To preserve comparability, the depth on the primary listing market for those securities listed on both the NASDAQ and TSX is used.

Stocks that trade at prices less than $1 are removed and the study only analyses trading between the hours of 9:30 a.m. and 4:00 p.m. To calculate market capitalisation, we use the outstanding shares as reported through Thomson Reuters Tick History when a firm lists or undergoes any change in shares. The most recent value for each day is then multiplied by the closing price on that day. When comparing price discovery measures for cross-listed securities, each Canadian trade price is converted into USD, calculated using the Reuters CAN/USD exchange index, matched at the nearest previous millisecond.

Analyst coverage data is acquired from the Wharton Research Data Services I/B/E/S database of analyst forecasts. This offers the number of analysts covering each security, as well as the proportion of buy, hold and sell recommendations. The coverage across countries, as well as the amount of disagreement between analysts, is used as a proxy for information asymmetry.

4.4. Method

Previous literature focuses on two main methods of analysing information transmission between price series: Hasbrouck's (1995) information share (IS) reflecting (in part) information impounding, and Gonzalo and Granger's (1995)

Common Factor Share (CFS) reflecting the avoidance of chasing transitory shocks. Both models stem from the vector auto-regressive state-space representation of prices (Baillie, Booth, Tse and Zabotina, 2002). Yan and Zivot (2010) show that to truly draw out the information leadership defined as the impounding of innovation in the permanent price, both measures must be combined.

Each method decomposes the impact of a price innovation into permanent and transitory components. Hasbrouck's (1995) Information Share (IS) measure examines the extent to which price series incorporate accurate information and trigger less noise trading and chasing of liquidity shocks relative to other price channels. Gonzalo and Granger's (1995) CFS measure captures the avoidance of noise trading and the chasing of liquidity shocks relative to other price channels. As a result, the Gonzalo Granger CFS measure can be used to strip out the transitory liquidity-based trading component of IS, yielding a measure of permanent information impounding.

Gonzalo and Granger (1995) first propose that a C(1,1) series could be decomposed into permanent and transitory components after estimating the vector of error-correction parameters $\hat{z}$. They derive a metric of price discovery from the fact that observed price levels are a weighted average of two factors: the estimated error-correcting adjustment parameters $\hat{z}$ times lagged prices P_{t-1} plus orthogonal permanent components $\Upsilon_{\perp} P_t$

$$Pt = A1\, \hat{\Upsilon}_{\perp} Pt + A2\, \hat{z}\, Pt\text{-}1 \qquad (4\text{-}1)$$

where $\Upsilon\hat{}\perp$ is derived as orthogonal to the estimated vector of error-correction parameters $\hat{z}$ and A1 and A2 are loading matrices.

Gonzalo-Granger's common factor share (CFS) is defined as the proportion of price innovations in competing channels that are driven by transitory shocks:

$$CFS_h = \delta_f^T / \Delta_h \tag{4-2}$$

where the determinant $\Delta_h = \delta_h^P \delta_f^T - \delta_f^P \delta_h^T$.

Information share (IS) decomposes the variance of implicit efficient price variations in one market compared to its rival(s). The Hasbrouck (1995) variance decomposition method confounds the source of the information. Yan and Zivot (2010) demonstrate that IS_h captures both the permanent information impounded in the home channel (δ_h^P) and the extent to which the competing channel is chasing transitory shocks δ_f^T:

$$IS_h = \delta_h^P \delta_f^T / \Delta_h \tag{4-3}$$

where δ_h^P and δ_f^T are long-run impact multipliers and again the determinant $\Delta_h = \delta_h^P \delta_f^T - \delta_f^P \delta_h^T$.

Thus, the CFS in (4-2) can be used in conjunction with the IS in (4-3) to isolate the relative impact multiplier in the home channel δ_h^P attributable to permanent shocks alone. Yan and Zivot's (2010) Permanent Information Impounding (PII) metric accomplishes this purpose:

$$PII_h = IS_h / CFS_h * CFS_f / IS_f = (\delta_h^P)/(\delta_f^P) \tag{4-4}$$

A high PII_h is unambiguously indicative of impounding a greater amount of permanent information in the home channel compared to the competing channel(s).

We adopt a unitised version of the PII metric proposed by Yan and Zivot (2010) and analysed by Harris, Aitken and Di Marco (2012a, 2012b) and Putnins (2013):[19]

$$PII_h = \frac{\left|\frac{IS_h CFS_f}{IS_f CFS_h}\right|}{\left|\frac{IS_h CFS_f}{IS_f CFS_h}\right| + \left|\frac{IS_f CFS_h}{IS_h CFS_f}\right|}. \tag{4 - 5}$$

Similarly, the Price Discovery Efficiency (PDE) metric is the ratio of the CFS of the home channel to the CFS of the rival channel (Harris, Aitken and DiMarco, 2012):

$$PDE_h = \frac{CFS_h}{CFS_f} = \frac{\delta_f^T}{\delta_h^T}\frac{\Delta_f}{\Delta_h} \tag{4-6}$$

[19] Putnins (2013) refers to this as an Information Leadership Share to echo the earlier Hasbrouck (1995) concept of an Information Share that confounds both information impounding and the avoidance of chasing transitory shocks.

where h is the home market and f is the foreign cross-listing. PDE is thus a metric of "bad trades" in which market participants chase transitory shocks, thereby inhibiting the price discovery efficiency of a channel. A higher PDE_h can be interpreted as a greater relative tendency of the competing market(s) to chase transitory liquidity-based shocks that contain no permanent information, reflecting relatively higher price discovery efficiency in the home market execution channel.

It is well recognised that the Vector Error Correction Model (VECM) parameters necessary for both IS and CFS, and therefore for PII and PDE, are ultrasensitive to lag-length specification. Therefore, the estimation of an optimal lag structure is crucial. The method used in this paper calculates the optimal lag length for every stock day. This is distinctly different from previous research that either fits an average lag length they believe to be representative over the period, or chooses a lag length arbitrarily. Ultimately, VECM models are an assessment of the dynamic interrelation between the lag structures of two or more information channels, and the validity of the model relies heavily on the accurate assessment of this lag structure.

The study utilises the MULMAR routine from the TIMSAC package developed by The Institute of Statistical Mathematics, Japan.[20] This allows us to optimise the lag length dynamically on a case-by-case basis to ensure that the most accurate estimates of the co-integrating vector and the price adjustment dynamics are calculate.

[20] http://cran.r-project.org/web/packages/timsac/timsac.pdf

Estimating on a daily basis also allows us to test that co-integration holds continuously rather than relying on the law of one price across days. This allows for the censoring of days when the time-series econometric assumptions of the equilibrium error correction model are violated. In these cross-listings, equilibrium error correction ignoring settlement and clearing costs is violated intraday on 4.8% of stock days. The Canadian sample is reduced to 25 securities by applying a filter where the number of days that fail the co-integration tests must be less than 5%. This results in 3.6% of the stock days being censored for the remaining 25 securities.

4.5. Specification and Measurement

While the ultimate goal is to undertake an event study of the price discovery changes around the implementation of a price improvement rule, it is necessary to control for other factors that may lead to exogenous shifts in the Price Discovery measures. To control for these effects, the model includes several covariates. Order book quality captures the rate at which an order will walk the order book. Informational asymmetry affects the level of knowledge about each security available to the market. A market where all participants are equally informed is more likely to follow a random walk where prices move with little unexplained variance or deviations from the true price. Liquidity controls aim to capture the cross-sectional differences in trading strategies and participants.

Stock-specific effects are controlled by market capitalisation and a series of liquidity controls. The quoted, effective and realised spreads are calculated from the consolidated best bid and offer, and measured in basis points relative to the midquote, m = (Ask + Bid/2). Quoted spread is measured as the time-weighted average of quoted spreads throughout the day—a daily average round trip transaction cost of immediately reversing a trade.

$$\text{Quoted Spread} = [(\text{Ask} - \text{Bid})/m] \times 10^4 \tag{4-7}$$

Effective and realised spreads take into account the cost of trading of individual trades benchmarked to the midpoint. Effective spreads measure the transaction cost of a marketable order relative to the current midquote, while realised spreads measure the profit of the liquidity provider relative to the prevailing midquote at t+5 minutes.

$$\text{Effective Spread} = 2q[(p_t - m_t)/m_t]10^4 \tag{4-8}$$

$$\text{Realised Spread} = 2q[(p_t - m_t)/m_{t+5}]10^4 \tag{4-9}$$

where q indicates the direction of the trade obtained using the Lee and Ready (1991) algorithm (+1 for buyer initiated, and -1 for seller initiated). The price p_t is measured at trade time, for effective spread the midpoint at the time of trade, m_t, and 5 minutes post trade time, m_{t+5}, for realised spreads. Both measures are weighted by the trade volume across all trades during regular hours.

Figure 4-3 shows that quoted and effective spreads increase, while realised spreads decline in the first 30 days immediately after the rule change. The descriptive statistics in Table 4-1 indicate, however, that across the entire period all three spread measures, quoted, effective and realised, are on average 5%, 7%, and 27% higher, respectively, post-rule change.

FIGURE 4-3: TIME SERIES OF LIQUIDITY MEASURES OVER EVENT PERIOD

This figure shows time weighted Quoted, Effective and Realised spread (volume weighted by stock), from 15 August 2012 to 15 December 2012. The vertical bar indicates the introduction of minimum price improvement requirements on 15 October 2012.

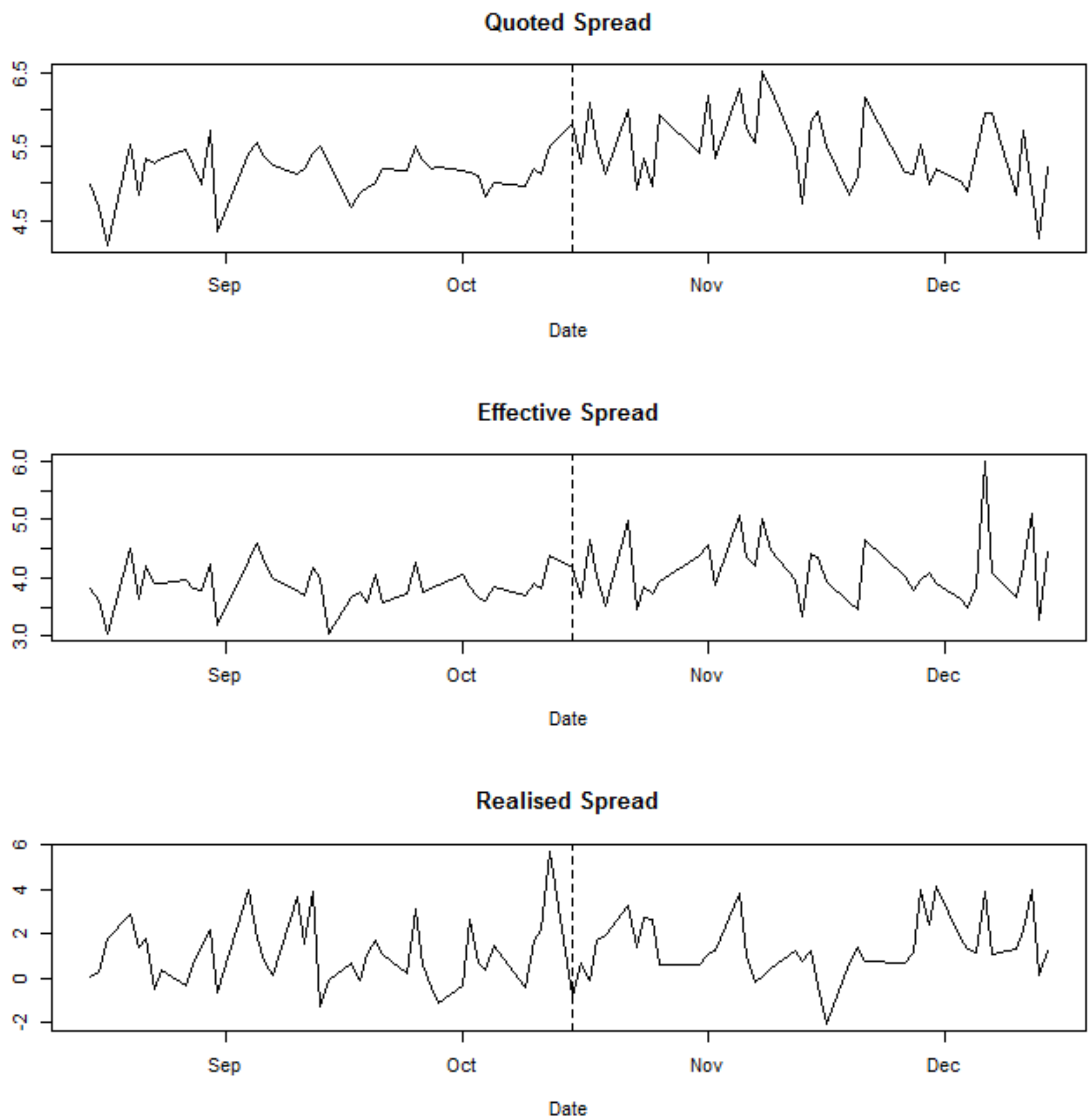


TABLE 4-1: **CANADA MARKET QUALITY SUMMARY STATISTICS PRE AND POST PI RULE**

This table shows summary statistics for Canadian listed securities, from 15 August 2012 to 15 December 2012. Data is separated into pre- and post- the October 12th implementation of the price improvement regulation.

	PRE			POST		
	mean	median	sd	mean	median	sd
Quoted Spread	5.12	3.96	0.46	5.37	3.77	0.55
Effective Spread	..86	2.82	0.37	4.12	2.78	0.42
Realised Spread (1s)	1.09	0.70	0.54	1.38	0.83	0.57
Market Capitalisation	16.77	16.62	0.75	16.74	16.69	0.73
Illiquidity	-19.29	-19.24	0.64	-19.28	-19.24	0.66
Analyst Recommendations	0.39	0.32	0.18	0.38	0.34	0.17
VIXC	2.78	2.77	0.07	2.79	2.78	0.07
Standard Deviation (60sec)	4.78	4.49	2.13	5.09	4.91	2.07
Auto-Correlation (10sec)	0.00	0.00	0.05	0.00	0.00	0.05
Auto-Correlation (60sec)	0.00	0.00	0.09	0.00	0.00	0.09
Auto-Correlation (30min)	-0.10	-0.11	0.26	-0.11	-0.12	0.27
Order Book Slope	0.14	0.10	1.52	0.04	0.08	1.45
Order Book Dispersion	-4.78	-4.82	0.20	-4.84	-4.84	0.15
Cost of Trading 100 Shares	-7.79	-7.76	0.66	-7.71	-7.82	0.61

To control for the liquidity level across stocks, Amihud's (2002) illiquidity measure ($ILLIQ_{it}$) is used. Amihud's (2002) measure calculates the intraday average hourly mid-quote return divided by the dollar volume traded in the hour – a dollar volume of trading required to move the price per hour. A stock which on average changes price in response to very little dollar volume is said to be highly illiquid.

$$ILLIQit = \log\left[1 + \frac{10^5}{H}\sum_{h=1}^{H}\frac{|r_{it,h}|}{\$Volume_{it,h}}\right] \tag{4-10}$$

where $r_{i,t,h}$ hourly return is based on the midprice for stock (i) on day (t), $\$Volume_{it,h}$ is the dollar volume traded in that hour (h). Consistent with Karolyi, Lee and Van Dijk (2012), the variable is log transformed and winsorised at the 99th percentile to reduce the impact of outliers.

Jain, Jain and McInish (2012) utilise three measures of order book quality that are found to contribute to price discovery in Japan's equity market. The cost of trading measures the cost at a given time of a marketable order, as opposed to the quoted spread which estimates the round trip transaction cost assuming there is adequate depth at the inside. Both the slope and dispersion of the order book measure the rate at which a large order would proceed down the order book if submitted at any given time. A market with inferior order book quality is susceptible to greater volatility from any given transitory liquidity shock.

Often market microstructure research focuses on measures such as spreads, which capture the liquidity at the top of the order book. While these measures are found to adequately represent costs to small orders as round trip transactions, they do not take into account how a large marketable order would impact the order book, potentially at multiple price levels. Increased values in any of the following measures indicate a greater resiliency in response to order book shocks.

The cost of trading (Kang and Yeo, 2008) captures the cost of trading a marketable order, taking into account the order's size. The cost of trading a 100 share order and a 1000 share order is incorporated. The round trip cost to trade for stock I is calculated as the cost above fair value (proxied by the midquote, m = (Best Ask + Best Bid)/2) to transact an order of size T,

$$\text{Cost of Trade}_i = \frac{\sum_{k=1}^{K} I_k^{buy}\left(m - P_k^{buy}\right) + \sum_{k=1}^{K} I_k^{sell}\left(P_k^{sell} - m\right)}{T\ x\ m} \tag{4-11}$$

where P_k is the k^{th} best price on the bid or ask, and I_k is the indicator variable of how many shares are executed at that price. I_k is measured as follows:

$$I_k^{buy} = \begin{cases} Q_i^{buy} & if\ T > \sum_{j=1}^{k} Q_j^{buy} \\ \left(T - \sum_{j-1}^{k-1} Q_j^{buy}\right) & if\ T > \sum_{j=1}^{k-1} Q_j^{buy}\ and\ T < \sum_{j-1}^{k-1} Q_j^{buy} \\ 0 & otherwise \end{cases} \tag{4-12}$$

$$I_k^{sell} = \begin{cases} Q_i^{sell} & if\ T > \sum_{j=1}^{k} Q_j^{sell} \\ \left(T - \sum_{j-1}^{k-1} Q_j^{sell}\right) & if\ T > \sum_{j=1}^{k-1} Q_j^{sell}\ and\ T < \sum_{j-1}^{k-1} Q_j^{sell} \\ 0 & otherwise \end{cases} \tag{4-13}$$

The slope of the order book measures the depth available at the top ten price levels as a function of price from the inside. A positive slope indicates greater order book resilience as prices move away from the inside depth. Conversely, if depth decreases as a function of distance from the inside, then an increasingly large marketable order would move through the order book at an accelerating pace. Naes and Skjeltorp (2006) measure the order book slope for stock I at time t as

$$Slope_{i,t} = \frac{DE_{i,t} + SE_{i,t}}{2} \tag{4-14}$$

where $DE_{i,t}$ and $SE_{i,t}$ represent the slope on the bid and ask respectively.

$$DE_{i,t} = \frac{1}{N_B}\left\{\frac{v_1^B}{p_1^B/p_0-1} + \sum_{\tau=1}^{N_B-1} \frac{v_{\tau+1}^B/v_\tau^B-1}{|p_{\tau+1}^B/p_\tau^B-1|}\right\} \tag{4-15}$$

$$SE_{i,t} = \frac{1}{N_A}\left\{\frac{v_1^A}{p_1^A/p_0-1} + \sum_{\tau=1}^{N_A-1} \frac{v_{\tau+1}^A/v_\tau^A-1}{|p_{\tau+1}^A/p_\tau^A-1|}\right\} \tag{4-16}$$

N_A and N_B represent the number of tick levels that contain orders on each side of the order book. τ denotes each tick level, where τ=0 is the best bid and offer. p_0 is the midpoint of the best bid and offer, $v^A{}_\tau$ and $v^B{}_\tau$ denote the natural logarithm of volume available to execute at each price level τ. The slope is scaled by 100 to fit parameter estimates, and measured as the time-weighted average order book slope. Table 4-1 shows that the order book slope declines on average -71% post-rule change.

