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The Impact of Regulation on Market Quality

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A thesis submitted in fulfilment
of the requirements for the degree of

Doctor of Philosophy (Finance)

Discipline of Finance
Business School

July 26, 2014

Declaration of Authorship

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 this 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.

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Sean Foley
(November, 2013)

Publications

The work that forms the basis of Chapter 3 - “Does Insider Trading Explain Price Run-Up?” has been published as follows:

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"An investment in knowledge pays the best interest."

Benjamin Franklin

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UNIVERSITY OF SYDNEY

Abstract

Department of Finance

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The Impact of Regulation on Market Quality

by Sean Foley

This dissertation studies the impact of market structure changes on market efficiency and integrity. Thematically, it is concerned with the actual behaviour of market participants and their associated impact on key market variables such as the degree of liquidity, the size of trading costs, the quality of price discovery and the integrity of the market itself. The fundamental changes to the trading landscape brought about by fragmentation have significantly changed the way that many traders execute transactions. In light of the vast and complex changes that have recently occurred in markets, this thesis conducts an empirical investigation of these microstructure issues. These studies contribute to the understanding of modern markets, the health of which is integral for effective price discovery and liquidity provision.

The four studies in this dissertation examine several key market microstructure issues, including: causes of the pre-bid price run-up ahead of takeover announcements; the impact high frequency trading has on market efficiency and integrity; and the effect of both the introduction and regulation of dark trading. The outcomes of these studies are comprehensively discussed and their contributions to the field are duly noted. Given the significant and rapid change occurring in current equity markets, the findings in this dissertation are relevant for market practitioners, exchange venue designers, and market regulators.

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Chapter 1

Introduction

Regulators internationally are charged with ensuring that equity markets are both fair and efficient. Over the last decade, rapid technological change has revolutionised the way modern equity trading is conducted. Such rapid changes may have unintended consequences for market quality, and it is within the ambit of regulators to ensure that these changes do not have a negative impact. To achieve this goal, it is imperative that empirical evidence is sought to answer these questions. Current evidence on the impact of new trading practices, such as high-frequency and dark trading are inconclusive, with findings indicating the practices are both beneficial and detrimental for market quality. Even older questions of regulatory importance, such as the link between pre-bid run-up and insider trading still do not have conclusive explanations. This lack of evidence hampers the ability of regulators to make informed decisions on any new regulatory initiatives. This thesis empirically analyses three core issues; whether insider trading contributes to the run-up in prices prior to takeover events; the impact of high-frequency trading (HFT) on market quality; and the effect of dark trading on lit markets. The examination of these questions provides evidence that can be used to inform debate about regulatory policy to ensure that regulatory practices are focused on improving both the efficiency and integrity of the market.

Both legislative change and significant technological progress have together enabled the creation of new exchanges that are able to compete effectively against the incumbent listing exchanges. The creation of these alternative trading venues encourages competition for liquidity provision. This has lead to "maker-taker" exchange pricing models and the rise of high-frequency trading which takes advantage of new inverted pricing models. The growth in high-frequency trading has been rapid, with the Tabb Forum estimating that high-frequency trading is responsible for over 60% of the value traded in the US in 2012. To accommodate for this new breed of high speed traders, exchanges have introduced a wide range of new innovations, including direct market access, co-location, and ongoing investment in new technology to ensure that their platforms are fast and capable of handling ever-increasing volumes of orders. Amid this environment of rapid fragmentation, innovative types of venues have developed to take advantage of the new opportunities high-frequency trading offers.

One of the most prevalent of these new types of venues is the "dark pool". This venue offers traders the ability to both hide the size of their order, and to execute trades at prices *between* the best bid and ask quoted in traditional markets. This allows traders to minimise their price impact and information transmission. By providing superior prices, dark pools are able to receive price priority, allowing them to execute orders in preference to the lit market. Innovations such as these have proven to be very popular, both with traders trying to avoid being "picked off" by front-runners, and with high-frequency traders keen to receive preferential execution.