Dispersion in the order book implies another source of higher cost as an order works through the book. It can be interpreted as a measure of the level of competition between liquidity providers. Following Kang and Yeo (2008), the study measures the level of dispersion as the distance between the price levels of orders further from the best bid and offer:

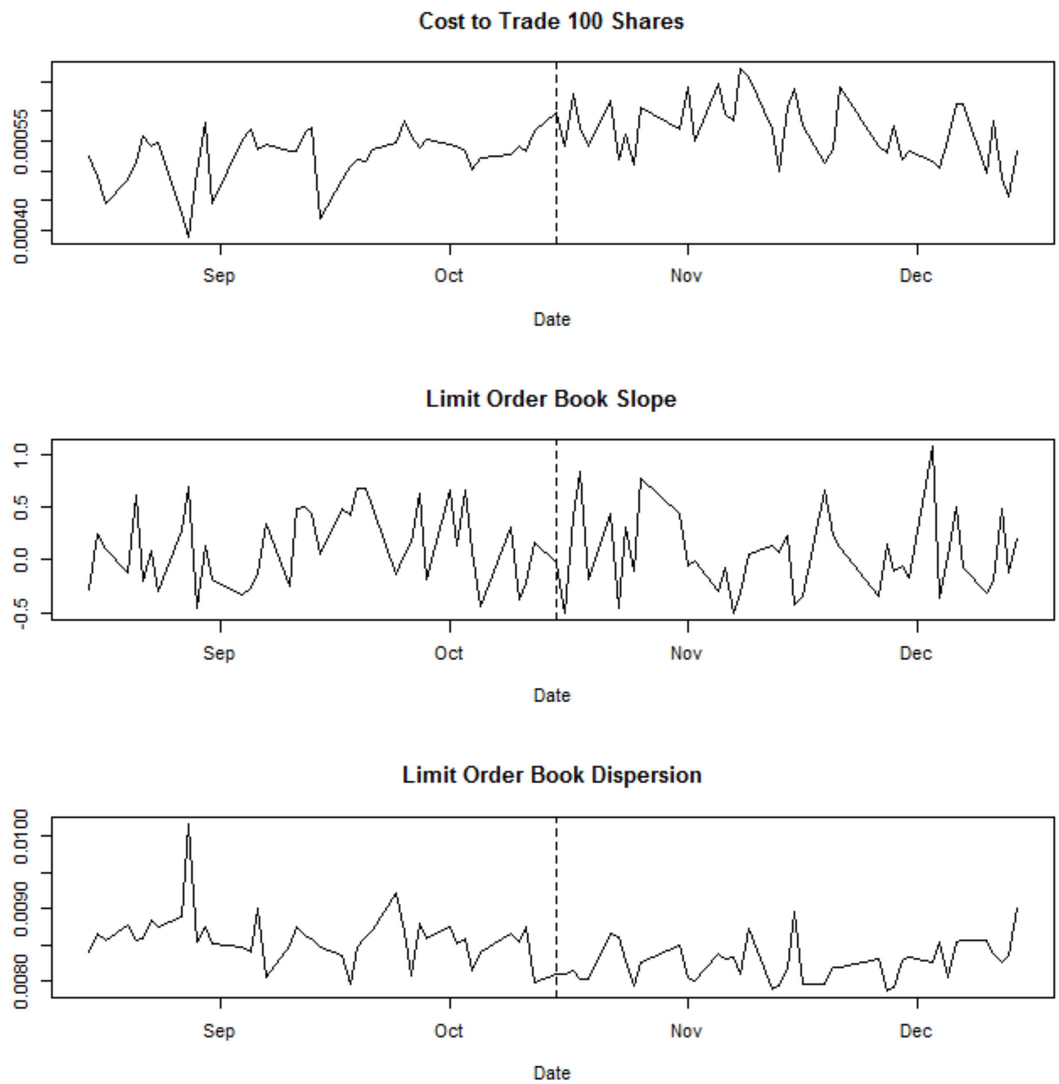
$$Dispersion = \frac{1}{2}\left(\frac{\sum_{j=1}^{n} w_j^{buy} Dst_j^{buy}}{\sum_{j=1}^{n} w_j^{buy}} + \frac{\sum_{j=1}^{n} w_j^{sell} Dst_j^{sell}}{\sum_{j=1}^{n} w_j^{sell}}\right) \tag{4-17}$$

where Dst_j is the price interval between the jth best bid or offer and its next best quote. Dst_j is weighted by the size of the orders placed at each price level (w_j), and then normalised by the sum of the total order volume available.

Figure 4-4 shows the cost to trade, LOB slope, and LOB dispersion components of order book quality exhibit substantial variation and appear to capture different aspects of market resiliency. Although all three are stationary across the four months under examination, the mean cost to trade 100 shares rises immediately after minimum price improvement requirements were introduced, while mean limit order book dispersion declines.

FIGURE 4-4: **TIME SERIES OF ORDER BOOK QUALITY MEASURES OVER THE EVENT PERIOD**

This figure shows time weighted Cost to Trade, Dispersion and Slope of the order book (volume weighted by stock), from 15 August 2012 to 15 December 2012. The vertical bar indicates the introduction of minimum price improvement requirements on 15 October 2012.



Analyst coverage data is acquired from the Wharton Research Data Services I/B/E/S database of analyst forecasts. This offers the number of analysts covering each security as well as the proportion of buy, hold and sell recommendations. We use the coverage across countries, as well as the amount of agreement between analysts, as a proxy for information asymmetries. Analyst recommendations are categorised as buy, sell or hold (b, s and h represent the percentage of total recommendations in each category). The count of each category is then used to calculate the Herfindal Index and normalised to a {0,1} scale:

$$N\ Herfindal = \frac{\sum b^2 h^2 s^2 - {}^{1}/_{3}}{1 - {}^{1}/_{3}} \tag{4-19}$$

To account for the informational efficiency of prices, the standard deviation and autocorrelation of mid-quote returns is calculated at 10-second, 60-second and 30-minute intervals. This measures the variability and predictability, respectively, of market deviations. The standard deviation and autocorrelation values are measured for each price interval k as

$$\text{Autocorrelation}_k = |\text{Corr}(r_{k,t}, r_{k,t+1})| \tag{4-20}$$

where $r_{k,t}$ indicates the mid-quote return at time t, of length k per stock day. This is measured by taking the absolute value of autocorrelation to measure the level of informational efficiency. Return predictability in either direction is equally inefficient. The standard deviation is measured at each interval k.

4.6. Model specification

This study focuses on the development of two models. The first analyses the stock-specific and order flow characteristics associated with information impounded into the Canadian market by dark trades. Figure 4-1 indicates that the price improvement rule affects the execution channel decision. This first model sheds light on the effect that the price improvement rule has on the information content of dark versus lit trading. The second model analyses the determinants of the relative contribution of the Canadian lit exchanges to price discovery for cross-listed securities on the US market which did not undergo the rule change. The descriptive statistics in Table 4-2 show that the price improvement rule significantly affected trading strategies and liquidity for these cross-listed securities. Quoted spreads increase by 25%, and realised spreads decline by 27%. The order book slope in the US for cross-listed Canadian stocks declines by 89%, and the negative order book slope in Canada quadrupled, implying acceleration up and down the book accompanying large declines in market resilience.

The information content of Dark trades in the Canadian market, measured as $\mathrm{PII}_{\mathrm{dark}}$, are regressed on hypothesised determinants as follows:

$$\mathrm{PIIdark}_{i,t} = \alpha_{i,t} + D_t Price\ Improvement + \sum \beta_{j,it} Order\ Book\ Quality_j + \sum \beta_{j,it} Informational\ Assymmetry_j + \sum \beta_{j,it} Informational\ Efficiency_j + \sum \beta_{j,it} Liquidity\ Controls_j + \beta_{it}\mathrm{MCAP}. \tag{4-21}$$

Price improvement constitutes a dummy variable of 1 after the implementation of the price improvement rule (15 October 2012). Several variables in each subset of determinants with over 0.7 pairwise correlation (following Tabachnick, B.G. and Fidell, L.S. (1996)) are removed. Order book effects include the cost of trading 100 shares, order book slope and dispersion. Informational Asymmetry is controlled for by the number of recommendations available for each security day. To capture the informational efficiency, the autocorrelation of mid-quote returns are included at 10-second, 60-second and 30-minute intervals, and the 60-second deviation in mid-quote returns. Liquidity is controlled for by the quoted, effective and realised spreads. MCAP is market capitalisation.

The information content of lit trades of cross-listed securities in Canada is regressed against their listed shares in the US where

$$PIIlit_{i,t} = \alpha_{i,t} + D_t Price\ Improvement + \beta_{it} \log\left(Trade\ Ratio\right) + \sum \beta_{j,it} Order\ Book_j + \sum \beta_{j,it} Informational\ Assymmetry_j + \sum \beta_{j,it} Informational\ Efficiency_j + \sum \beta_{j,it} Liquidity\ Controls_j + \beta_{it}\mathrm{MCAP} \tag{4-22}$$

The log of the ratio of trades in the Canadian market to the US market (Trade Ratio) controls for variation in the trading intensity between each market. The liquidity controls are the ratio of quoted, effective and relative spreads between each market, such that a higher value indicates a greater spread in the Canadian market. The ratio of values between markets is also used for the cost of trading, dispersion, and slope of the limit order book. The limit order book is included for both markets as the ratio of the dispersion of prices is difficult to interpret as a coefficient. Informational asymmetry is measured in each market as the number of recommendations and the normalised Herfindal index of analyst consensus. The model controls for the Market capitalisation, VIX and VIXC (log values). Informational efficiency variables are included for both markets as the first principal component of 10-second, 60-second and 30-minute midquote return autocorrelation and standard deviations. The above specification is also used to analyse the price discovery efficiency PDE_{lit} in the lit market for cross-listed stocks.

TABLE 4-2: **CROSS LISTED MARKET QUALITY SUMMARY STATISTICS PRE AND POST PI RULE**

This figure shows summary statistics for Canada/US Cross listed securities, from 15 August 2012 to 15 December 2012. Data is separated into pre- and post- the October 12th implementation of the price improvement regulation.

	PRE			POST		
	mean	median	sd	mean	median	sd
Trade Ratio	1.17	1.06	0.72	1.1	1.08	0.57
Quoted Spread	0.95	0.88	0.43	1.19	0.90	1.33
Effective Spread	0.98	0.93	0.30	1.07	0.97	0.55
Realised Spread (1s)	1.75	0.89	1.01	1.28	0.91	0.30
Market Capitalisation	14.89	14.35	1.89	14.85	14.16	1.99
Analyst Consensus (CAN)	0.37	0.32	0.28	0.38	0.33	0.25
Analyst Recommendations (CAN)	8.62	8.50	5.19	8.22	8.50	4.55
Analyst Consensus (USA)	0.16	0.06	0.18	0.15	0.06	0.16
Analyst Recommendations (USA)	4.09	2.00	7.58	4.90	2.00	8.60
VIXC	2.78	2.77	0.07	2.79	2.77	0.07
VIXC	15.46	15.53	1.20	16.71	16.62	1.23
Standard Deviation (CAN)	0.00	0.00	0.00	0.00	0.00	0.00
Standard Deviation (USA)	0.00	0.00	0.00	0.00	0.00	0.00
Auto-Correlation (CAN)	-0.03	-0.06	0.26	0.03	0.00	0.25
Auto-Correlation (USA)	-0.04	-0.10	0.26	0.05	0.01	0.26
DISP	0.04	0.01	0.31	0.13	0.01	0.56
Order Book Slope (USA)	0.09	0.03	0.65	0.01	0.03	0.61
Order Book Slope (CAN)	-0.04	-0.01	1.10	-0.19	-0.10	1.07
Cost of Trading	1.05	1.05	0.05	1.03	1.05	0.08

4.7. Results

4.7.1. Information Leadership of Dark Trading

Determinants of the Information Leadership Share for Dark trades in Canada are reported in Table 4-3. Results indicate that the introduction of a mandated price improvement regulation reduces the information content (PII) of dark trades by 19%, controlling for order book quality and numerous characteristics of the trade sequences. This supports the principal hypothesis that the price impact advantage for informed traders offered by dark rather than lit markets would be reduced by mandated price improvement signalling the presence of information. This result is in-line with the findings of Nimalendran and Ray (2014) in which informed traders utilise dark crossing networks to capture the value of fleeting technical information. The introduction of a price improvement rule in Canada forces informed traders into the lit market, thereby relatively decreasing the price information in the dark market.

TABLE 4-3: OLS REGRESSION OF INFORMATION LEADERSHIP SHARE FOR CANADIAN DARK TRADING

This table shows the regression output of the Information Leadership Share for dark trades vs lit trades in Canada, from 15 August 2012 to 15 December 2012.

			Dependent variable:
			Information Leadership Share
	(1)	(2)	(3)
Intercept	-1.87	-3.961**	-0.937
	(1.722)	(1.556)	(1.271)
Price Improvement	-0.186***	-0.177***	-0.186***
	(.058)	(0.058)	(0.058)
Effective Spread	.032**	0.072***	0.033**
	(0.015)	(0.012)	(0.015)
Realised Spread	-0.009*	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)
Market Capitalisation	-0.479***	-0.559***	-0.473***
	(0.071)	(0.069)	(0.071)
Illiquidity	-0.597***	-0.557***	-0.584***
	(0.069)	(0.066)	(0.068)
Number of Recommendations	0.312*	0.232	0.330*
	(0.174)	(0.173)	(0.174)
VIXC	-0.56	-0.064	
	(0.424)	(0.424)	
Standard Deviation (60sec)	-0.156***	-0.127***	-0.160***
	(0.018)	(0.016)	(0.017)
Autocorellation (10s)	-0.681	-1.140*	
	(0.597)	(0.590)	
Autocorellation (60s)	-2.288***	-2.152***	-2.417***
	(0.342)	(0.340)	(0.320)
Autocorellation (30m)	0.138	0.133	
	(0.110)	(0.110)	
Order Book Slope	-0.025		
	(0.019)		
Order Book Dispersion	0.291*		0.318*
	(0.177)		(0.176)
Cost of Trading 100 Shares	0.318***		0.435***
	(0.091)		(0.090)
Observations	1,977	1,977	1,977
R2	0.105	0.100	0.104
Adjusted R2	0.102	0.098	0.102

*p<0.1; **p<0.05; ***p<0.01

As the cost of trading a larger order size increases, the relative price impact advantage of dark trading over lit markets increases. A priori, dark venues would then attract more informed trades. The measure of Cost of Trading 100 shares is positive and significant. That is, informed participants move their difficult trades over to institutional counterparties on dark venues seeking to reduce their price impact. This preference of informed traders for the dark is especially pronounced in small stocks (i.e., the market capitalisation variable is negative and significant) because the natural buy-side counterparties are absent. When illiquidity in the dark increases, and therefore the realised spread paid to liquidity suppliers increases, the migration of informed traders away from the lit market declines. Realised spread is negative and significant, even though the cost of immediacy (i.e., the effective spread) for completing larger trades is positive and significant.

The Autocorrelation and Standard deviation of the mid-quote (at 60-seconds) are associated with a reduced information content of dark trading, while longer and shorter autocorrelations are insignificant.[21] The standard deviation indicates the size and frequency of movements in the lit order book, while the autocorrelation indicates the short-term predictability of the best bid and offer in the lit order book. Changes in the mid-quote can occur either due to new orders, cancellations or lit executions, but not dark executions. Therefore, the negative effect of standard deviation implies the

[21] Table 4 shows none of these autocorrelation measures of informational efficiency is collinear in the dark trading sample whereas all the standard deviation measures are highly collinear.

lit order book must be leading the dark pools in information content. The lower PII_{dark} with increased predictability of the lit market is interpreted as mitigating the advantage of dark pool participants in real-time modelling of the stock-specific state of the market.

TABLE 4-4: **CORRELATION MATRIX OF INFORMATIONAL EFFICIENCY MEASURES FOR DARK TRADING SAMPLE**

This table shows the correlation matrix across selected measures of informational efficiency in the Canadian dark trading sample.

	StDev (10s)	StDev (60s)	StDev (30min)	AutoCorr (10s)	AutoCorr (60s)
StDev (10s)					
StDev (60s)	0.98				
StDev (30min)	0.80	0.84			
AutoCorr (10s)	-0.03	0.12	0.16		
AutoCorr (60s)	-0.02	0.04	0.22	0.32	
AutoCorr (30min)	0.05	0.06	0.03	0.03	0.01

4.7.2. Information Leadership in Cross-Listed Securities

The model applied in Table 4-5 is unable to discern any change in the information content (as measured by the Permanent Information Impounding component) of Canadian trades relative to the US cross-listings around the implementation of the price improvement regulation. We find that the information leadership is inversely related to the number of analyst recommendations and by a lack of consensus in the home market. These results indicate that when there is more conflicting information available at home about a firm, then there is also likely a balance of price leadership in each direction. These results are consistent with Aitken, Almeida, Harris and McIninsh (2008) who find that stocks with a low analyst following, a high standard deviation in the analyst earnings per share estimates, and stocks from difficult to analyse industries have a higher incidence of informed trading.

High market capitalisation stocks have a higher information content on the Canadian market relative to their US cross-listings. This result is most likely due to large market capitalisation stocks already having a large investor following prior to their cross-listing. Small capitalisation stocks may look to cross list to increase liquidity and investor base. Large capitalisation stocks often choose to cross list for various other reasons such as broadening product identity, facilitating foreign acquisitions and to offer share and option plans for foreign employees.[22]

The trade ratio, which measures the number of trades in the Canadian market compared to the US market, is negatively related to PIICAN, controlling for liquidity and order book quality. Small size trades markedly outweigh medium and block trades in these trade counts. Consistent with Barclay and Warner (1993) and Eun and Sabherwal (2003), small size trades are low in information content.

---

[22] Khanna and Palepu (2003)

TABLE 4-5: PERMANENT INFORMATION IMPOUNDING IN CROSS LISTED SECURITIES

This table shows the regression output of the Information Leadership Share for dark trades vs lit trades in Canada, from 15 August 2012 to 15 December 2012.

	Dependent variable:		
	Information Leadership Share		
	(1)	(2)	(3)
Intercept	-1.397	-1.686	-0.706
	(2.021)	(1.907)	(0.900)
Price Improvement	0.020	0.058	-0.002
	(0.092)	(0.058)	(0.058)
Trade Ratio	-0.186**	-0.226**	-0.191**
	(0.091)	(0.096)	(0.090)
Effective Spread	0.128	0.275**	
	(0.129)	(0.110)	
Realised Spread	-0.001	-0.005	
	(0.005)	(0.032)	
Market Capitalisation	0.158***	0.183***	0.158***
	(0.058)	(0.061)	(0.057)
Analyst Consensus (CAN)	-0.412*	-0.440*	-0.331
	(0.213)	(0.232)	(0.207)
Number of Recommendations (CAN)	-0.035**	-0.033*	-0.037**
	(0.017)	(0.018)	(0.017)
Analyst Consensus (USA)	-0.555	-0.322	-0.576
	(0.600)	(0.660)	(0.592)
Number of Recommendations (USA)	0.008	0.004	0.010
	(0.014)	(0.801)	(0.014)
VIXC	-0.110	-0.574	
	(0.732)	(0.732)	
VIX	-0.384	11.688	
	(0.66)	(32.043)	
Standard Deviation (CAN)	9.390	0.019	9.867
	(28.484)	(0.162)	(28.687)
Standard Deviation (USA)	3.375		2.252
	(29.313)		(29.050)
Autocorrelation (CAN)	0.043		0.029
	(0.148)		(0.147)
Order Book Slope (CAN)	-0.044		
	(0.035)		
Order Book Slope (USA)	0.022		
	(0.059)		
Order Book Dispersion	0.224		
	(0.178)		
Cost of Trading 100 Shares	0.069		
	(1.252)		
Observations	789	789	789
R2	0.062	0.056	0.051
Adjusted R2	0.028	0.029	0.030

*p<0.1; **p<0.05; ***p<0.01

Table 4-5, Column 2 shows that many of these information leadership results for cross-listings change markedly when measures of order book quality (slope, dispersion, and cost to trade) are omitted, even though all three are insignificant in the full model in Column 1. However, Table 4-6 indicates that in the cross-listings sample, the dispersion of the limit order book and the cost of trading 100 or 1000 shares are highly collinear (r = -0.79 and -0.54, respectively). Therefore, in Table 4-5, Column 3, we re-estimate with cost of trading alone included among the order book quality variables. Cost of trading 100 shares becomes negative and statistically significant. In cross-section, as the cost of trading a larger order size of cross-listed securities increases, the informed trades in the Canadian lit markets decline, as expected.

The sets of informational asymmetry variables (analysts' recommendations and consensus in both countries), and informational efficiency variables (autocorrelation at home and the standard deviations in both countries) become insignificant. The trade ratio, analyst consensus and number of recommendations at home, but not in the foreign market, are also negative and significant for Canadian price discovery.

TABLE 4-6: CORRELATION MATRIX OF ORDER BOOK QUALITY MEASURES FOR CROSS LISTED SECURITIES

This table shows correlations of the order book quality statistics calculated for US-Canadian Cross-listed securities, from 15 August 2012 to 15 December 2012.

	Order Book Slope(CAN)	Order Book Slope (USA)	Dispersion	Cost of Trading (100 shares)	Cost of Trading (1000 shares)
Order Book Slope(CAN)					
Order Book Slope (USA)	0.09				
Dispersion	0.02	-0.08			
Cost of Trading (100 shares)	-0.06	0.03	-0.79		
Cost of Trading (1000 shares)	-0.07	-0.02	-0.54	0.73	

4.7.3. Price Discovery Efficiency in Cross-Listed Securities

In Table 4-7, Column 1, increases in the trade ratio, signifying numerous small trades in the Canadian market relative to the US market, increases Price Discovery Efficiency (PDE) because fewer liquidity shocks are mistaken for information-based permanent trends. Alternatively, illiquidity reflected by higher effective spreads and a larger order book slope reduces PDE for the same reason. Higher autocorrelation of the mid-quote indicates return predictability, and violates random walking fully efficient prices, indicating that participants would be rational to chase more shocks, lowering PDE. The order book dispersion and the cost of trading 100 shares are also shown to be significant factors detracting from PDE. For example, it is found that a 10% increase in order book dispersion reduces price discovery efficiency by 8.11%. If limit order prices are more widespread, a market is more susceptible to price swings that may reverse as marketable orders move farther through a book before being filled. As a result, participants would more frequently chase illusory trends that prove to be transitory shocks.

TABLE 4-7: CANADIAN PRICE DISCOVERY EFFICIENCY IN CROSS LISTED SECURITIES

This table shows the regression output of the Price Discovery Efficiency in US –Canadian cross-listed securities, from 15 August 2012 to 15 December 2012.

	Dependent variable:		
	Information Leadership Share		
	(1)	(2)	(3)
Intercept	1.775	-0.359	-0.929***
	(2.764)	(1.854)	(0.110)
Price Improvement	-0.124	-0.194*	-0.172**
	(0.126)	(0.101)	(0.084)
Trade Ratio	0.493***	0.501**	0.512***
	(0.123)	(0.080)	(0.068)
Effective Spread	-0.271	-0.350***	-0.310***
	(0.177)	(0.100)	(0.093)
Realised Spread	-0.004	-0.022	
	(0.007)	(0.044)	
Market Capitalisation	0.036	0.029	
	(0.079)	(0.041)	
Analyst Consensus (CAN)	-0.004	-0.260	
	(0.291)	(0.176)	
Number of Recommendations (CAN)	-0.008	-0.003*	
	(0.024)	(0.019)	
Analyst Consensus (USA)	0.345	-0.252	0.198
	(0.823)	(0.244)	(0.183)
Number of Recommendations (USA)	0.001	0.004	
	(0.019)	(0.010)	
VIXC	-1.330	-0.647	
	(1.005)	(0.819)	
VIX	1.761*	0.311	
	(0.912)	(0.755)	
Standard Deviation (CAN)	-25.725	9.135	
	(39.701)	(26.907)	
Standard Deviation (USA)	12.638	0.432	
	(40.343)	(27.877)	
Autocorrelation (CAN)	-0.348*	-0.390**	-0.353**
	(0.202)	(0.165)	(0.163)
Order Book Slope (CAN)	0.026		
	(0.048)		
Order Book Slope (USA)	0.135		
	(0.082)		
Order Book Dispersion	-0.811***		
	(0.242)		
Cost of Trading 100 Shares	-4.169**		
	(1.714)		
Observations	789	789	789
R2	0.172	0.056	0.051
Adjusted R2	0.142	0.029	0.030

*p<0.1; **p<0.05; ***p<0.01

Not taking into account such differences in the quality of the order book, it is found that PDE in the Canadian market is reduced by 19.4% as a result of the price improvement rule (Table 4-7, Column 2). Since optimising informed traders prefer to use both dark and lit execution venues (Nimalendran and Ray, 2014), traders with weakly price-sensitive information are forced, at the margin, to take liquidity from quoting exchanges to minimise the price impact of their trades. The finding that PII_{dark} declines after the rule change is consistent with this interpretation.

Overall, order book quality is affected. Informed traders adjust their trading strategies and limit order postings when their dark trading is constrained. Order book dispersion, and the cost of trading large parcels of shares must be controlled to address this issue. What this means in practice is that when larger orders execute at multiple prices, the market exhibits transitory price volatility. When larger orders take out the top levels of the order book, this must be refreshed more quickly by the liquidity providers. Otherwise, illusory trends are set in motion, and PDE suffers.

4.8. Summary

This study provides a comprehensive analysis of the role that dark trading plays in the discovery of informationally-efficient security prices. The factors that lead to informative dark trading are analysed in addition to the effect of IIROC's price improvement rule (implemented 15 October 2012) on permanent information impounding and price discovery efficiency in cross-listed securities. The price improvement rule has pushed price discovery back into the lit market in Canada.

Further, no evidence is found to suggest that price discovery shifts from the Canadian market to the cross-listed US market.

In addition to liquidity variables and time-series metrics of information efficiency, three new measures of order book quality are controlled for and findings show that these contribute important price discovery insights, consistent with Jain, Jain and McInish (2012).

Dark trading in Canada contributes very little information to the market, averaging only 7.1% of the permanent information impounding. Although the information leadership share of dark trades declines after the introduction of the price improvement rule, there are few serious ramifications given the low information content of dark trades before the ruling. Further, the price improvement rule does not increase the informational content of the Canadian market relative to the US market. On this basis, future research should assess the effects of dark trades on the price discovery process in the US market, where dark trading already constitutes 38% of trading volume.

5. Joint impact of Fragmentation and Algorithmic Trading on Market Quality

5.1. Introduction

This final study addresses the joint impact of HFT/AT and fragmentation on market quality (both fairness and efficiency). Without a regulatory authority that reintegrates multi-venue information to conduct effective market surveillance, market fragmentation invites a greater incidence of market manipulation. However, market fragmentation has also facilitated algorithmic and high frequency trading (AT/HFT) which seeks to trade against transitory price shocks, and can thereby impose real-time self-discipline on the market. When a manipulator tries to dislocate the price of a stock, AT/HFT can often identify this situation, arbitrage between execution channels, and stop the manipulation in its tracks. In the wake of the recent fragmentation of the US order flow across alternative trading systems and dark venues, it is hypothesised that stocks in which AT/HFTs do not participate are more likely to exhibit wider spreads and integrity breaches of trade-based manipulation than those in which AT/HFTs trade frequently.

Dark trading increases the incidence of successful manipulation events by subtracting liquidity from the lit market, making it easier to move prices and then profit by closing positions at lower price impact in the dark. This mechanism is laid out by Klock, Schied and Sun (2011), who show in an Almgren-Chriss model, that dark trading's differences in cross-venue impact create the opportunity for trade-based manipulation. It is suggested that fragmentation in lit venues will cause a similar degradation of market quality because of varying levels of price impact, but it is anticipated that the added transparency in lit markets will largely mitigate this effect.

The most similar research to the investigation conducted in this chapter is a recent market quality study of the impact of HFT/AT on the London Stock Exchange and the NYSE Euronext Paris pre- and post-MiFID. Aitken, Harris, Aspris, and Foley (2014) hypothesise that HFT/AT modelling of the 'state of the market' information renders trade-based manipulation less profitable, even when manipulators execute against uninformed counterparties. In London and Paris equities, with essentially no dark venues during 2003-2011, fragmentation by HFT/AT is shown to both decrease spreads and enhance market integrity by reducing the incidence of closing price manipulation. The research conducted in this thesis represents the first study to analyse the joint effect that dark trading *and* fragmentation play on spreads and market manipulation.

5.2. Data

To study the cross-sectional determinants of HFT/AT participation and market manipulation at the individual stock level over a long time series, it is necessary to use publically available rather than regulatory case data. The data used in this study encompasses all listed securities on the NASDAQ between 2010 and 2013. The depth, trade and quote data used for the analysis is obtained from Thompson Reuters Tick History (TRTH) which is provided by the Securities Industry Research Centre of Asia-Pacific (SIRCA). Information is acquired regarding bid and ask quotes (time stamped to the nearest millisecond) for up to 10-levels of the order book from each of the 13 lit exchanges. The study utilises intra-day information related to market prices, volume, number of level 1 orders/trades, as well as all changes to the 10-level order book.

5.2.1. HFT/AT Participation Metric

The empirical evidence regarding HFT/AT participation is relatively sparse and varies widely. In their 2010 response to the Committee of European Securities Regulators (CESR), the LSE identified HFT participation at 32% of total UK equities trading. Jarnecic and Snape (2010) find in their 2009 sample, 40-64% of LSE trades included a HFT participant on at least one side. NYSE Euronext calculated that in the overall European market, 23% of total traded value involved HFT participants in the first quarter of 2010.

Brogaard's (2010) analysis of U.S equity markets finds that 60-80% of all NASDAQ trades involve a HFT participant as either a liquidity provider or demander. Ito and Lyden (2012) construct an undisclosed measure of HFT participation for the largest 15 stocks traded on NASDAQ, NYSE and BATS in the US, and show that HFTs participate in one side of trades 87% of the time. Brogaard (2010), Jarnecic and Snape (2010) and Ito and Lyden (2012) all find that HFT participants are more active in larger stocks than smaller stocks, and are comparatively more active towards the end of the day. The intraday participation pattern is interpreted as indirect evidence of market makers seeking to close the day with zero inventory positions, rather than end-of-day manipulation.

To proxy for HFT/AT, the number of order cancellations to trade executions is matched against the limit order book immediately prior to trades. Following the methodology employed in Hasbrouck and Saar (2010), in this study it is assumed that the dominant economic event is the arrival of a marketable limit order. When an incoming marketable limit order executes against more than one standing limit order, multiple messages are generated for each standing limit order. The study cumulates each marketable order arrival (with the same millisecond time-stamp) in the same direction that are unbroken by any non-execution message, as a single marketable order.

Using the trade and 10-level quote data, any decrease in quoted depth is caused by either an execution against an incoming market order or a cancellation or amendment request. All trades and quotes are matched by time and price to account for all quoted depth reductions due to trade executions. The study then analyses the change in quoted depth for the remaining quote updates and defines each into one of the following three categories:

(i) If the new quote update only increases depth at any of the 10 levels from the previous quote, it is considered to be due to the addition of a limit order;

(ii) If the quote update contains additions to depth at some levels and reductions in depth at others, *it* is considered to be an amendment.

(iii) If the quote update contains only reductions in depth at any of the 10 levels and is not associated with a corresponding trade, it is considered to be due to a cancellation.

These cancellations are compared to the number of trades to arrive at the Cancel to Trade Ratio (CTR), which is used use to identify the rate of HFT/AT participation. The CTR is used in previous empirical work including Aitken, Aspris, Foley and Harris (2014) to identify the level of HFT participation. CTR is found to be highly correlated, with explicit measures of HFT/AT due to the high rate of order submissions and cancellations necessary to conduct a high frequency trading strategy. A similar measure is message traffic, which captures both new order entries and cancellations, such as in Hendershott, Jones and Menkveld (2011).

5.2.2. Market Efficiency Metric: Effective Spreads

Transaction costs are measured by the volume-weighted effective spread calculated on a per-trade basis and averaged across the month. The study estimates round-trip trading costs as effective spreads, measured as the trade price minus the midpoint of the bid-ask spread immediately prior to trades, multiplied by two to reflect both entry and exit trade. This number is transformed into a percentage of the share price to arrive at the final statistic:

$$\textit{Effective Spread} = 200 \times D \times ((\textit{Price} - \textit{Mid})/\textit{Mid}) \tag{5-1}$$

where D is the direction of the trade. A value of 1 is given for buyer-initiated trades, and a value of - 1 for seller-initiated trades, using the Lee-Ready algorithm.
Price is the trade price for stock i at time t, and Mid is the midpoint price of the ask and the bid for stock i at time t.

This metric is constructed for each trade on each stock traded on the respective market for each day in the month. The average daily spread for each stock is then constructed as the volume-weighted average of the effective spread on each trade, for each stock. This daily-stock effective spread is then converted to a daily-market-wide effective spread by equally weighting the daily-stock spread experienced by each of the stocks traded on that day. To reach the monthly-market wide effective spread utilised in this paper, the average of each daily-market-wide effective spread is computed for every trading day in the month.

5.2.3. Market Integrity Metric: End-of-day Market Manipulation

Market manipulation involves creating a false or misleading representation of the possibility of undisclosed information with the intent to affect the market price. Market manipulation induces artificial price volatility that degrades informational efficiency of stock prices. Market manipulation is estimated by examining the number of suspected instances of dislocation of end-of-day prices (particularly around end of month and option expiry dates) so that they no longer represent the true forces of supply and demand.

Potential motivations for manipulating end-of-day prices include attempts to modify the value of managed funds to alter the appearance of their performance and increase their ranking relative to competitors. This may be particularly associated with end-of-month or end-of-quarter reporting periods:

- To profit from derivatives positions in the underlying stock;
- To obtain a favourable price in pre-arranged off-market trades;
- To alter their customers' inference of broker execution ability;
- To maintain a stock's listing on an exchange with minimum price requirements;

- To gain inclusion in an index near stock index rebalancing days and;
- To avoid margin calls

However, not all abnormal closing prices are the result of deceitful trading strategies intended to dislocate the close. Some reasons why stock prices may naturally close at unusual levels include:

- Announcements or changes in underlying instruments near the close or during the closing auction may cause large price movements;
- Brokers with a mandate to sell certain quantities of stock may be forced to become aggressive to liquidate before the end of the trading day;
- Some market participants may not like to hold inventory overnight and are obliged to liquidate at the close, irrespective of price;
- Participants who enter large market orders at the closing auction may unwittingly cause large price movements if they are not mindful of the indicative closing price or the amount of depth available on the opposite side of the order book.

Distinguishing between the various forms of abnormal end-of-day prices is a challenging task. In this paper, attempts to mark the close are measured as abnormally large end-of-day price changes that exceed pre-determined stock-specific thresholds. For each stock and trading day, the price change of the last 15 minutes of trading is compared to a distribution of historical price changes which occurred during the previous 30 trading days.

$$\Delta EOD_{i_t} = \frac{P_{eod,i_t} - P_{eod-15m,i_t}}{P_{eod-15m,i}} \tag{5-2}$$

$$\overline{\Delta EOD_i} = \frac{1}{30} \sum_{t=-31}^{t=-1} \Delta EOD_{i_t} \tag{5-3}$$

where ΔEOD is the return between the closing price and the price 15-minutes prior to the close, $\overline{\Delta EOD}$ is the average return over a rolling window of 30 trading days prior to the day being analysed, and σ_i is the standard deviation of $\overline{\Delta EOD}$i over the same period. Manipulative behaviour is suspected when an end-of-day price change exceeds 3 standard deviations above or below the mean of the distribution of prior observations.

$$\textit{Potential Positive Manipulation if } R_{i_t} > \overline{\Delta EOD_i} + 3 * \sigma_i \tag{5-4}$$

$$\textit{Potential Negative Manipulation if } R_{i_t} < \overline{\Delta EOD_i} - 3 * \sigma_i \tag{5-5}$$

End-of-day prices that are not the result of the genuine forces of supply and demand are likely to exhibit next-day price reversion. Instances of abnormal end-of-day price changes that are followed by a price reversion of 50% or more on the open of the next trading day are considered successful attempts at marking the close (MTC). These are referred to as instances of "dislocating the end of day price" ("EOD price"). In the absence of this reversion, no manipulation is considered to have occurred.

5.3. Methodology

5.3.1. A simultaneous structural equations model for market quality research

The empirical model used in this study directly addresses the fact that quoted spreads and measures of market integrity are simultaneously determined. Market manipulation raises volatility and reduces order aggressiveness, leading to higher bid-ask spreads. Conversely, quoted spreads are a non-trivial execution cost of market manipulation. Higher quoted spreads, therefore, reduce the incidence of manipulation, *ceteris paribus*. Market integrity, efficiency, and the level of AT are also simultaneously determined. Lower spreads reduce the cost of high frequency trading. On the other side, an increase in the level of high-frequency trading potentially leads to lower bid-ask spreads if high-frequency trading leads to improved market integrity.

A three-stage least squares (2SLS) estimation method is adopted in the belief that residual errors in efficiency (spreads), integrity (EOD manipulation) and AT participation will likely be cross-equation correlated. The empirical model structure is a simultaneous set of three structural equations describing market integrity (AI – end-of-day manipulation alerts), market efficiency (SPR – the effective spread), and a specific market design change (AT – AT participation):

$$AI_{i,t} = \alpha + \beta_1 \widehat{SPR}_{i,t} + \beta_2 \widehat{AT}_{i,t} + \beta_3 VIX_t + \beta_4 Ret_{i,t} + \beta_5 EOQ\ Dummy_t + \beta_{6-8} Quartile\ Dummy_{\ i,t} + \beta_9 LitFRAG_{i,t} + \beta_{10} DarkFRAG_{i,t} + \epsilon_{i,t} \quad (5\text{-}6)$$

$$SPR_{i,t} = \alpha + \beta_1 \widehat{AI}_{i,t} + \beta_2 \widehat{AT}_{i,t} + \ \beta_3 ADDV_{i,t} + \ \beta_4 VIX_t +$$

$$\beta_{5-8} Year\ Dummy_t + \ \beta_9 LitFRAG_{i,t} + \ \beta_{10} DarkFRAG_{i,t} + \ \epsilon_{i,t} \qquad (5\text{-}7)$$

$$AT_{i,t} = \alpha + \beta_1 \widehat{SPR}_{i,t} + \beta_2 \widehat{AI}_{i,t} + \ \beta_3 Price_{i,t} + \ \beta_4 Intraday\ Volatility_{i,t} +$$

$$\beta_5 EOQ\ Dummy_{i,t} + \ \beta_{6-9} Year\ Dummy_t + \beta_9 LitFRAG_{i,t} +$$

$$\beta_{10} DarkFRAG_{i,t} + \ \epsilon_{i,t} \qquad (5\text{-}8)$$

where AI = Alert incidence of end-of-day trade-based manipulation weighted by the dollar value cost of dislocating the stock price; SPR = Effective spreads, a measure of the implicit transaction cost of a round trip transaction; AT = A proxy for the level of HFT/AT participation using the Cancel-to-Trade Ratio (CTR); ADDV = Total trading in the security, measured as the log of average daily volume in dollars; VIX = Log of the end-of-month level of the VIX index; Price = Log of the monthly average stock price; Intraday Volatility = The log standard deviation of returns measured as the average standard deviation of daily returns; EOQ Dummy = A dummy variable for end of financial quarter months; Quartile Dummy = A dummy variable to indicate whether the security is in the 2nd, 3rd, or 4th trading activity quartile, measured by the monthly average daily dollar volume; Year Dummy = Dummy variable by year

LitFRAG = Hirschen-Herfindal Index of Fragmentation across lit venues; DarkFrag = The percentage of trading executed through the TRF facility relative to total market trading (TRF trading plus the total trading on the lit venues).

The instrumental variables for the endogenous variables are based on reduced-form equations of all the exogenous and pre-determined regressors; hat symbols signify these predicted values. Because each of the endogenous variables could in principle affect each of the others, the order condition for identification is ensured by excluding from each equation two control variables present elsewhere in the system. In the case of end of day dislocation, these variables are price, intraday volatility and year dummies. For effective spread, these are price, intraday volatility, quarterly dummies and end of quarter dummy. For the algorithmic trading equation, these are average dollar volume traded and quarterly dummies. In each case, the excluded variables are control variables found to be insignificant in preliminary single-equation estimations of the focal equation, but highly significant in the other two structural equations.

5.4. Descriptive Statistics

This section presents the descriptive statistics of the data underlying the Two Stage Least Squares regression methodology. Table 5.1 below presents the summary statistics pre and post Reg NMS. The numbers are explained further in the following figures.

TABLE 5-1: UNIVARIATE STATISTICS FOR NYSE 2003 TO 2012

This table gives the descriptive statistics over the entire period where stock values are weighted by dollar traded per month to achieve a market-month value.