It is not clear whether the legislation that regulates high-frequency trading, dark trading, and insider trading is promoting efficiency and integrity for the market as a whole. The combination of market fragmentation and innovation is rapidly creating a trading environment that is segmented into the "haves" and "have nots". That is, there is a growing distinction between those who are able to access and profit from innovations like dark pools and high-frequency trading, such as large institutional traders, and those who cannot, such as traditional retail investors. Regulators appear to be struggling to keep up with the increasing avenues for manipulation that such innovations create. Misconduct such as layering, quote stuffing, closing price manipulation, lit-dark ramping and phantom liquidity all pose significant risks to the integrity of the market. In response to these risks, many regulators have begun instituting regulations designed to limit the practices of high-frequency and dark trading. Such regulations vary between jurisdictions. Among the changes are the introduction of transactions taxes, messaging taxes, minimum price improvement regulations and minimum quantities for dark trades.

Despite a lack of empirical evidence, a raft of regulatory changes aimed at improving the fairness and efficiency of markets have been implemented without sufficient due diligence. In light of this, the first part of this thesis is dedicated to not only analysing the integrity of the market, but also the interplay between integrity and efficiency, particularly with respect to high-frequency trading, and the apparent effect that insider trading has on pre-bid run-up in takeover targets. The second half of this thesis focuses on the effects of dark market fragmentation, by providing evidence on the impact of the introduction and subsequent regulation of dark pools. Taken as a whole, this thesis presents empirical research into the market quality impacts of equity market regulation. New evidence is provided on the problem of insider trading, the relative merits of high-frequency and dark trading, all with an eye towards improving the efficiency and integrity of the market through evidence based regulation.

1.1 Does insider trading explain price run-up?

Insider trading is a breach of market integrity, and despite extensive study, its impacts on the market remain difficult to identify, study, and regulate against. The potential for sizeable gains based on snippets of undisclosed and price sensitive information fuels the public's fascination with this issue. Due to such potential for inequitable gain and negative impact on market quality, insider trading is a criminal act that regulators are charged with identifying and eliminating. Due to its surreptitious nature , however, identifying insider trading remains a challenging task. For this reason, many academics (and regulators) have conducted research aimed at identifying the "footprints" of this illegal conduct.

Empirical researchers over several decades have focused on takeover events to identify evidence of insider trading. With large premiums, a high degree of information asymmetry, and a large number of individuals working on the deal prior to announcement, takeovers provide a fertile field within which insiders may profit.Indeed, such suspicions would appear vindicated, as international evidence has identified a persistent and substantial target stock price run-up prior to the announcement of takeover bids. Various papers, including Dodd (1980), Jarrell and Poulsen (1989), Betton and Eckbo (2000), and Bris (2005), have identified and documented pre-bid price run-up across different time periods and financial market structures.

While considerable empirical evidence substantiates this pre-bid run-up, the cause of its existence is the subject of much debate. Potential causes covered in the literature include illegal insider trading (Meulbroek, 1992); market speculation of industry dynamics (Jensen and Ruback, 1983); and rumours of an impending takeover based on market information, such as those related to toehold acquisitions (Jarrell and Poulson, 1989). This chapter accounts for all of these sources, and focuses on the potential impact toehold purchases have in signalling an impending bid.

Previous theoretical (Bris, 2002) and empirical (Jarrell and Poulsen, 1989; Aitken and Czernkowski, 1992, Betton, Eckbo and Thorburn, 2008b) works suggest that toehold stakes acquired prior to takeovers may have the capacity to generate pre-bid run-up. Primarily owing to a lack of data, prior studies have found conflicting evidence for any link between toeholds and pre-bid run-ups. Betton and Eckbo (2000) report that the existence of toeholds reduces the magnitude of price run-up, while Jarrell and Poulson (1989) identify that as toeholds increase so to does the size of the pre-bid run-up. This lack of consensus is likely driven by the absence of information regarding the accumulation of target shares by the bidder, a problem acknowledged in these previous studies.

These mixed findings, as well as the availability of information regarding toehold purchases, have shaped the direction of the essay contained in Chapter 3, wherein the causes of the pre-bid price run-up are examined, drawing on data that includes the bidders toehold purchases, rumours in the news media and price sensitive announcements. This analysis of the pre-bid price run-up provides two main contributions. Firstly, it provides a framework within which to measure the level of information leakage in a market, which will be of interest to both market operators and regulators. Secondly, this study also reveals the potential impacts of toehold acquisition timing for market participants, especially bidders considering acquiring a pre-announcement stake in a target company.

1.2 The Impact of HFT on Market Efficiency and Integrity

High-frequency trading has grown in recent years to represent over 50% of trading volume in the US, with estimates for markets in Asia and Europe ranging between 20% and 30%. Despite such a sizeable proportion of trading being executed by high-frequency participants, its implications for market quality are not well understood. While high-frequency trading was once designed to more efficiently execute strategies already in use by human traders, it is now used for a range of purposes including principal trading. Much criticism has been levelled against high-frequency traders, with specific concerns including: that it magnifies the potential for market volatility (such as during the 2010 “Flash Crash”); that “rogue” algorithms have the ability to cause market disruption by erroneously trading billions in hours without human intervention (such as the Knight Capital episode); and that the liquidity that appears to be generated by high-frequency traders is not actually accessible - it evaporates as soon as traders try to act on posted orders.

Recent academic literature has provided new evidence on the impact of HFT on market quality. The theoretical findings of Jovanovic and Menkveld (2011) suggest that HFT participants may generate welfare gains, increasing efficiency through the reduction of the bid-ask spread. The authors argue that this is because HFT participants are able to update their information set faster than a traditional market maker, hence increasing their ability to avoid adverse selection, and thus reducing the cost of liquidity provision. On the other hand, Jovanovic and Menkveld (2011) warn that the ability of HFT participants to update their information set faster than human traders may reduce the willingness of human participants to enter the market for fear of trading with a better informed HFT participant.

One of the principal limitations in conducting empirical studies on HFT involves establishing and maintaining an adequate, standardised definition of the practice. Existing studies have proxied this using measures such as the order-trade ratio (Jovanovic and Menkveld (2011), Malinova, Park and Riordan (2013)), cancel-trade ratio (McInish and Upson (2012)), and exchange-identified accounts (Jarnecic and Snape (2010), Brogaard (2010) and Groth (2011)). This variation in techniques for identifying the exact level of HFT participation has resulted in significant disagreement in the empirical literature. Jovanovic and Menkveld (2011), present evidence that high-frequency trading is beneficial for market efficiency and their findings are consistent with studies such as Jarnecic and Snape (2010), Hendershott, Jones and Menkveld (2011), Brogaard (2010)and Hasbrouck and Saar (2013).

Despite the positive associations linked to high-frequency trading, a large body of literature suggests significant adverse effects associated with this activity. Kirilenko, Kyle, Samadi and Tuzun (2011) show that HFT participants played a big part in causing the May 6th 2010 “Flash Crash” in e-mini futures. McInish and Upson (2012) find that HFT participants are able to use their superior speed of execution to extract rents from “slower” traders, implying HFT participants are intermediating between “true” market participants. Anand and Venkataraman (2012) examine HFT market makers and find that these traders cease trading when markets become unprofitable (due to increased volatility or asymmetric information), exacerbating volatility and reducing depth at the time it is most required.

Keeping these conflicting findings in mind, Chapter 4 examines how HFT impacts the efficiency and integrity of the LSE and NYSE-Euronext Markets (Paris). Using data from 2003 to 2011, a unique three-stage least squares framework is used that captures the interrelationship between market efficiency, market integrity, and high-frequency trading. The results from this study add to the regulatory debate on high-frequency trading by showing that market design changes, such as the introduction of HFT, have positive implications for market efficiency and integrity. In meeting their mandate of ensuring that markets are kept fair and efficient, it is important that any assessment of a market design change such as the introduction of HFT assesses not only the impact on each of these individual elements of market quality, but also the interplay between its many dimensions.