	PRE RegNMS					POST Reg NMS				
	min	mean	median	max	sd	min	mean	median	max	sd
Marking the Close (EOD Count)	1.00	12.47	10	90	12.16	0	23.22	8	260	48.03
Marking the Close (EOD 1,000,000s USD)	0.07	6.07	1.61	177.78	23.48	0	92.18	1.38	2240.76	341.5
Effective Spread (bps)	3.58	5.34	5.07	9.47	1.15	4.39	6.34	5.55	14.7	2.24
Cancel to Trade Ratio	2.51	4.43	4.23	6.24	0.93	2.42	4.52	4.18	13.34	1.8
Order to Trade Ratio	2.65	4.49	4.34	6.25	0.91	2.49	4.61	4.34	13.58	1.77
Dark Fragmentation	0.00	1.71	0	8.44	2.74	7.35	13.37	12.67	22.44	4.19
Lit Fragmentation	0.11	0.20	0.15	0.46	0.1	0.43	0.64	0.6	0.83	0.13
Intraday Volatility	0.01	0.01	0.01	0.01	0	0.01	0.01	0.01	0.04	0.01
Return	-0.06	0.01	0.01	0.07	0.03	-0.23	0.02	0.02	0.62	0.11
Price (USD)	37.83	75.14	50.59	249.85	46.94	64.38	344.62	283.03	1342.84	222.33
Average Daily Turnover (1,000,000s USD)	113.61	159.41	158.12	214.08	22.62	28.91	114.24	97.32	653.66	78.48
VIX	10.82	15.66	14.94	32.22	4.52	15.28	25.97	22.53	62.64	10.53

Regulation NMS presents a structural change in fragmentation of the order flow and in algorithmic trading. Although both dark fragmentation and lit fragmentation have significantly grown, RegNMS does not appear to have a direct univariate impact on AT (see Figure 5-1).

FIGURE 5-1: **CANCEL TO TRADE RATIO ON THE NEW YORK STOCK EXCHANGE 2003 – 2012**

This figure shows the dollar volume-weighted Cancel to Trade Ratio on the NYSE from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

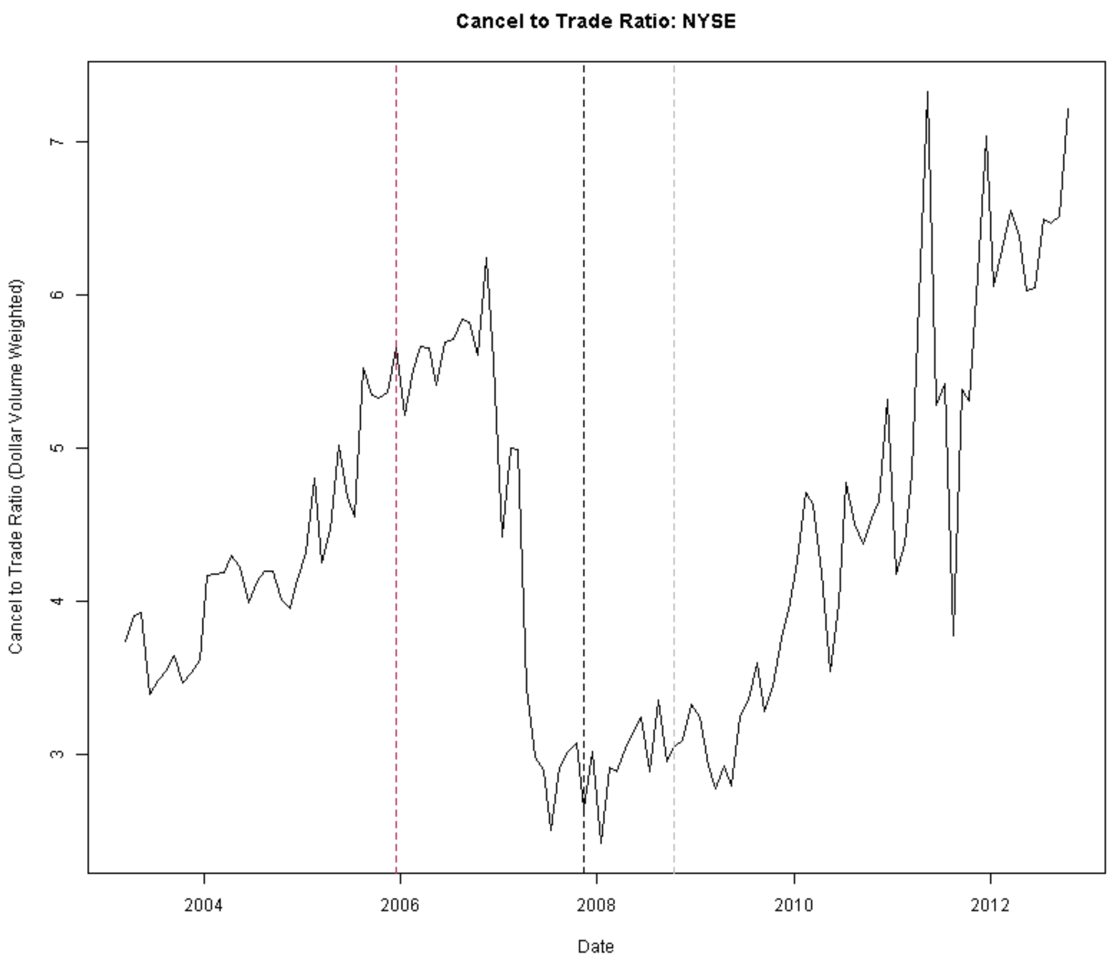


Figure 5-2 presents the relationship between rising fragmentation and three institutional changes associated with the introduction of the Hybrid trading system on the NYSE, the implementation of Reg NMS, and the replacement of NYSE specialists with designated market makers. Figure 5-3 shows from 2006 to 2012 a clear degradation in the percentage of trading taking place on the NYSE primary market.

FIGURE 5-2: NORMALISED HERFINDAL INDEX OF FRAGMENTATION ACROSS 13 EQUITIES MARKETS FOR STOCKS LISTED ON THE NEW YORK STOCK EXCHANGE 2003 – 2012

This figure shows the dollar volume-weighted level of fragmentation between equity markets for NYSE listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

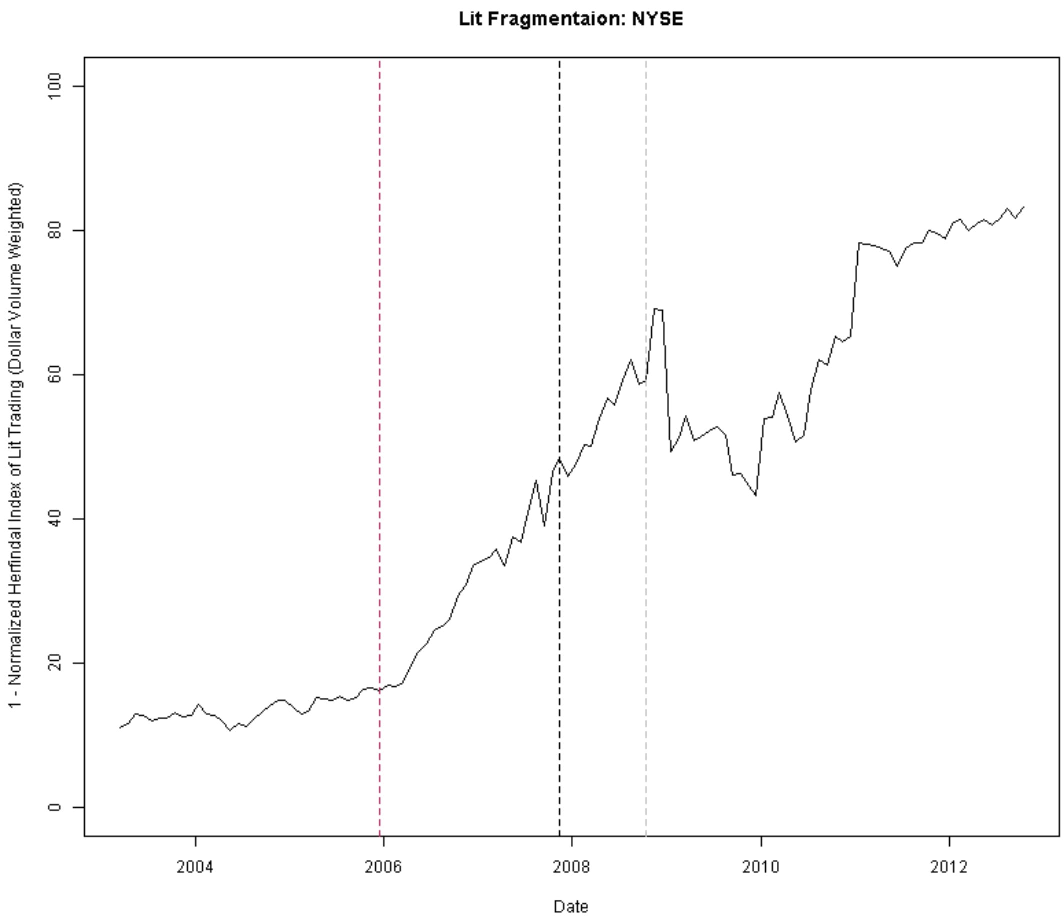


FIGURE 5-3: OFF MARKET TRADING IN NYSE-LISTED STOCKS 2003 – 2012

This figure shows the dollar volume-weighted % of trading taking place off-market for NYSE listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

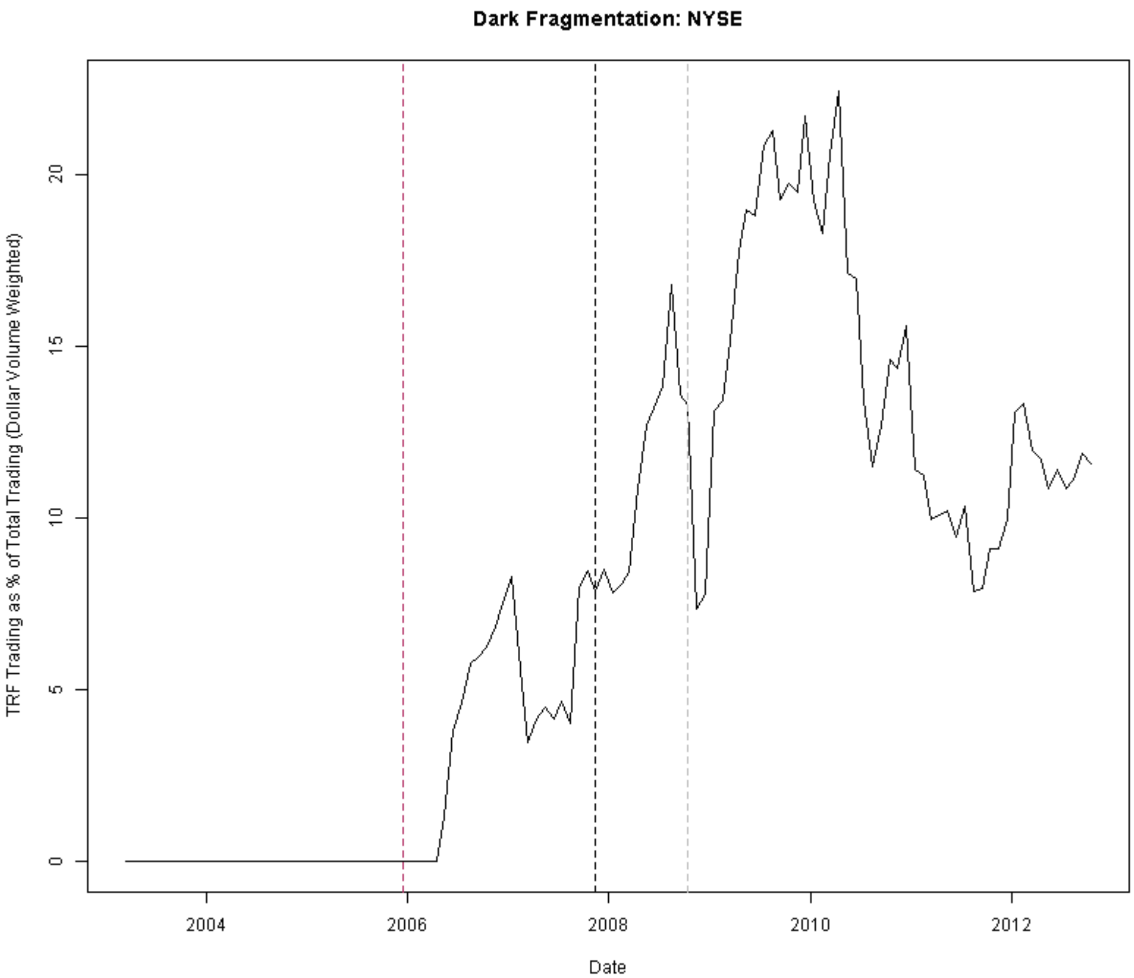
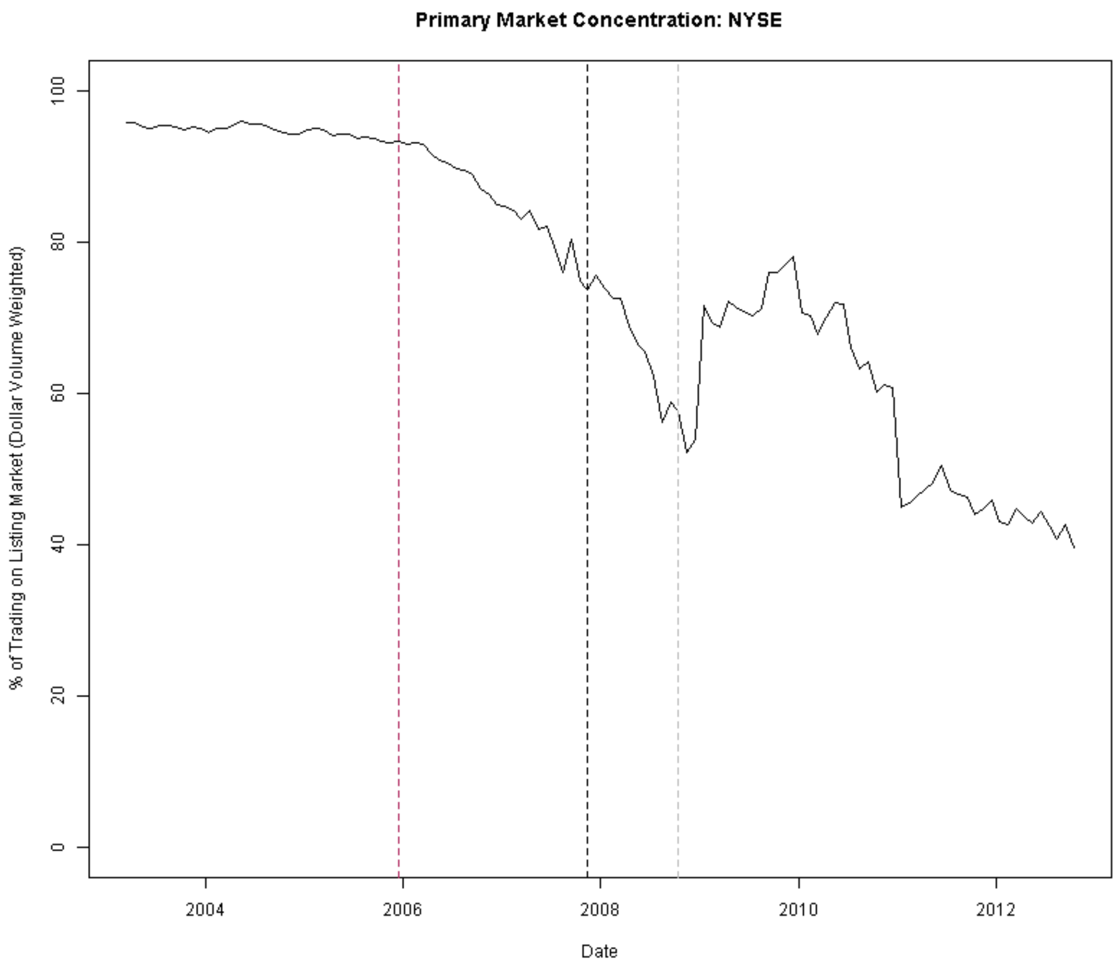


FIGURE 5-4: **PRIMARY MARKET TRADING IN NYSE-LISTED STOCKS 2003 - 2012**

This figure shows the dollar volume-weighted % of trading taking place on the NYSE for NYSE listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.



Univariate t-tests pre- and post-RegNMS are performed to illuminate the effects of this structural change. Table 5-2 shows RegNMS increased the level of dark fragmentation seven-fold from 1.7% to 13.3% (significant at the 1% level); further, it increased the level of lit fragmentation three-fold from 0.20 to 0.64 (measured as 1 – Normalised Herfindal Index of Lit Market venue trading). RegNMS does not appear to have a direct univariate impact on end-of-day dislocations (see Figure 5-5). Post-RegNMS, there is an immediate 18% increase in effective spreads (Figure 5-7), and a 50% increase in intraday volatility (Figure 5-8).

TABLE 5-2: WILCOXON RANK SUM TEST FOR DIFFERENCE IN MEANS PRE AND POST REGNMS

The table below presents summary statistic results for a wilcoxon rank sum test across each of the measures for the two stage least squares models and regression coefficients. The tests are run pre and post the introduction of Reg NMS. There is a significant change in the average Price, Daily Dollar Turnover and level of Volatility in the market.

		Mean	p value	Significance
	PRE	POST		
Marking the Close ($EOD)	$6,072,951	$92,182,767	0.65	
Marking the Close (count EOD)	12.47	23.22	0.13	
Effective Spread	0.053	0.063	0.01	**
Cancel to Trade Ratio (CTR)	4.427	4.519	0.47	
Order to Trade Ratio	4.488	4.607	0.58	
Dark Fragmentation (% TRF Trading)	1.71%	13.37%	0	***
Lit Fragmentation (1 - Normalised Herfindal Index)	0.2	0.638	0	***
Volatility (Intraday)	0.009	0.014	0	***
Returns	0.01	0.02	0.95	
Price	$75.14	$344.62	0	***
Daily Dollar Turnover	$159,408,393	$114,240,329	0	***

***, **, and * indicate significance at 1%, 5% and 10% respectively

FIGURE 5-5: **TOTAL VALUE ($USD) OF END OF DAY DISLOCATIONS IN NYSE-LISTED STOCKS 2003 – 2012**

This figure shows the total estimated dollar loss due to end of day dislocations for NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

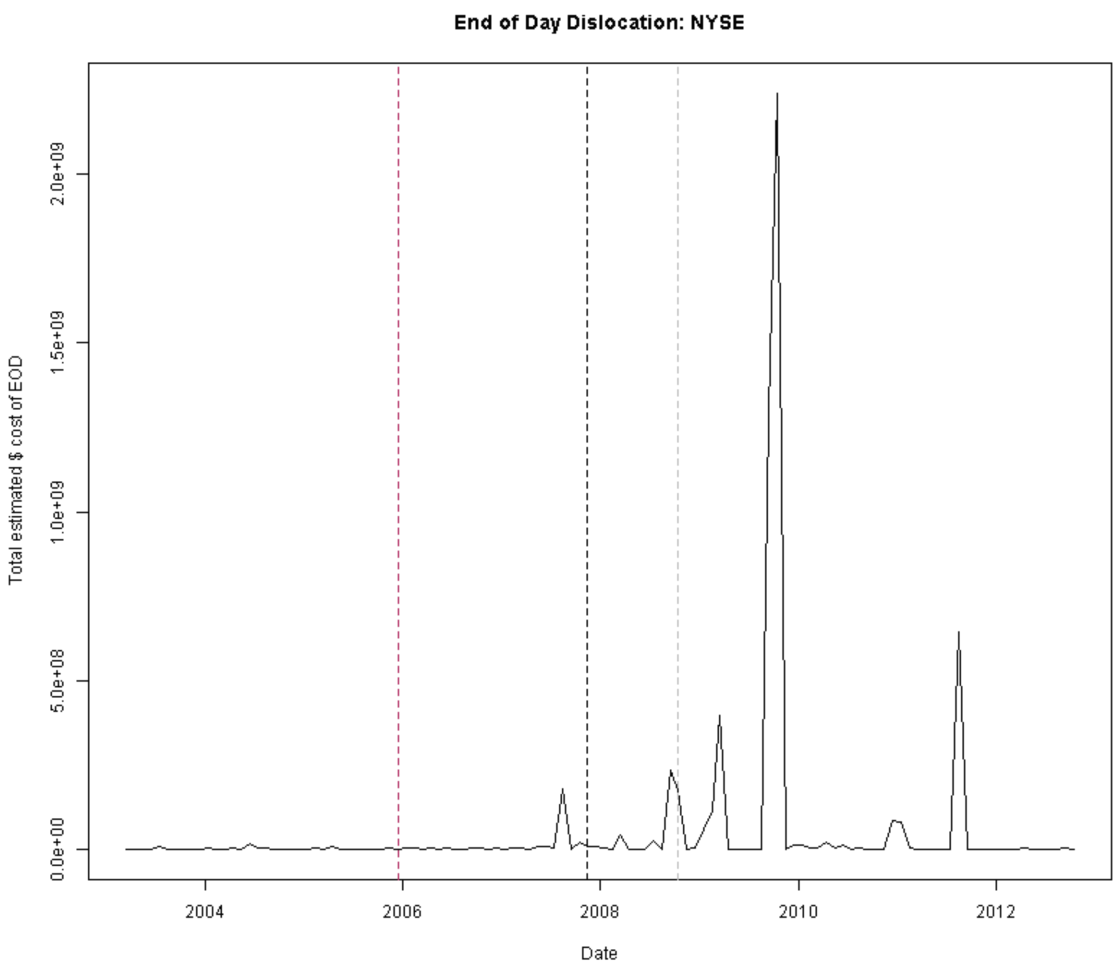


FIGURE 5-6: **TOTAL NUMBER OF END OF DAY DISLOCATIONS IN NYSE-LISTED STOCKS 2003 - 2012**

This figure shows the total number end of day dislocations for NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