1.3 The Market Quality Impacts of Dark Trading

The final two chapters of this dissertation are concerned with the market quality impacts of dark trading. Dark trading refers to trades that are executed without pre-trade transparency. These venues allow trades to be executed at prices within the best bid and ask in the underlying lit markets; in this way, these dark trades avoid generating an explicit impact on price. While this kind of trading has occurred for many years in the form of upstairs block trades, the recent move to introduce dark pools of liquidity (continuously matching buyers and sellers) has raised concern amongst regulators and market participants worldwide.[1]

Proponents of dark trading argue that the hidden nature of dark pools makes them an ideal mechanism for large traders. As their orders are not displayed, they cannot be front-run. Hence, such a mechanism has the capacity to encourage latent liquidity to be expressed on-market without alerting the market to the trading intentions of the users of the dark pool. Furthermore, dark pools may have advantages for market makers who are informed about the true value of traded assets, and would normally have to reveal this information through price impact if aggressive provision of liquidity is pursued. The addition of dark orders allows them to compete with each other more aggressively without displaying their private information. Such a situation could lead to tighter spreads and more efficient prices - an overall improvement in market quality.

Opponents of dark trading, however, argue that informed traders may utilise dark pools to avoid disclosing their information to the market. This has the capacity to reduce the efficiency of the market, as the information contained within the trades does not become part of the price discovery process. Taken to the extreme, if all traders should choose to trade in the dark then the lit market would no longer generate prices, resulting in market failure.

The existence of potential benefits of accessible latent liquidity and more competitive liquidity providers, contrasted against potential adverse effects emanating from the price

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[1] See, for example, The U.S. Securities Exchange Commission proposed “Regulation of non-public trading venues” in 2009, the Committee of European Securities Regulators review of dark trading 10-394 in 2010, the Investment Industry Regulatory Organization of Canada 2012 “HOT” study and the 2013 Australian Securities Investment Commission report 331 “Dark Trading and High Frequency Trading”.

discovery process, suggests there could be an optimum level of dark trading, a theoretical “tipping point”, at which the benefits of dark trading are maximised with respect to the costs.

The level of dark trading has risen rapidly since its introduction in the last decade. By 2012, dark trading was responsible for upwards of 15% of US consolidated volume, 14% in Australia and 10% in Canada.[2] Concern about the rapid rise of dark trading has led the Australian and Canadian regulators to introduce measures to ensure that the practice remains fair and in the best interest of the investing community. Minimum price improvement regulations are one example of such an initiative, aiming to avoid the situation that has evolved in the U.S., where orders with no economic price improvement take precedence over existing limit order book orders. Unsubstantial price improvement allows orders to receive price priority, so that they are executed before the best priced orders in the lit market. This has the effect of creating a two-tiered market, whereby those who have access to dark pools are able to “skip” the lit market queue, thus gaining an unfair competitive advantage.

Recent theoretical papers have provided conflicting evidence on the impact of dark pool trading. Zhu (2012) models the choice between lit and dark venues - as a problem of execution probability. As informed traders are likely to cluster on the same side of the market, their execution probability in the dark will be lower than that of uninformed traders. As such, informed traders will prefer to trade in the lit market, resulting in a higher risk of adverse selection, consequently improving price discovery, but also increasing spreads and price impact, hence reducing market quality. Using a Kyle (1985) framework, Ye (2012) produces conflicting results, finding that informed traders use both lit and dark venues, reducing their aggressiveness in lit venues so as to improve the profitability of their contemporaneously submitted dark orders. Such reduced aggressiveness in the lit market, however, is found to hamper the price discovery process.

In a related study, Boulatov and George (2013) argue that informed traders face a tradeoff in lit markets: if they submit aggressive limit orders they may earn a profit

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[2] The US estimate is from Rosenblatt Securities for April 2013. The Australian estimate is from the Australian Securities and Investments Commission Report 331 for the September quarter 2012 and includes some internalization. The Canadian estimate combines statistics from the Investment Industry Regulatory Organization of Canada

from providing liquidity but will also give away some of their private information. In equilibrium, while some informed traders will use aggressive market orders, others will use limit orders with low levels of aggressiveness, in order to limit the information revealed. With the addition of a dark venue, the authors find that these informed traders can now profit without revealing their private information. This results in more traders using (non-displayed) limit orders, which allows them to profit from their information without revealing it to the market. This leads to increased competition between market makers for liquidity provision, improving both liquidity and informational efficiency.