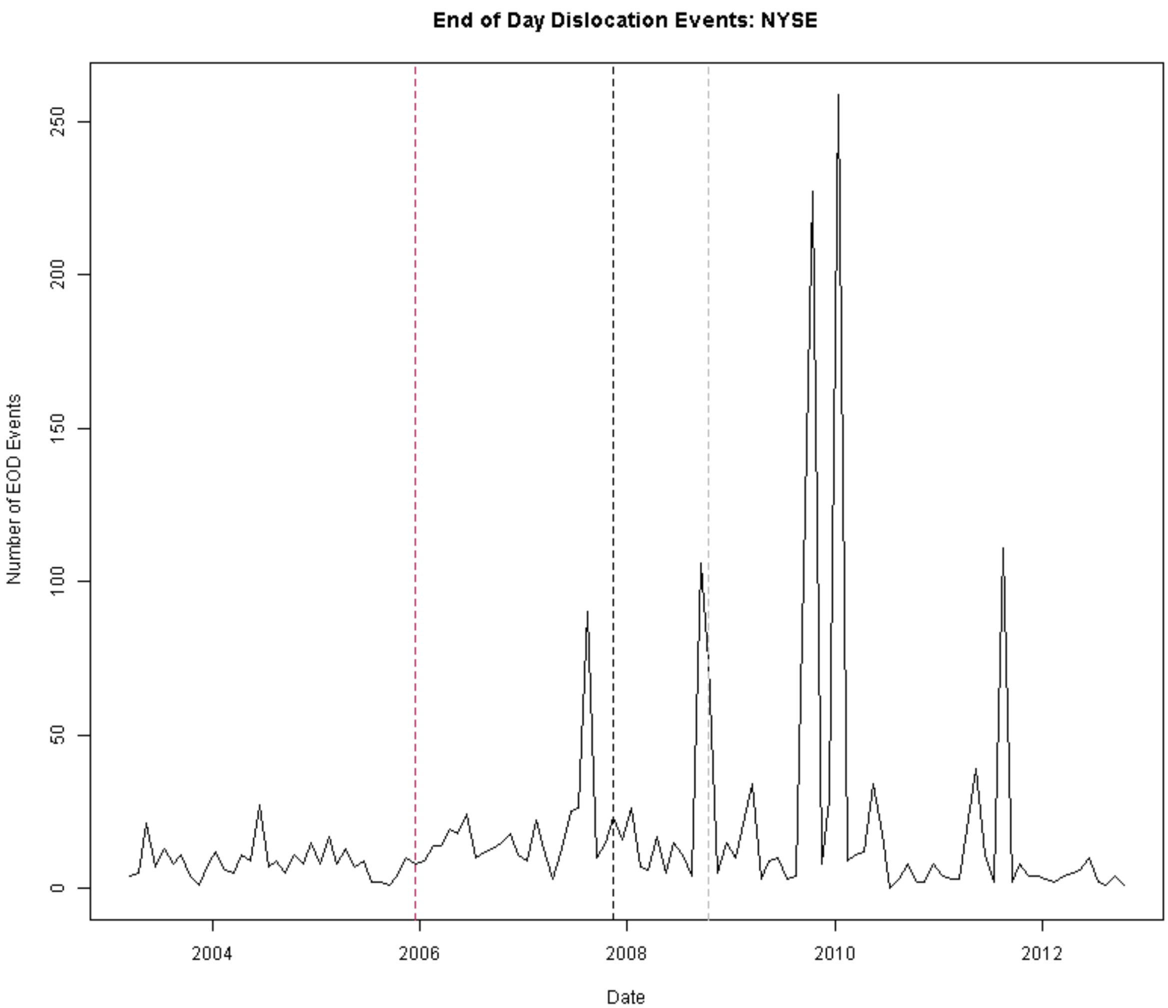


FIGURE 5-7: **EFFECTIVE SPREAD IN NYSE-LISTED STOCKS 2003 - 2012**

This figure shows effective spread (in basis points) for NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

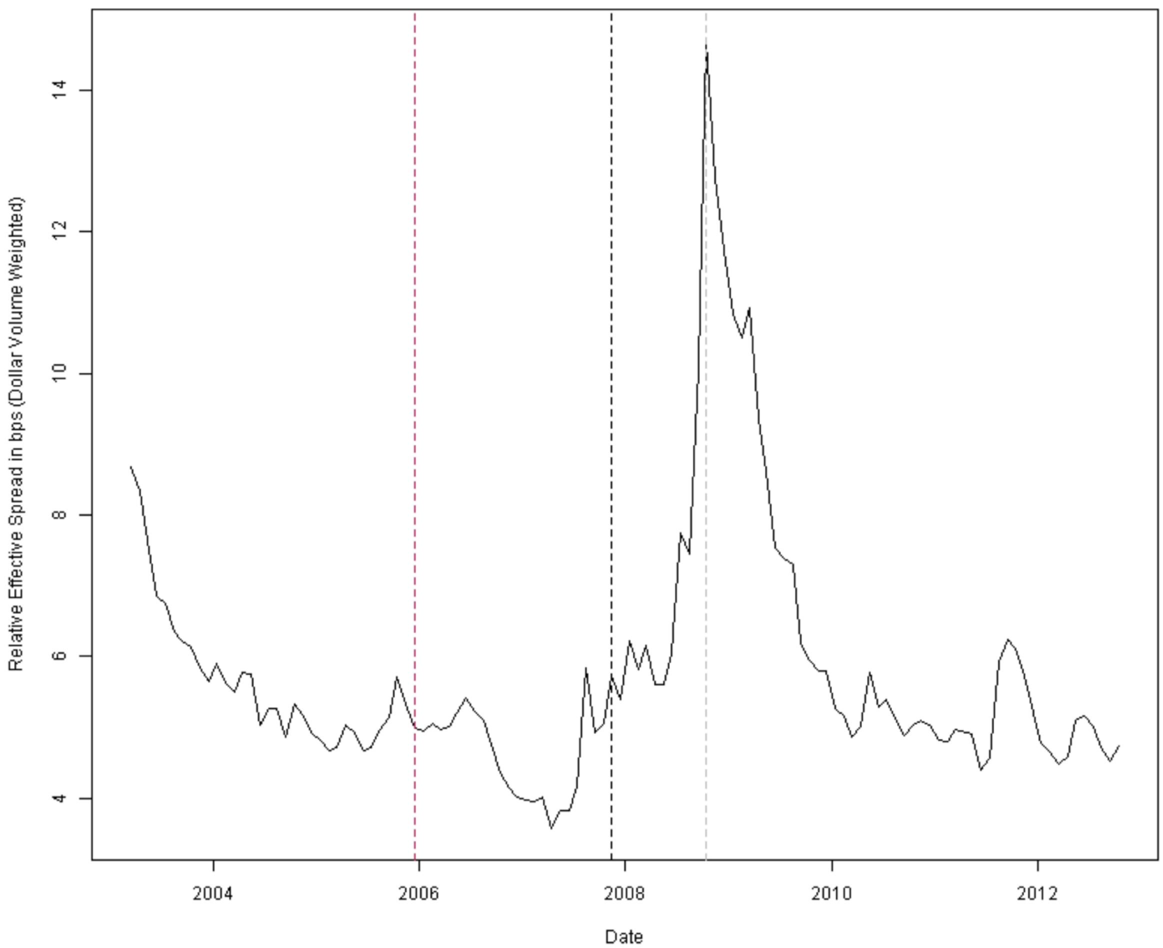


FIGURE 5-8: **INTRADAY VOLATILITY IN NYSE-LISTED STOCKS 2003 - 2012**

This figure shows intraday volatility for NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

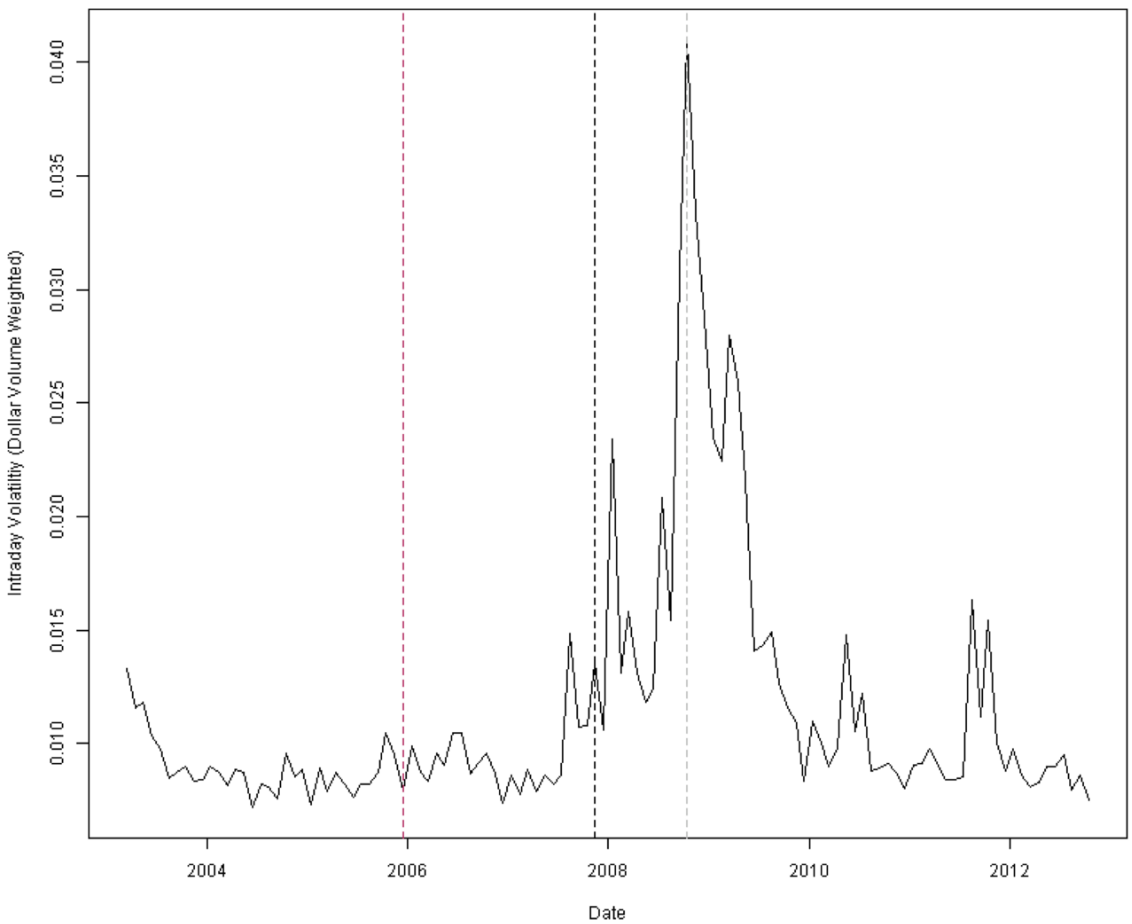


Figure 5-9 illustrates the rapid growth in both TRF trading and Lit market fragmentation over the period. Both of these measures appear highly correlated, but in periods of high volatility, this correlation reverses. This is seen throughout 2009-2010 during the GFC where Lit fragmentation sharply declines and TRF fragmentation increases. During periods of high macro-economic volatility, it appears that participants are driven back to the primary listing venue as well as to the full breadth of dark venues. This point is illustrated in Figures 5-10 and 5-11 where a shock in the VIX is immediately followed by an increase in TRF trading and Primary Market share.

FIGURE 5-9: COMPARISON OF LIT AND DARK FRAGMENTATION IN NYSE-LISTED STOCKS 2003 - 2012

This figure shows the normalised Herfindal index of lit markets in the US and the % of off- market trading for NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

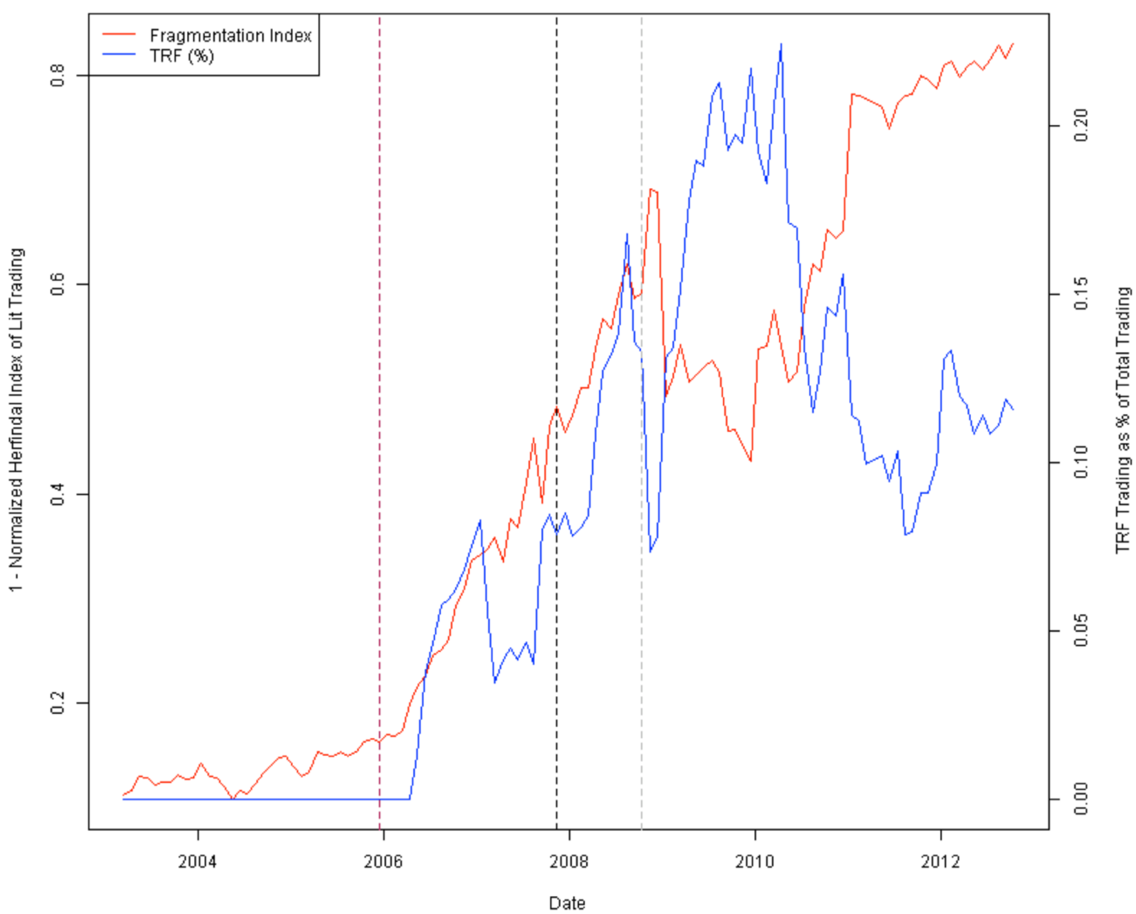


FIGURE 5-10: **DARK FRAGMENTATION IN NYSE-LISTED STOCKS 2003 – 2012 AND VIX**

This figure shows the % of off market trading for NYSE-listed stocks compared to the VIX Index from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008.

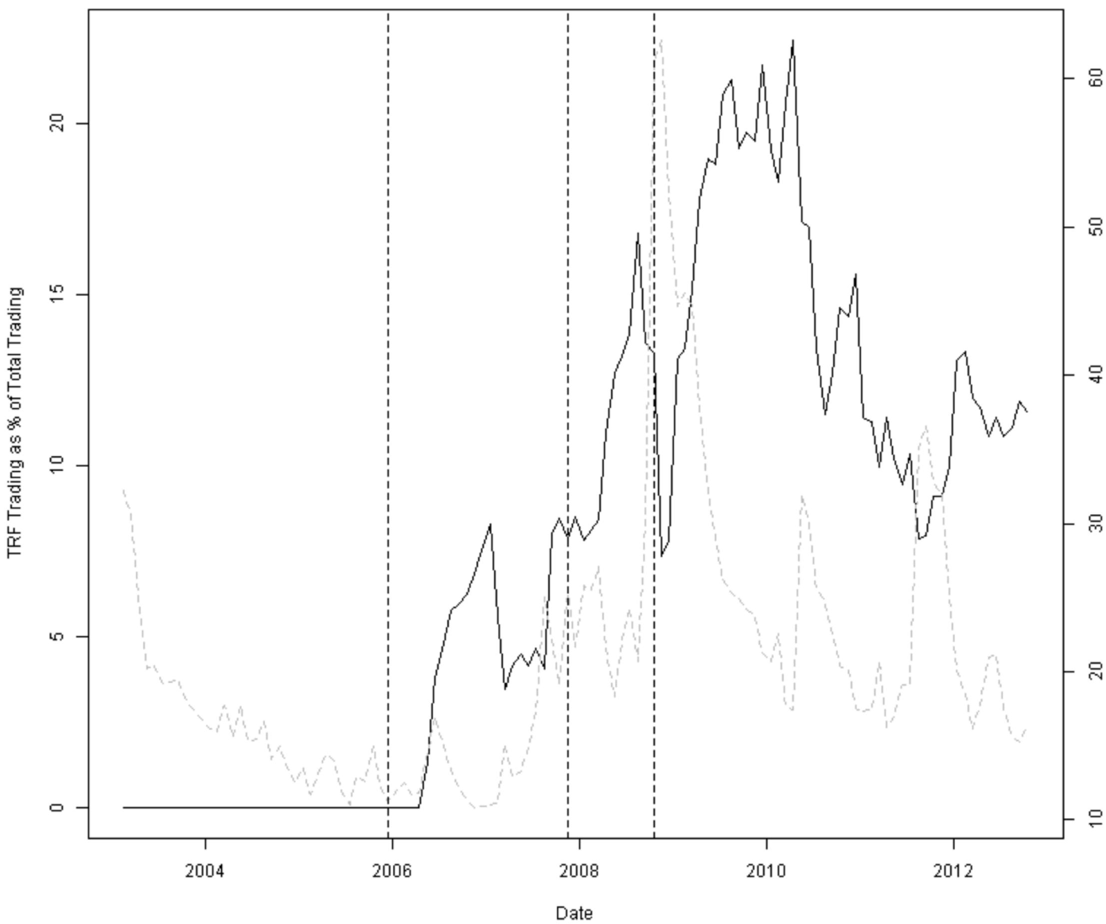
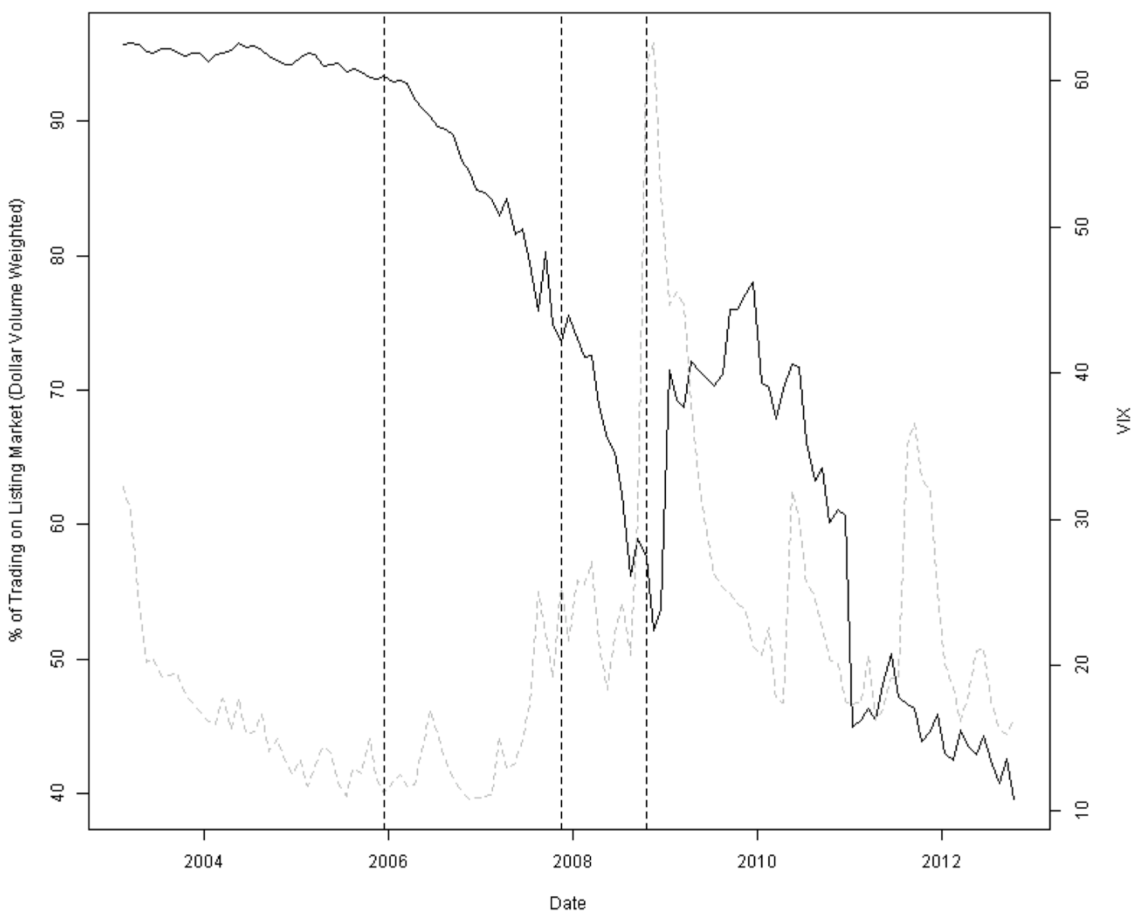


FIGURE 5-11: **PRIMARY MARKET TRADING IN NYSE-LISTED STOCKS 2003 – 2012 AND VIX**

This figure shows the % of trading on the NYSE for NYSE-listed stocks compared to the VIX Index from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008



It is not immediately clear from the univariate analysis, what the relationship between AT, Fragmentation and End of Day Dislocations is. Figure 5-12 shows the growth in both the number of EOD events and the level of AT in the market (proxied by CTR); a very similar trend exists between EOD events and the percentage of off-exchange trading in Figure 5-13 (similarly for lit fragmentation in Figure 5-14).