As yet, empirical analyses of dark pools have not provided any definitive insight as to their impact on market quality. One of the main hindrances in conducting research on dark pools is the opacity of the data. As there is no pre-trade transparency, participants in dark pools (and hence their operators) are understandably reluctant to provide trading data for academic research. This has made it necessary for authors to find dark pool data from proprietary sources, limiting generalisations that can be made from such research. Empirical studies of dark pools have been hampered by a number of issues. These include the potential endogeneity of market quality and dark trading, the need for many participants to engage with dark order types before the introduction of dark venues will have a meaningful impact, and the difficulty of acquiring complete dark market data.

Keeping these limitations in mind, a number of these empirical studies find results consistent with the theoretical works of Zhu (2012) - that dark pools result in a higher concentration of informed trading on the lit market, hence increasing quoted spreads, effective spreads and price impact. These studies include: Degryse, de Jong and Van Kervel (2011) who use data from the Dutch market; Weaver (2011), who uses data from the US trade reporting facility; and Nimalendran and Ray (2013) who use proprietary data from a US dark pool. In addition, Comerton-Forde and Putnins (2013) examine the Australian market, finding that orders executed in the dark are less informed than those on the lit market. Importantly, the authors estimate the tipping point at which dark trading becomes detrimental, finding that as dark volume exceeds 10% of total trading, informational efficiency is reduced.

Other previous empirical literature has shown that dark trading may be beneficial for market quality. Buti, Rindi and Werner (2011) use voluntarily reported data in the US to show that high levels of dark trading are associated with reduced spreads, increased depth and reduced volatility. Bloomfield, O'Hara and Saar (2011) use an experimental framework to determine that the addition of dark order types increases depth without adversely affecting spreads.

The final two essays presented in this dissertation provide empirical evidence on the market quality impacts of dark trading. These studies use careful empirical design and unique Canadian data to overcome many of the problems previously mentioned. Thus, Chapter 5 in this dissertation analyses the impact of the introduction of dark trading on the Toronto Stock Exchange (TSX) in 2011. This introduction of dark orders was conducted in a staggered way, providing a set of control stocks that help to overcome the issue of endogeneity. On the 1st of April 2011 dark trading was introduced for the constituents of the TSX60 (the main index). On the 20th of May 2011 dark trading was activated for the remaining stocks. The TSX is the primary venue for trading in Canada, and the dark order types that were introduced directly interacted with marketable lit orders. The staggered introduction of dark orders combined with the necessity of all market participants to interact with dark orders allows for the construction of an event study that overcomes many of the empirical issues faced by research into dark pools.

This thesis finds that the introduction of dark trading initially causes traders to become more cautious, reducing the aggressiveness of their orders and hence increasing both quoted and effective spreads. As dark trading becomes established in the market and participants are more comfortable with its' operation, dark trading is found to encourage more aggressive quoting behaviour as traders try to interact with observed dark liquidity. This results in a more competitive environment for liquidity suppliers, narrowing both quoted and effective spreads. The increased competition between liquidity suppliers and the existence of dark mid-point orders reduces volatility and price impact on the lit market.

The final essay of this dissertation, as presented in Chapter 6, consists of an analytical study of the minimum price improvement regulation which was introduced in Canada during October 2012. This regulation change made it infeasible to conduct dark market making, and made it more costly to send liquidity-taking retail orders to the dark market. As a result this caused a sudden drop in the market wide level of dark trading. The findings of this study indicate that dark trading encourages more aggressive competition between market makers, overall resulting in lower quoted, effective and realised spreads, and hence reflecting the reduced returns to liquidity provision. Similarly, measures of efficiency including volatility, midpoint autocorrelation and the incorporation of market-wide information are all improved by dark trading.

The introduction of the minimum price improvement regulation by the Canadian regulator was a world first. Subsequent to the introduction, similar regulations have been implemented by the Australian Securities and Investment Commission, with European and US regulators also debating the regulation of dark pools. As such, the evidence on the impact of this regulation is topical for both regulators and market participants, as well as providing an opportunity to gather evidence on the desirability or otherwise of dark trading as a whole.

1.4 Summary

The four essays that comprise this dissertation examine issues relating to the regulation of equity markets. The issues explicitly analysed focus on shifts in the trading landscape, and their potential impact on market quality. As changes are brought about through regulation or technological change, it is important to understand what impacts these changes have on trading costs, the price discovery process and the integrity of equity capital markets. Such research is motivated by a number of factors, including the lack of consensus in the extant literature regarding the impact of the analysed changes, as well as the desire to ensure that market regulators and practitioners are able to make informed decisions that deliver greater fairness, efficiency, liquidity and integrity for all market participants. This thesis is therefore concerned with the promotion of equity capital markets that are both fair and efficient.

The remainder of this dissertation is organised as follows. Following this introduction, Chapter 2 provides a detailed review of relevant prior literature. The analytical Chapters 3, 4, 5 and 6 examine the specific issues outlined above, with particular focus on the efficiency and integrity of the market. Each chapter contains sections that describe the data, sample, research design, empirical results, robustness tests and the conclusions reached. Chapter 7 concludes by highlighting how the evidence presented in this dissertation can be used by academics, practitioners and regulators to help organise better and more efficient responses to the new challenges posed by technology and fragmentation, and to generally ensure the efficiency and integrity of the market.

Chapter 2

Literature Review

2.1 Literature Review

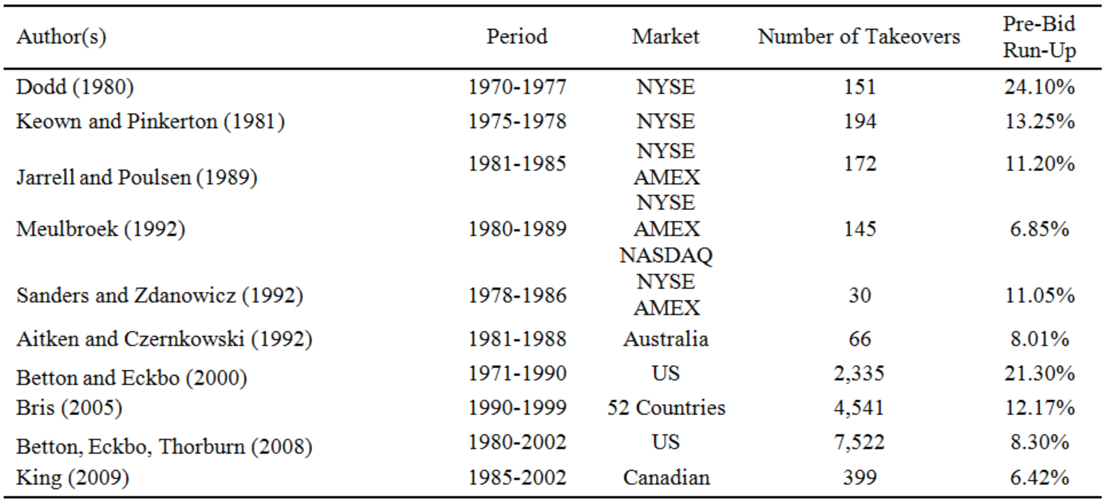
This dissertation consists of multiple empirical studies of the impact of market design changes on the efficiency and integrity of the financial equities markets. This chapter analyses the literature central to the four essays presented in this dissertation, and critically discusses the motivation for the empirical analyses of the subsequent chapters.

Section 2.2 of this chapter reviews the literature related to insider trading, and the potential explanations for price run-ups prior to takeover events. Section 2.3 explores the emerging literature related to high-frequency trading behaviour. Section 2.4 reviews the literature concerning market manipulation, specifically end-of-day manipulation. Finally, section 2.5 discusses the literature related to market transparency and the emergence of dark pools.

2.2 Pre-Bid Run-up and Insider Trading

A considerable body of empirical evidence has accumulated over the last few decades showing a persistent and substantial target stock price run-up prior to the announcement of a takeover bid. Table 2.1 reports how this effect is robust to different time periods and financial market structures, with the average pre-bid run-up found to be