FIGURE 5-12: NUMBER OF EOD EVENTS VS CANCEL TO TRADE RATIO IN NYSE-LISTED STOCKS 2003 – 2012

This figure shows the total number of EOD events in NYSE listed stocks compared to the dollar volume-weighted Cancel to Trade Ratio from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008

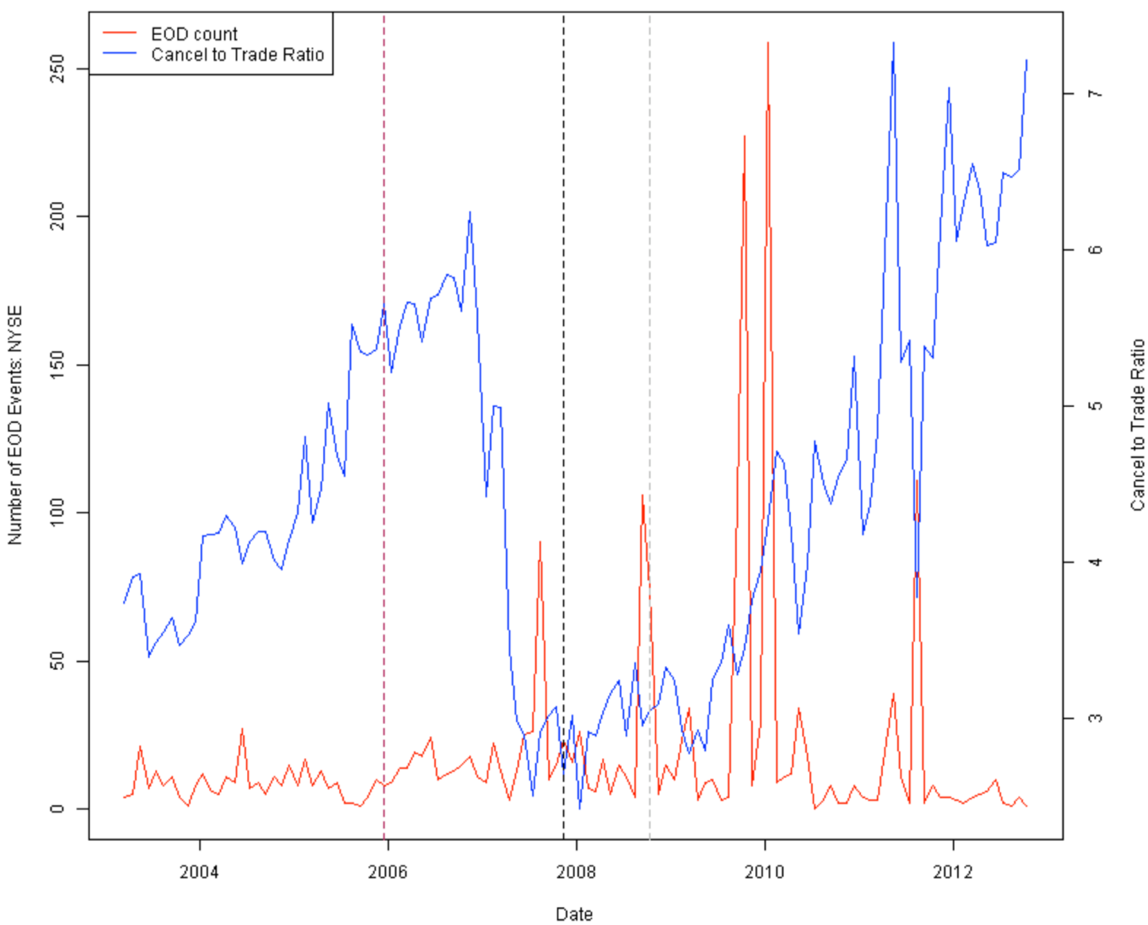


FIGURE 5-13: **NUMBER OF EOD EVENTS VS PERCENTAGE OF DARK TRADING IN NYSE-LISTED STOCKS 2003 – 2012**

This figure shows the total number of EOD events in NYSE-listed stocks compared to the dollar volume-weighted % of Off-Exchange trading from January 2003 to December 2012. The vertical bars (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008

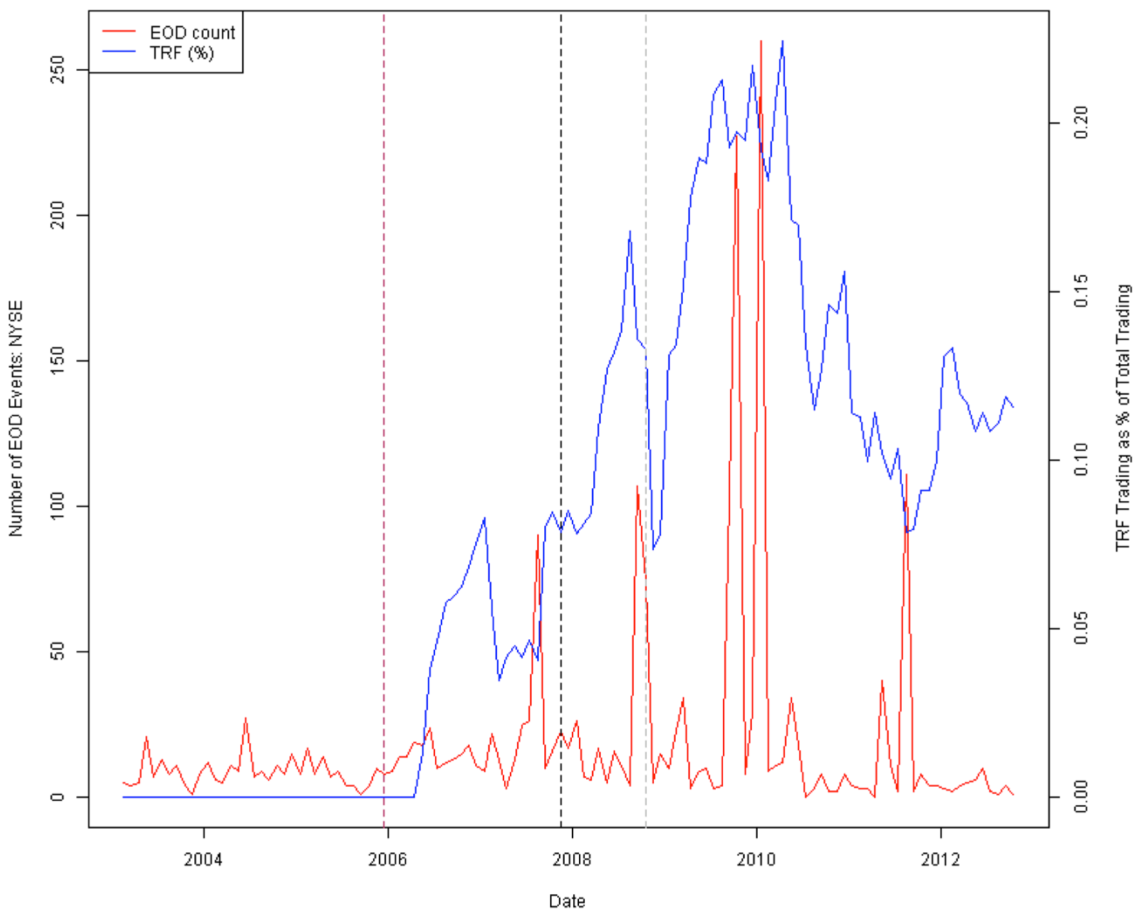
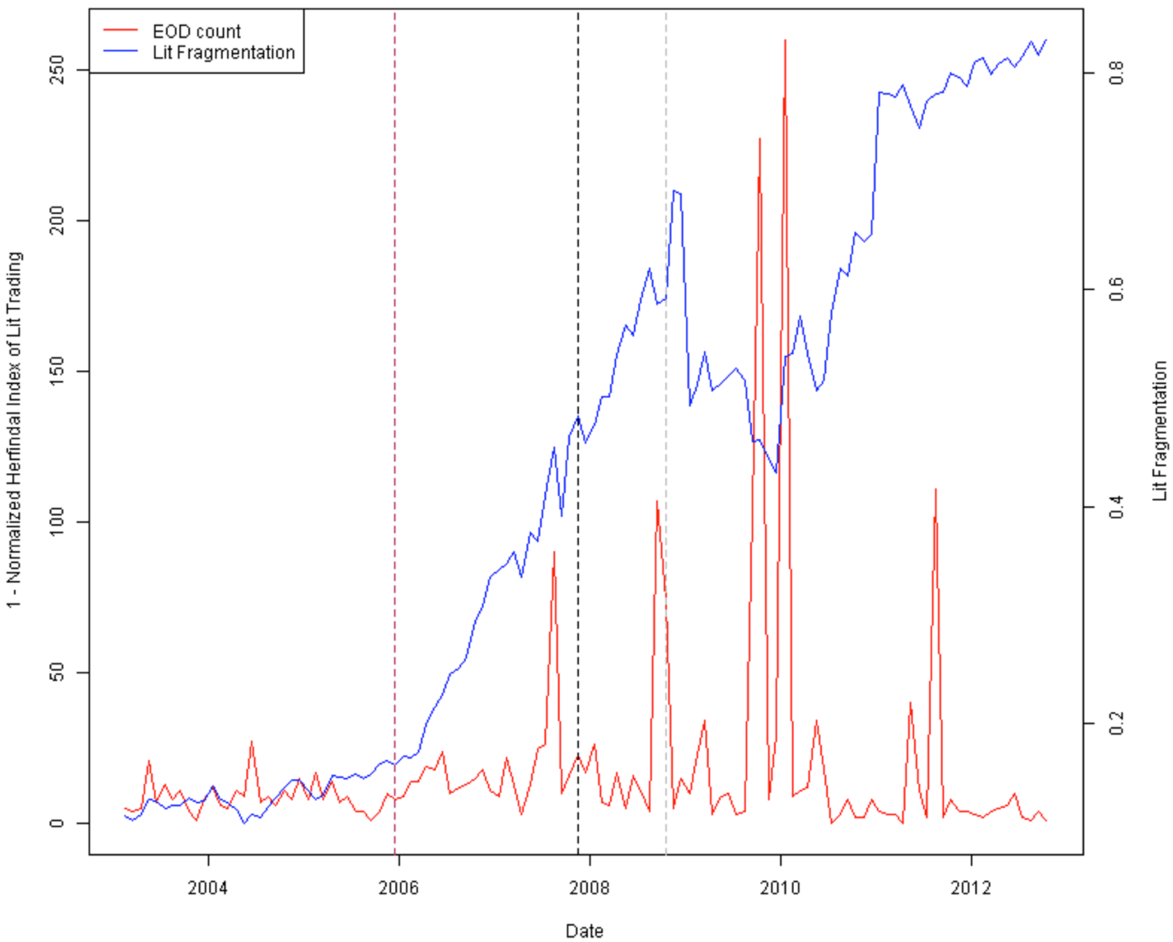


FIGURE 5-14: **NUMBER OF EOD EVENTS VS LIT FRAGMENTATION IN NYSE-LISTED STOCKS 2003 – 2012**

This figure shows the total number of EOD events in NYSE-listed stocks compared to the dollar volume weighted % of normalised Herfindal index of lit markets in NYSE-listed stocks from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008



It is clear from Figures 5-15 and 5-16 that there is a high level of correlation in the growth of AT and Fragmentation, but it is not immediately obvious what the drivers are and how these affect the level of End of Day dislocations. It is the purpose of this chapter to disentangle these results using the 2-stage least squares simultaneous equation systems.

FIGURE 5-15: **PERCENTAGE OF DARK TRADING VS CANCEL TO TRADE RATIO IN NYSE-LISTED STOCKS 2003 – 2012**

This figure shows the dollar volume weighted % of Off-Exchange trading in NYSE-listed stocks compared to dollar volume-weighted Cancel to Trade ratio from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008

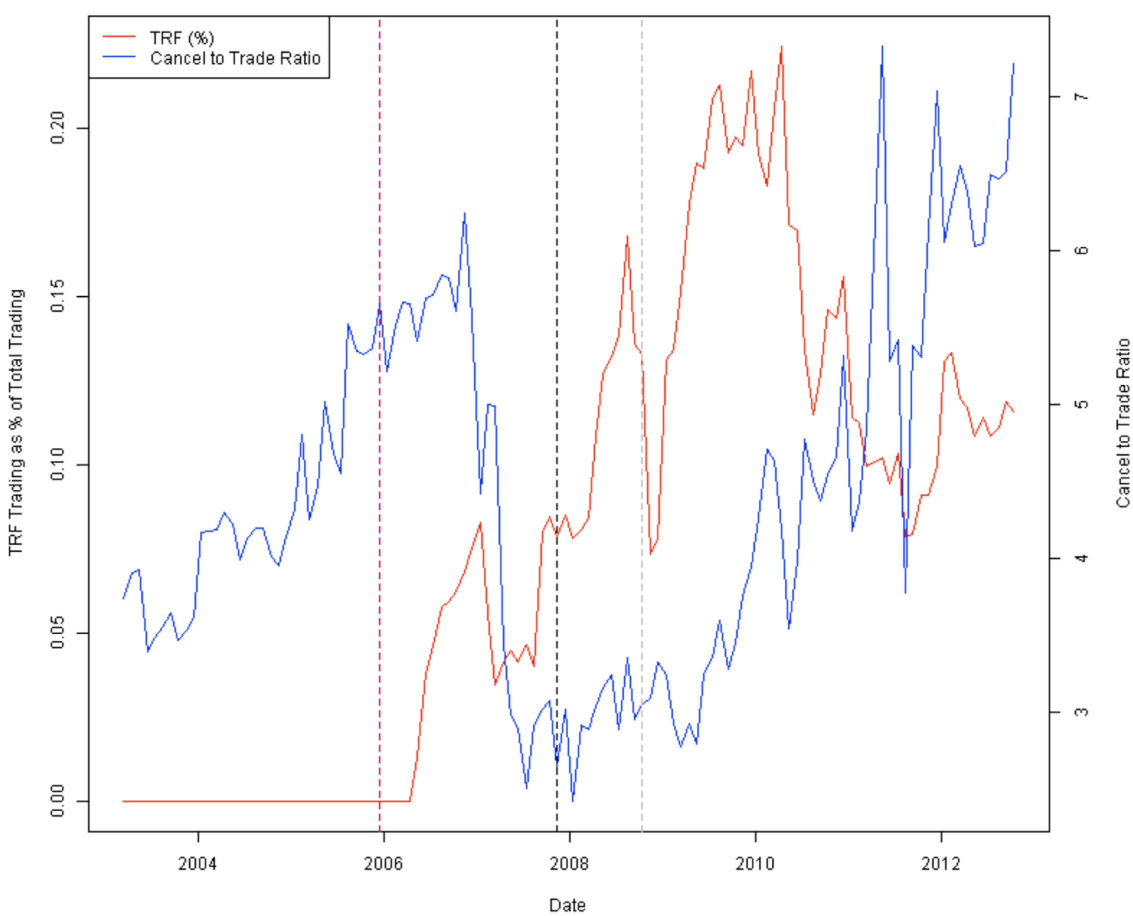
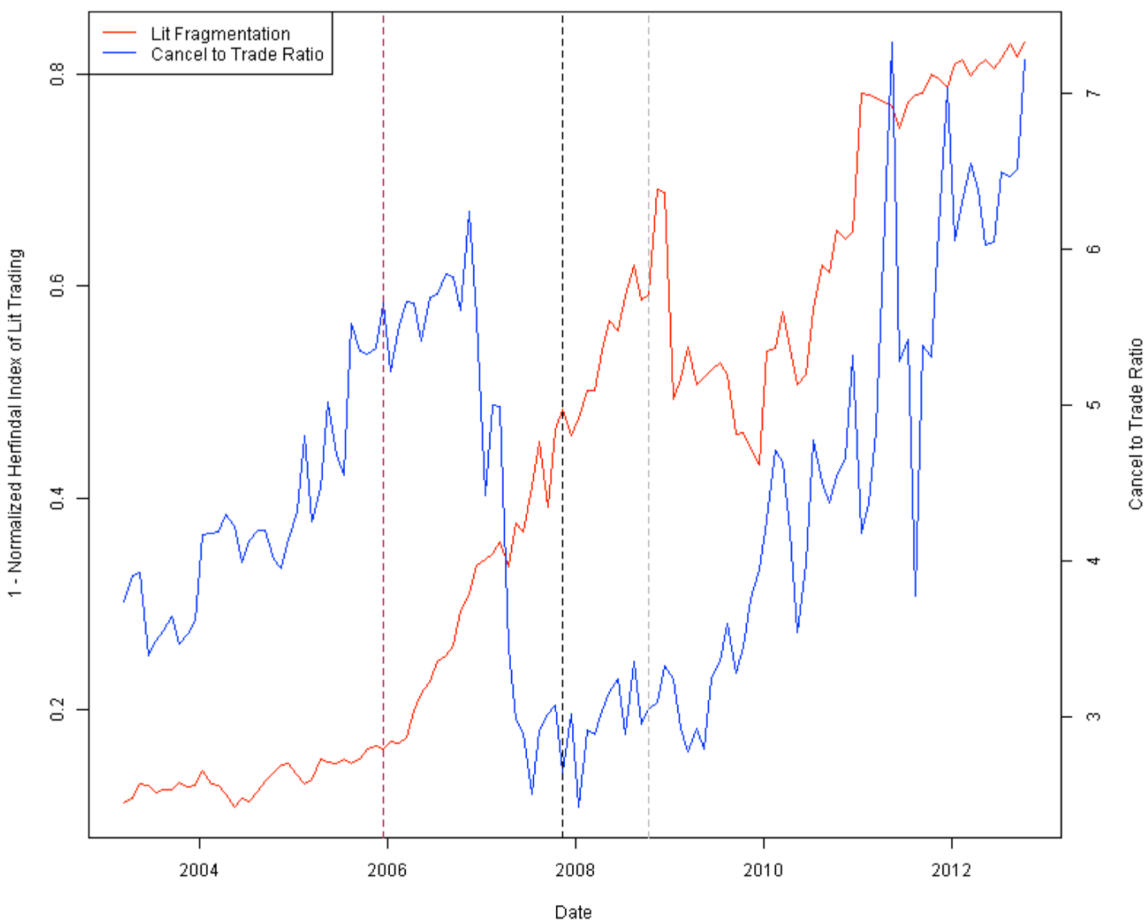


FIGURE 5-16: LIT MARKET FRAGMENTATION VS CANCEL TO TRADE RATIO IN NYSE-LISTED STOCKS 2003 – 2012

This figure shows the dollar volume-weighted % of normalised Herfindal index of lit markets in NYSE-listed stocks compared to dollar volume-weighted Cancel to Trade ratio from January 2003 to December 2012. The vertical bars indicate (from left to right) the introduction of NYSE's Hybrid market in December 2005, RegNMS roll-out completion in November 2007 and the removal of specialists and introduction of DMM's in October 2008



The regressions are split into two distinct time periods, pre- and post- the introduction of Regulation National Market System (RegNMS) in November 2007. Chow-tests for structural breaks are estimated across each of the three market quality equations for both dark and lit fragmentation. Across all six tests, it is found that the hypothesis that the pre- and post-data should be pooled must be rejected, with F-statistics ranging from 9.96 to 203.96. In the following sections, regressions results are referred to as either in the pre-RegNMS or post-RegNMS regimes. This confirmed structural break is not surprising as RegNMS is possibly the most significant regulatory change in the recent history of US markets. The introduction of RegNMS greatly unified both listing exchanges and ATSs by requiring trades to only occur at the venues that meet the National Best Bid or Offer. Although this unifies quote price discovery, each venue still offers widely different levels of depth and thus price impact to their target segments, making cross-market arbitrage strategies an on-going source of trading profits.

5.5. Results

Table 5-3 below reports pre-tests of instrumental variable exogeneity and strength. Panel A shows that the 2SLS residuals for alert incidence marking the close MTC (the proxy for end-of-day manipulation), for effective spreads, and for the cancelation-to-trade ratio (the proxy for HFT/AT participation) all are uncorrelated with their respective first-stage independent variables and control variables. Hence, the instruments are not endogenous in the model. Panel B shows Yugo-Stock tests for each of the three estimating equations. It is rejected that the 2SLS estimates retain more than 10% of the simultaneity bias in the OLS estimates with 95% confidence. Hence, EOD dislocation hat, effective spread hat, and log CTR hat are strong instruments. Economically speaking, these instruments are effective at adding and removing covariates from the first stage, which act as shocks to each equation.

TABLE 5-3: SPECIFICATION PRETESTS OF ENDOGENEITY AND OVERIDENTIFYING RESTRICTIONS

Panel A in the table below presents the results of the Endogeneity pre-tests for the instruments included in the seconds stage of the Two Stage Least Squares Model. Panel B presents an alternative specification test for the Two Stage Least Squares Model; the Yugo Stock Test for Instrumental Variable Weakness across each equation.

Panel A - Endogeneity Test for Instruments and Control Variables						
2SLS residuals regressed on IVs and control variables	Pre-RegNMS	MTC	Spread	AT		
	nR2 ~ χ2 (95% c.v. = 18.55)	6.97	5.53	11.57		
	Post-RegNMS					
	nR2 ~ χ2 (95% c.v. = 19.81)	14.32	5.89	8.16		
Panel B - Yugo-Stock (2005) Test of Instrumental Variable Weakness						
		Critical Values for 2SLS Bias > 10/20/30% of OLS Bias	Pre RegNMS All IVs	Pre Excluded IVs Only	Post RegNMS All IVs	Post Excluded IVs Only
Manipulation Equation	F stats	16.88 / 9.92/6.16	26.44**	31.98**	60.81**	71.86**
Spread Equation		17.70/10.22/6.20	4.0E4**	3.1E4**	4.2E4**	4.0E4**
AT Equation		18.30/10.43/6.22	1.2E4**	1549**	2.1E4**	1967**

Pre- and post-RegNMS estimates are reported separately in Tables 5-4 and 5-5. There is strong evidence of the principal hypothesis – a heretofore-undiscovered feedback loop between algorithmic trading, fragmentation and market quality. Post-RegNMS, in Table 5-5, lit and dark market fragmentation reduce liquidity, directly increasing the cost of trading, as expected. However, the lit fragmentation and the algorithmic trading it facilitates indirectly decrease the cost of trading by reducing the incidence of end-of-day dislocations which are artificial sources of induced volatility that otherwise would trigger large and significant increases in the effective spread. Dark fragmentation in contrast increases end-of-day manipulation, thereby significantly widening spreads.

TABLE 5-4: 2SLS STRUCTURAL EQUATIONS MODEL PRE REGNMS

This table reports the results of the Two Stage Least Squares regression to determine the joint effect of the predictor variables on Market Quality prior to the introduction of Reg NMS. The data incorporates 2003-2007. The first equation presents the results for EOD dislocation measure of market integrity. The second equation presents the results for effective spread; which measures market efficiency. The thirds equation presents the results for Algorithmic trading as a time varying design driver of market quality.

	Dependent variable:		
	EOD Dislocation	Effective Spread	Algo. Trading
	(1)	(2)	(3)
Effective Spread hat (log bps)	-0.001		0.917***
	(0.001)		(0.004)
EOD Dislocation hat (count)		32.836***	-22.447***
		(0.414)	(0.331)
Algo. Trading hat (log CTTR)	-0.004***	-0.481***	
	(0.001)	(0.005)	
Ave. Daily Dollar Volume (log)		-0.588***	
		(0.001)	
VIX (log)	0.014***	-0.460***	
	(0.002)	(0.013)	
Price (log)			0.582***
			(0.004)
Intraday Volatility (log)			-0.341***
			(0.004)
EOQ Dummy	-0.001		-0.005
	(0.001)		(0.004)
Quartile 2 Dummy	-0.005***		
	(0.001)		
Quartile 3 Dummy	-0.009		
	(0.002)		
Quartile 4 Dummy	-0.002		
	(0.003)		
2004		-0.208***	0.349
		(0.007)	(0.007)
2005		-0.098***	0.393***
		(0.008)	(0.007)
2006		-0.234***	0.658***
		(0.009)	(0.006)
2007		-0.671***	0.523***
		(0.009)	(0.008)
Lit Fragmentation (Norm. Herf)	0.012***	0.377***	-0.065***
	(0.003)	(0.010)	(0.013)
Dark Fragmentation (TRF pct)	0.019*	-0.155***	-0.032
	(0.011)	(0.036)	(0.050)
Constant	-0.018	9.047***	0.441***
	(0.009)	(0.047)	(0.020)
Observations	58,877	58,877	58,877
R2	0.004	0.871	0.706
Adjusted R2	0.004	0.871	0.706
			*p<0.1; **p<0.05; ***p<0.01

Prior to the best quote-trade discipline enforced by RegNMS, the manipulation-reducing effect of algorithmic trading was half as large as post-RegNMS (comparing the estimates for Algo Trading hat in the EOD Dislocation equation in Column 1 of Tables 5-4 and 5-5). In the pre-RegNMS regime, both dark and lit fragmentation themselves increase manipulation, which indirectly widen spreads. One persistent finding is that in both regimes, the year dummy variables show that algorithmic trading continuously increases and effective spreads continuously decline, *ceteris paribus*. Nevertheless, the contribution of this chapter is that it establishes that the full effect of HFT/AT on market efficiency depends upon more than that finding. Specifically, the feedback loops involving the indirect effects of lit and dark fragmentation on market quality are critical to understanding the effect.

TABLE 5-5: 2SLS STRUCTURAL EQUATIONS MODEL POST REGNMS

This table reports the results of the Two Stage Least Squares regression to determine the joint effect of the predictor variables on Market Quality after the introduction of Reg NMS. The data incorporates 2008-2012. The first equation presents the results for EOD dislocation measure of market integrity. The second equation presents the results for effective spread; which measures market efficiency. The thirds equation presents the results for Algorithmic trading as a time varying design driver of market quality.

	Dependent variable:		
	EOD Disolocation	Effective Spread	Algo. Trading
	(1)	(2)	(3)
Effective Spread hat (log bps)	-0.001		0.878***
	(0.001)		(0.003)
EOD Dislocation hat (count)		19.433***	-20.532***
		(0.208)	(0.237)
Algo. Trading hat (log CTTR)	-0.004***	-0.177***	
	(0.001)	(0.004)	
Ave. Daily Dollar Volume (log)		-0.546***	
		(0.001)	
VIX (log)	0.014***	0.626***	
	(0.002)	(0.005)	
Price (log)			0.530***
			(0.002)
Intraday Volatility (log)			-0.350***
			(0.004)
EOQ Dummy	-0.001		-0.070***
	(0.001)		(0.003)
Quartile 2 Dummy	-0.005***		
	(0.001)		
Quartile 3 Dummy	-0.009		
	(0.002)		
Quartile 4 Dummy	-0.002		
	(0.003)		
2008		-0.071***	0.176
		(0.008)	(0.009)
2009		-0.606***	0.716***
		(0.009)	(0.010)
2010		-0.606***	0.855***
		(0.009)	(0.009)
2011		-0.323***	0.662***
		(0.009)	(0.010)
2012		-0.101***	0.477***
		(0.010)	(0.010)
Lit Fragmentation (Norm. Herf)	-0.040***	0.250***	0.165***
	(0.004)	(0.013)	(0.014)
Dark Fragmentation (TRF pct)	0.060***	0.722***	-0.405***
	(0.007)	(0.018)	(0.020)
Constant	0.007	4.354***	0.569***
	(0.012)	(0.033)	(0.020)
Observations	61,537	61,537	61,537
R2	0.009	0.881	0.801
Adjusted R2	0.009	0.881	0.801

*p<0.1; **p<0.05; ***p<0.01

5.5.1. Algo Trading Equation

Beginning with the Algo Trading equation in Column 3, with one exception, the determinants of HFT/AT participation are consistent across the pre- and post-RegNMS regimes. Higher reduced-form predicted spreads and lower manipulation across stocks and over time increases HFT/AT, conditional on several other factors. These findings are indicative of the liquidity suppling / market-making function of HFT/AT traders in offering unmarketable limit orders. It should be expected that marketable limit orders (when HFT/ATs are demanding liquidity to exploit their superior state-of-the-market modelling) will decline with higher spread transaction costs and with fewer opportunities for informational advantage from manipulation-induced transitory pricing errors.

Consistent with previous research (Ye and Yao, 2014, Hasbrouck and Saar, 2011), HFT/AT increases with the stock price and decreases with intraday volatility. Similar to Brogaard, Hendershott and Riordan (2014), this study finds that overall HFT/AT order flow is negatively correlated with transitory pricing errors in high incidence environments like end-of-quarters; here manipulation events have been controlled for separately, so the HFT/AT market-makers withdraw for adverse selection reasons at the end of quarters, and this is statistically significantly in the less noisy environment post-RegNMS.

Once RegNMS cleansed the consolidated tape of numerous trade-throughs, lit market fragmentation with its attendant differential depth and price impact expanded the opportunities for profitable HFT/AT trading strategies.[23] Dark fragmentation, on the other hand, did the opposite and, to some degree, this was the intended purpose. Like internalisation programs in the pre-RegNMS era, trading in the dark has made quote price competition less transparent, which reduces not only front running, but also the arbitrage trading and related strategies that Brogaard, Hendershott and Riordan (2014) find HFT/AT participants favour over a sub-five-second time frame.

5.5.2. Effective Spread Equation

As to the determinants of effective spreads (Table 5-4, Column 2) in this richer modelling environment incorporating market quality feedback and the joint effect of fragmentation and dark trading, the level of lit fragmentation widens the effective spread, while off-exchange fragmentation reduces it. This makes sense in the pre-RegNMS period, where lit market fragmentation split liquidity between venues that were disparate platforms tied together only by intraday arbitrage. In the case of dark fragmentation, the off-exchange venues evolved originally as an outlet for informed traders. By drawing informed traders away from the lit markets to off-exchange venues, the level of informed trading on the lit market declined in the pre-RegNMS period, and lit market effective spreads therefore decreased.

[23] Prior to that, the reverse holds; greater lit fragmentation created many more trade through exceptions allowed by NYSE trading rules.

Post-RegNMS in Table 5-5 Column 2, several striking differences emerge. With RegNMS's unification of the lit exchanges through the NBBO, lit fragmentation now decreases the incidence of end of day dislocations while increasing algorithmic trading. Unlike in the pre-RegNMS period, increased algorithmic trading now works to both reduce the effective spread and reinforce the effect of lit fragmentation, lowering the incidence of end of day dislocation. Dark fragmentation is not similarly beneficial; post-RegNMS, off-exchange trading now increases market manipulation directly. In addition, off-exchange trading acts to reduce the level of algorithmic trading which indirectly widens the effective spread by increasing the incidence of end-of-day dislocation.

Perhaps the starkest reminder of how much RegNMS altered the institutions of trading in the lit market, the VIX is positively related to effective spreads post-RegNMS, but negatively related to effective spreads in the earlier, noisy period. By imposing a discipline on quote reporting and trade-throughs, RegNMS made the volatility of trade prices much more closely linked to the adverse selection costs embedded in equilibrium effective spreads.

As a liquidity metric, average daily dollar volume is (as expected) negatively related to effective spreads, with very similar magnitude estimates in both the pre-RegNMS and post-RegNMS periods. The essence of the previously undiscovered feedback loop appears at the top of Column 2. Algo Trading lowers effective spreads in both regulatory regimes, with large magnitude estimates. Post-RegNMS, a doubling of the cancellation to trade ratio from its median of 4.18 to 8.36 decreases effective spreads by 12.3 bps. Pre-RegNMS, the increase in transaction cost efficiency was even larger at 33.3 bps.

Finally, even standardised coefficients cause the feedback effect from higher EOD dislocation onto effective spreads to be very large across both regulatory regimes. The 19.433 post-RegNMS partial derivative with respect to EOD dislocation in Column 2 becomes 0.280, constituting the largest partial effects on effective spreads. Aitken, Harris, and Ji (2014) establish this link between trade-based manipulation and higher effective spreads across leading stock exchanges worldwide. The findings of this research for US equities markets establish the same result; that lower market quality increases implicit transaction cost metrics of market efficiency across securities and over time within a market.

5.5.3. EOD Dislocation Equation

As to the determinants of end-of-day manipulation in Column 1, a manipulator's execution costs of establishing a false trend rise steeply with the implicit transaction cost of round trips. As expected, therefore, the higher the effective spread, the lower the EOD dislocation. HFT/AT is uniquely capable of detecting the "state of the market", and then trading against the false trend before the manipulator can profit from the price dislocation and close his/her own position. As expected, the VIX is positively related to manipulation incidence. Uninformed traders are more likely to mimic a manipulator's false trend the larger the anticipated price move at 68% likelihood, as predicted by the VIX. End-of-quarter timing (EOQ dummy variable) triggers increased surveillance, which reduces attempted EOD manipulation.

In the more disciplined quotation and trade price institutional environment post-RegNMS, the magnitude of this estimated effect quadruples and becomes statistically significant.

Finally, this chapter highlights the role of fragmentation in facilitating HFT/AT, and the resulting changes in market quality. Pre-RegNMS, fragmentation of the order flow made effective surveillance more difficult. The consequence was a significant increase in EOD manipulation. However, Post-RegNMS the opportunity for profitable HFT/AT has been advantaged by the differing depth and price impact in a fragmented market place that, even conditioning on Algo Trading, lit market fragmentation is responsible for reducing EOD manipulation. In contrast, this chapter's main finding is that in the richer modelling environment of investigating feedback loops between market quality and market efficiency, fragmentation into the dark has increased market manipulation, which in turn raises effective spreads and detracts from transaction cost efficiency.

5.6. Summary

The findings of this study make it clear that in the post-Reg NMS institutional environment, fragmentation of the lit market order flow, and the ensuing increase in competition, especially from HFT/ATs and alternative trading systems, is overwhelmingly positive for both aspects of market quality. This is evidenced by the fact that effective spreads (related to market efficiency) and end-of-day manipulation (related to market integrity) have both fallen. A doubling of the cancellation-to-trade proxy for HFT/AT 2004-2013 has lowered effective spreads by 12 basis points. In this sense, the lit fragmentation facilitated by RegNMS has clearly benefited transaction cost efficiency.

The net effect of off-exchange fragmentation is in stark contrast to that of lit fragmentation discussed above. Fragmentation of trading into the dark has detracted from market fairness by increasing closing price manipulation and has further had a negative impact on spreads. There has been a 2% to 14% increase in TRF dark share volume between 2004 and 2013, increasing effective spreads by 8 basis points. The gains as a result of enhanced competition for lit order flow that accompanied RegNMS are in this way counteracted by increased spreads as a result of dark fragmentation This outcome may be sufficient to require a review of the policy stance on fragmentation into the dark.

In addition to manipulation at the close, if trading ahead of price-sensitive announcements and front running have increased with fragmentation into the dark, then efficiency gains must be traded off against these deleterious effects on market quality. Here it is demonstrated that such market fairness violations triggered by trading in the dark increase effective spreads by an order of magnitude similar to the decreases attributable to lit market fragmentation.

6. Conclusions

The aim of this dissertation is to examine the combined effect of algorithmic trading and market fragmentation on market quality. Market quality is understood as the combination of market efficiency and market integrity. The literature review in chapter two illustrates that research around algorithmic trading and fragmentation tends to focus on market efficiency, with an overall lack of evidence regarding the combined impact of both market features on market integrity. Some initial studies on HFT and market integrity indicate a positive relationship. The work in this thesis extends this research by jointly estimating the growth in algorithmic trading and fragmentation. The research illustrates the highly correlated growth in algorithmic trading and fragmentation over the past decade, and postulates that these two new developments in financial markets are co-joint. Therefore, it is argued that any study on one feature may be mis-specifying the significance of the other.

Based on the above understanding, this dissertation undertakes three research studies to work towards a unifying approach of analysing market quality. The first two components, documented in chapters three and four, advance research in specific areas, exploring algorithmic trading and dark trading respectively. Neither of these areas are fully developed in the literature, and thus the research represents a substantial contribution to the academic study.

The study in chapter three analyses the causal impact of a shock to HFT by utilising stock splits as a change in relative tick size. This work provides further insight into the effect of HFT on the market by combining a proprietary data set that can more accurately specify liquidity providing HFT, with a causal research design.

The study in chapter four analyses the impact of price improvement regulation as a shock to dark trading levels to price discovery. The study furthers the literature by using dynamic lag estimation in the vector error correction framework first developed by Hasbrouck (1995) and Gonzalo and Granger (1995). Findings offer preliminary insight into the impact of regulation on dark trading and its effect on price discovery. It is ultimately established that, in the Canadian case, the price improvement regulation proved to be an effective means of limiting dark trading without negatively impacting aggregate price discovery.

The study in chapter five represents the culmination of the thesis, building on understandings of dark trading, market fragmentation and HFT, as analysed in the previous chapters. The final study utilises a structural equations model to jointly model the impact of fragmentation and algorithmic trading on the US equities market. This is the first study to undertake such research. The findings from each of the three studies are summarised below.

In chapter three, a unique data set of the daily percentage of trading executed by HFT and ELP illustrate how changes in relative tick sizes can alter trading behaviour. It is found that liquid securities can increase their liquidity provision by widening their spreads. Further, less liquid securities can also increase market-making activity in their stocks by simply widening the relative tick size. Message traffic has previously been associated with nefarious trading strategies and HFT strategies. The findings suggest that firms across all liquidity types can decrease message traffic by splitting their stocks and widening the relative tick size. Ultimately, increased relative tick-size can create a generally beneficial outcome for less liquid securities, simultaneously increasing the quality of the trading behaviour, while decreasing transactions costs. For more liquid securities, increased tick size may have some cost in terms of market efficiency. However, a stock split still offers a unique avenue for managers to reduce message traffic in their company, short of regulatory changes.

The research conducted in chapter three also contributes to past literature by supporting previous theories on tick sizes with empirical evidence. In line with the theories put forward by Harris (1991), Angel (1997) and Huang and Stoll (1994), the research in chapter three finds direct causal evidence that increasing the relative tick size improves transaction costs by lowering spreads. However, establishing the optimal price and tick size is a difficult challenge. If the tick size is too wide and the quoted spread is heavily constrained, then the fastest liquidity providers will gain time priority due to their relative speed advantage. This may cause greater depth, but it will force slower traders to cross the spread more often, reducing their ability to provide liquidity passively.

The findings from chapter three lead to the recommendation that companies looking to split their stock for liquidity reasons do so in a manner that ensures the relative tick size approaches, but does not reach, the constrained minimum quoted spread. The time precedence offered by the greater relative tick size will likely incentivise liquidity providers to enter the market. This competition may drive the quoted spread tighter to become tick constrained, without offering excessive profits to liquidity providers in detriment to liquidity takers.

Chapter four analyses the factors that lead to informative dark trading and the effect of IIROC's price improvement rule on permanent information impounding and price discovery efficiency in cross-listed securities. The price improvement rule has the effect of pushing price discovery back into the lit market in Canada. Further, the study finds no evidence that price discovery shifts from the Canadian market to the cross-listed US market. Additionally, the study in chapter four uses a methodology that controls for three new measures of order book quality and finds that these contribute important price discovery insights, consistent with Jain, Jain and McInish (2010).

Dark trading in Canada contributes very little information to the market. Because of this limited contribution, the decline in information leadership share of dark trades after the introduction of the price improvement rule is of limited concern. Moreover, the price improvement rule does not increase the informational content of the Canadian market relative to the US market. It is suggested that future research should assess the effects of dark trades on the price discovery process in the US market where dark trading constitutes 38% of trading volume.

The final study in chapter five shows that, in the post-Reg NMS institutional environment, fragmentation of the lit market order flow and the ensuing increase in competition (especially from HFT/ATs and alternative trading systems) has had an overwhelmingly positive effect on market quality. Both effective spreads (relating to market efficiency) and end-of-day manipulation (relating to market integrity) are reduced. The study in chapter five illustrates that a doubling of the cancellation-to-trade proxy for HFT/AT 2004-2013 lowered effective spreads by 12 basis points. In this sense, the lit fragmentation facilitated by Reg NMS has clearly benefited transaction cost efficiency.

However, the net effect of off-exchange fragmentation has been harmful to market quality. Fragmentation of trading into the dark has detracted from market fairness by increasing closing price manipulation. In addition, the study in chapter five shows a 2% to 14% increase in TRF dark share volume between 2004 and 2013, which has increased effective spreads by 8 basis points. Based on these findings, it is suggested that the policy stance regarding fragmentation into the dark may need to be explored further to take into account the impact on both market fairness and market efficiency consequences.

In addition to manipulation at the close, if trading ahead of price-sensitive announcements and front running have increased with fragmentation into the dark, then efficiency gains must be traded-off against these deleterious effects on market quality. The study in chapter five demonstrates that such market fairness violations, triggered by trading in the dark, have had a harmful impact on market efficiency. The result has been an increase in effective spreads by an order of magnitude similar to the decreases attributable to lit market fragmentation.

Ultimately, the combined research in this thesis explores the impact of unique market elements including HFT and algorithmic trading participants, and market fragmentation. Findings from the research suggest that overall, increases in HFT and algorithmic trading have a positive impact on market quality in terms of both fairness and efficiency. Conversely, while lit market fragmentation may benefit market quality in terms of efficiency, fragmentation into the dark has a negative impact on both aspects of market quality, increasing market integrity violations and negatively impacting spreads. Further research could be conducted to evaluate the impact of these factors in diverse markets. In general, it is suggested that financial market research should attempt to evaluate the impact of emergent market features and market design changes on both aspects of market quality: fairness and efficiency.

References

A

Abadie, Alberto. 2005. "Semiparametric Difference-in-Differences Estimators." *The Review of Economic Studies* 72 (1): 1–19. doi:10.1111/0034-6527.00321.

Admati, Anat R., and Paul Pfleiderer. 1988. "A Theory of Intraday Patterns: Volume and Price Variability." *Review of Financial Studies* 1 (1): 3–40. doi:10.1093/rfs/1.1.3.

Ahn, Hee-Joon, Jun Cai, Kalok Chan, and Yasushi Hamao. 2007. "Tick Size Change and Liquidity Provision on the Tokyo Stock Exchange." *Journal of the Japanese and International Economies* 21 (2): 173–94. doi:10.1016/j.jjie.2005.10.008.

Ahn, Hee-Joon, Charles Q. Cao, and Hyuk Choe. 1998. "Decimalization and Competition among Stock Markets: Evidence from the Toronto Stock Exchange Cross-Listed Securities." *Journal of Financial Markets* 1 (1): 51–87. doi:10.1016/S1386-4181(97)00002-5.

Aitken, Michael, and Carole Comerton-Forde. 2005. "Do Reductions in Tick Sizes Influence Liquidity?" *Accounting & Finance* 45 (2): 171–84. doi:10.1111/j.1467-629x.2004.00128.x.

Aitken, Michael J., Angelo Aspris, Sean Foley, and Frederick H. deB Harris. 2014. "Market Fairness: The Poor Country Cousin of Market Efficiency." SSRN Scholarly Paper ID 2440671. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2440671.

Allen, Franklin, and Douglas Gale. 1992. “Stock-Price Manipulation.” *Review of Financial Studies* 5 (3): 503–29. doi:10.1093/rfs/5.3.503.

Anand, Amber, Carsten Tanggaard, and Daniel G. Weaver. 2009. “Paying for Market Quality.” *Journal of Financial and Quantitative Analysis* 44 (06): 1427–57. doi:10.1017/S0022109009990421.

Anderson, Hamish D., and Yuan Peng. 2013. “From Cents to Half-Cents and Its Impact on Liquidity.” SSRN Scholarly Paper ID 2229025. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2229025.

Angel, James J. 1997. “Tick Size, Share Prices, and Stock Splits.” *The Journal of Finance* 52 (2): 655–81. doi:10.1111/j.1540-6261.1997.tb04817.x.

B

Bacidore, Jeffrey, Robert H. Battalio, and Robert H. Jennings. 2003. “Order Submission Strategies, Liquidity Supply, and Trading in Pennies on the New York Stock Exchange.” *Journal of Financial Markets*, Execution costs, 6 (3): 337–62. doi:10.1016/S1386-4181(03)00003-X.

Bennett, Paul, and Li Wei. 2006. “Market Structure, Fragmentation, and Market Quality.” *Journal of Financial Markets* 9 (1): 49–78. doi:10.1016/j.finmar.2005.12.001.

Bessembinder, Hendrik. 2003. “Trade Execution Costs and Market Quality after Decimalization.” *Journal of Financial and Quantitative Analysis* 38 (04): 747–77. doi:10.2307/4126742.

Bessembinder, Hendrik, and Herbert M. Kaufman. 1997. “A Cross-Exchange Comparison of Execution Costs and Information Flow for NYSE-Listed Stocks.” *Journal of Financial Economics* 46 (3): 293–319. doi:10.1016/S0304-405X(97)00032-9.

Bloomfield, Robert J.; O'Hara, Maureen; Saar, Gideon. "Hidden Liquidity: Some New Light on Dark Trading" Journal of Finance 70.5 (2015): 2227-2274

Bolton, Patrick, Tano Santos, and Jose A. Scheinkman. 2016. "Cream-Skimming in Financial Markets." The Journal of Finance (2016).

Booth, G. Geoffrey, Ji-Chai Lin, Teppo Martikainen, and Yiuman Tse. 2002. “Trading and Pricing in Upstairs and Downstairs Stock Markets.” *Review of Financial Studies* 15 (4): 1111–35. doi:10.1093/rfs/15.4.1111.

Boulatov, Alex, and Thomas J. George. 2013. “Hidden and Displayed Liquidity in Securities Markets with Informed Liquidity Providers.” *Review of Financial Studies*, January, hhs123. doi:10.1093/rfs/hhs123.

Brogaard, Jonathan A., Thomas Brennan, Robert Korajczyk, Robert Mcdonald, and Annette Vissing-jorgensen. 2010. *High Frequency Trading and Its Impact on Market Quality*.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan. 2014. “High-Frequency Trading and Price Discovery.” *Review of Financial Studies* 27 (8): 2267–2306. doi:10.1093/rfs/hhu032.

C

Chaboud, Alain P., Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega. 2014. "Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market." *The Journal of Finance* 69 (5): 2045–84. doi:10.1111/jofi.12186.

Chakraborty, Archishman, and Bilge Yılmaz. 2004. "Manipulation in Market Order Models." *Journal of Financial Markets* 7 (2): 187–206. doi:10.1016/j.finmar.2003.11.001.

Chakravarty, Sugato, Stephen P. Harris, and Robert Wood. 2001. "Decimal Trading and Market Impact." SSRN Scholarly Paper ID 266877. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=266877.

Chakravarty, Sugato, Venkatesh Panchapagesan, and Robert A. Wood. 2005. "Did Decimalization Hurt Institutional Investors?" *Journal of Financial Markets* 8 (4): 400–420. doi:10.1016/j.finmar.2005.05.002.

Chordia, T., Roll, R. & Subrahmanyam, A. (2008) Liquidity and market efficiency . *Journal of Financial Economics,* 87(2), 249-268.

Chung, Kee H., Chairat Chuwonganant, and D. Timothy McCormick. 2006. "Does Internalization Diminish the Impact of Quote Aggressiveness on Dealer Market Share?" *Journal of Financial Intermediation* 15 (1): 108–31. doi:10.1016/j.jfi.2004.10.002.

Colby, Robert L. D., and Erik R. Sirri. 2010. "Consolidation and Competition in the US Equity Markets." *Capital Markets Law Journal* 5 (2): 169–96. doi:10.1093/cmlj/kmq004.

Comerton-Forde, Carole, and Tālis J. Putniņš. 2015. "Dark Trading and Price Discovery." SSRN Scholarly Paper ID 2183392. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2183392.

Coughenour, Jay F., and Lawrence Harris. 2004. "Specialist Profits and the Minimum Price Increment." SSRN Scholarly Paper ID 537785. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=537785.

Cumming, Douglas J., Feng Zhan, and Michael J. Aitken. 2013a. "Exchange Trading Rules, Surveillance, and Insider Trading." SSRN Scholarly Paper ID 2101826. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2101826.

———. 2013b. "High Frequency Trading and End-of-Day Price Dislocation." SSRN Scholarly Paper ID 2145565. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2145565.

Cvitanic, Jaksa, and Andrei A. Kirilenko. 2010. "High Frequency Traders and Asset Prices." SSRN Scholarly Paper ID 1569067. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1569067.

// D

Degryse, Hans, Van Achter, and Gunther Wuyts. 2008. “Shedding Light on Dark Liquidity Pools.” SSRN Scholarly Paper ID 1303482. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1303482.

// E

Easley, David, Nicholas M. Kiefer, and Maureen O’Hara. 1996. “Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow.” *The Journal of Finance* 51 (3): 811–33. doi:10.2307/2329223.

Eun, Cheol S., and Sanjiv Sabherwal. 2003. “Cross-Border Listings and Price Discovery: Evidence from U.S.-Listed Canadian Stocks.” *The Journal of Finance* 58 (2): 549–76. doi:10.1111/1540-6261.00537.

“Evidence-Based Policy Making for Financial Markets: AFairness and Efficiency Framework for AssessingMarket Quality: The Journal of Trading.” 2016. Accessed January 9. http://www.iijournals.com/doi/abs/10.3905/jot.2011.6.3.022.

// F

Fama, Eugene F. 1997. “Market Efficiency, Long-Term Returns, and Behavioral Finance.” SSRN Scholarly Paper ID 15108. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=15108.

Foley, Sean, and Tālis J. Putniņš. 2015. “Should We Be Afraid of the Dark? Dark Trading and Market Quality.” SSRN Scholarly Paper ID 2279719. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2279719.

Foster, F. Douglas, and S. Viswanathan. 1990. “A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets.” *Review of Financial Studies* 3 (4): 593–624. doi:10.1093/rfs/3.4.593.

Frederick H. deB, Harris, and Elisa Maree DiMarco. 2012. “European Market Quality Pre-/Post-MiFID: A Panel Discussion of Metrics for Market Integrity and Efficiency.” *The Journal of Trading* 7 (4): 7–26. doi:10.3905/jot.2012.7.4.007.

G

Goldstein, Michael A., and Kenneth A. Kavajecz. 2000. “Eighths, Sixteenths, and Market Depth: Changes in Tick Size and Liquidity Provision on the NYSE.” *Journal of Financial Economics* 56 (1): 125–49. doi:10.1016/S0304-405X(99)00061-6.

Gonzalo, Jesus, and Clive Granger. 1995. “Estimation of Common Long-Memory Components in Cointegrated Systems.” *Journal of Business & Economic Statistics* 13 (1): 27–35. doi:10.2307/1392518.

H

Hagströmer, Björn, and Lars Nordén. 2013. “The Diversity of High-Frequency Traders.” *Journal of Financial Markets*, High-Frequency Trading, 16 (4): 741–70. doi:10.1016/j.finmar.2013.05.009.

Harris, Frederick H. deB, Michael J. Aitken, and Shan Ji. 2014. "A Worldwide Examination of Exchange Market Quality: Greater Integrity Increases Market Efficiency." SSRN Scholarly Paper ID 1890928. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1890928.

Harris, Frederick H. deB, Michael J. Aitken, Di Marco, and Elisa-Maree. 2012. "Price Discovery Efficiency and Permanent Information Impounding on Nyse Euronext Paris." SSRN Scholarly Paper ID 2029338. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2029338.

Hasbrouck, Joel. 1995. "One Security, Many Markets: Determining the Contributions to Price Discovery." *The Journal of Finance* 50 (4): 1175–99. doi:10.2307/2329348.

Hasbrouck, Joel, and Gideon Saar. 2013. "Low-Latency Trading." *Journal of Financial Markets*, High-Frequency Trading, 16 (4): 646–79. doi:10.1016/j.finmar.2013.05.003.

Hasbrouck, Joel, and George Sofianos. 1993. "The Trades of Market Makers: An Empirical Analysis of NYSE Specialists." *The Journal of Finance* 48 (5): 1565–93. doi:10.1111/j.1540-6261.1993.tb05121.x.

Hatheway, Frank, Amy Kwan, and Hui Zheng. 2014. "An Empirical Analysis of Market Segmentation on U.S. Equities Markets." SSRN Scholarly Paper ID 2275101. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2275101.

Hendershott, Terrence, Charles M. Jones, and Albert J. Menkveld. 2011. "Does Algorithmic Trading Improve Liquidity?" *The Journal of Finance* 66 (1): 1–33. doi:10.1111/j.1540-6261.2010.01624.x.

Hendershott, Terrence, and Ryan Riordan. 2013. "Algorithmic Trading and the Market for Liquidity." *Journal of Financial and Quantitative Analysis* 48 (04): 1001–24. doi:10.1017/S0022109013000471.

Hirschey, Nicholas. 2013. "Do High-Frequency Traders Anticipate Buying and Selling Pressure?" SSRN Scholarly Paper ID 2238516. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=2238516.

Huang, Roger D., and Hans R. Stoll. 2001. "Tick Size, Bid-Ask Spreads, and Market Structure." *Journal of Financial and Quantitative Analysis* 36 (04): 503–22. doi:10.2307/2676222.

J

Jain, Pankaj K., Pawan Jain, and Thomas H. McInish. 2012. "Evolution of Volatility, Trade Price Location, Correlations, and Speed of Trading in the Limit Order Book." SSRN Scholarly Paper ID 1913982. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1913982.

Jarnecic, Elvis, and Mark Snape. 2010. "An Analysis of Trades by High Frequency Participants on the London Stock Exchange." Working Paper, June. http://scholar.google.com/scholar?cluster=6208338118143691073&hl=en&oi=scholarr.

Jovanovic, Boyan, and Albert J. Menkveld. 2015. “Middlemen in Limit Order Markets.” SSRN Scholarly Paper ID 1624329. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1624329.

K

Kadapakkam, Palani-Rajan, Srinivasan Krishnamurthy, and Yiuman Tse. 2005. “Stock Splits, Broker Promotion, and Decimalization.” *Journal of Financial and Quantitative Analysis* 40 (04): 873–95. doi:10.1017/S0022109000002015.

Kearns, Michael, Alex Kulesza, and Yuriy Nevmyvaka. 2010. “Empirical Limitations on High Frequency Trading Profitability.” SSRN Scholarly Paper ID 1678758. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1678758.

Kirilenko, Andrei A., Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun. 2014. “The Flash Crash: The Impact of High Frequency Trading on an Electronic Market.” SSRN Scholarly Paper ID 1686004. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1686004.

L

Lau, Sie Ting, and Thomas H. McInish. 1995. “Reducing Tick Size on the Stock Exchange of Singapore.” *Pacific-Basin Finance Journal* 3 (4): 485–96. doi:10.1016/0927-538X(95)00019-H.

M

Madhavan, Ananth. 1995. “Consolidation, Fragmentation, and the Disclosure of Trading Information.” *Review of Financial Studies* 8 (3): 579–603. doi:10.1093/rfs/8.3.579.

Madhavan, Ananth, and Minder Cheng. 1997. “In Search of Liquidity: Block Trades in the Upstairs and Downstairs Markets.” *Review of Financial Studies* 10 (1): 175–203. doi:10.1093/rfs/10.1.175.

Madhavan, Ananth, and Seymour Smidt. 1993. “An Analysis of Changes in Specialist Inventories and Quotations.” *The Journal of Finance* 48 (5): 1595–1628. doi:10.1111/j.1540-6261.1993.tb05122.x.

McInish, Thomas H., and James Upson. 2012. “Strategic Liquidity Supply in a Market with Fast and Slow Traders.” SSRN Scholarly Paper ID 1924991. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1924991.

N

Nimalendran, Mahendrarajah, and Sugata Ray. 2014. “Informational Linkages between Dark and Lit Trading Venues.” *Journal of Financial Markets* 17 (January): 230–61. doi:10.1016/j.finmar.2013.02.003.

O

O'Hara, Maureen, and Mao Ye. 2011. "Is Market Fragmentation Harming Market Quality?" *Journal of Financial Economics* 100 (3): 459–74. doi:10.1016/j.jfineco.2011.02.006.

P

Putniņš, Tālis J. 2013. "What Do Price Discovery Metrics Really Measure?" *Journal of Empirical Finance* 23 (September): 68–83. doi:10.1016/j.jempfin.2013.05.004.

R

Ronen, Tavy, and Daniel G Weaver. 2001. "'Teenies' Anyone?" *Journal of Financial Markets* 4 (3): 231–60. doi:10.1016/S1386-4181(00)00023-9.

S

Sarr, Abdourahmane and Lybek, Tony 2002. Measuring Liquidity in FInancial Markets. IMF Working Paper

Schultz, Paul. 2000. "Stock Splits, Tick Size, and Sponsorship." *The Journal of Finance* 55 (1): 429–50. doi:10.1111/0022-1082.00211.

Seppi, Duane J. 1990. "Equilibrium Block Trading and Asymmetric Information." *The Journal of Finance* 45 (1): 73–94. doi:10.1111/j.1540-6261.1990.tb05081.x.

Siow, Audris S., and Michael J. Aitken. 2004. "Ranking World Equity Markets on the Basis of Market Efficiency and Integrity." SSRN Scholarly Paper ID 490462.

Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=490462.

Smith, Brian F., D. Alasdair S. Turnbull, and Robert W. White. 2001. “Upstairs Market for Principal and Agency Trades: Analysis of Adverse Information and Price Effects.” *The Journal of Finance* 56 (5): 1723–46.

T

“Tabachnick, B.G. and Fidell, L.S. (1996) Using Multivariate Statistics. 3rd Edition, Harper Collins Publishers, New York.|Reference|Scientific Research Publish.” 2016. Accessed January 9. http://www.ljemail.org/reference/ReferencesPapers.aspx?ReferenceID=1273022.

W

Wang, Jiang. 1994. “A Model of Competitive Stock Trading Volume.” *Journal of Political Economy* 102 (1): 127–68.

Weaver, Daniel G. 2014. “The Trade-At Rule, Internalization, and Market Quality.” SSRN Scholarly Paper ID 1846470. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1846470.

Y

Yan, Bingcheng, and Eric Zivot. 2007. “The Dynamics of Price Discovery.” SSRN Scholarly Paper ID 617161. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=617161.

Ye, Mao. 2011. "A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network." SSRN Scholarly Paper ID 1521494. Rochester, NY: Social Science Research Network. http://papers.ssrn.com/abstract=1521494.

Z

Zhu, Haoxiang. 2013. "Do Dark Pools Harm Price Discovery?" *Review of Financial Studies*, December, hht078. doi:10.1093/rfs/hht078.