Table 2.1: Insider Trading Literature Summary



Author(s)	Period	Market	Number of Takeovers	Pre-Bid Run-Up
Dodd (1980)	1970-1977	NYSE	151	24.10%
Keown and Pinkerton (1981)	1975-1978	NYSE	194	13.25%
Jarrell and Poulsen (1989)	1981-1985	NYSE AMEX	172	11.20%
Meulbroek (1992)	1980-1989	NYSE AMEX NASDAQ	145	6.85%
Sanders and Zdanowicz (1992)	1978-1986	NYSE AMEX	30	11.05%
Aitken and Czernkowski (1992)	1981-1988	Australia	66	8.01%
Betton and Eckbo (2000)	1971-1990	US	2,335	21.30%
Bris (2005)	1990-1999	52 Countries	4,541	12.17%
Betton, Eckbo, Thorburn (2008)	1980-2002	US	7,522	8.30%
King (2009)	1985-2002	Canadian	399	6.42%

between 4 and 24 per cent. Although there is considerable consensus regarding the nature and magnitude of the run-up, the reasons for its existence are less clear. While anecdotal evidence suggests that unchecked illegal insider trading is the cause, there have been several explanations suggested in the academic literature. Whilst these explanations do include the actions of illegal insider traders (Meulbroek, 1992), it has also been suggested that the run-up is based on market speculation of industry dynamics, and therefore perpetuated by market anticipators (Jensen and Ruback, 1983), or that it reflects takeover rumours based on market information such as those related to toehold acquisitions (Jarrell and Poulson, 1989). The stock price run-up effect observed in target firms prior to takeover announcements has been documented across a range of different market structures through time. A survey by Bris (2005) reports an average price run-up of between 4 and 17 per cent for 4,500 deals across 52 countries. Unfortunately, studies of the cause of this pre-bid run-up have been unable to conclusively explain the reason for this observed phenomenon. The possibilities explored in the current literature include the insider trading hypothesis first posited by Keown and Pinkerton (1981) that the trading of insiders' will generate these returns; rumours in the news media (Pound and Zeckhauser (1990), Sanders and Zdanowicz (1992)) and the market anticipation hypothesis first proposed by Jensen and Ruback (1983), where the analysis of public information leads traders to identify takeover targets.

2.2.1 Insider Trading

Insider trading was formally provided as an explanation for abnormal pre-bid price movements by Keown and Pinkerton (1981). The authors, observing average pre-bid run-ups of 13% for over 200 US takeovers, argue that the evidence is symptomatic of widespread illegal trading on inside information. This conclusion is supported by studies of prosecuted insider trading episodes undertaken by Meulbroek (1992), Cornell and Sirri (1992) and Chakravarty and McConnell (1999).

While Keown and Pinkerton (1981) rely on the extent to which share prices move ahead of public takeover announcements to form this opinion, Meulbroek (1992) identifies the specific days on which insiders traded in a study of 183 episodes of insider trading during the 1980's. The author documents that almost half of the observed pre-bid run-up is experienced on days in which insiders traded, concluding that the trading of insiders provided information to the market.

Subsequent to Meulbroek's (1992) study, further studies of insider trading and pre-bid price run up subsequent to Meulbroek's (1992) examine cases of illegal prosecuted insider trading, particularly in two infamous 1980's takeover deals. Cornell and Sirri (1992) were the first to obtain the daily volumes of prosecuted insider traders. They examine the impact of insider's trading volume on the daily return of Campbell-Taggart stock and find a positive correlation between the amount of insider trading and positive price increases. Chakravarty and McConnell (1999) analyse the trades of infamous insider Ivan Boesky in the Nestle takeover bid for Carnation. The detailed trade-by-trade nature of the data used in the prosecution enables the authors to conduct the first hourly, intraday analysis of an insiders trades. The authors find a positive correlation between the hourly portion of insiders' trades and significant contemporaneous increases in the stock price of the target firm, supporting the insider trading hypothesis of Keown and Pinkerton (1981).

2.2.2 Market Anticipation from Public Information

Jensen and Ruback (1983) propose an alternative explanation for the abnormal price movements observed prior to takeover events, suggesting that the pre-bid run-up is a function of market anticipation derived from public information. The authors reason that public rumours of impending takeovers are traded upon by speculators, which is ultimately being reflected in share price movements prior to the official announcement. Anticipation can be more than just deal specific, however, with takeovers shown to be clustered through time, further facilitating takeover target prediction.[3]

Although Jensen and Ruback (1983) do not specifically address the mechanisms by which market anticipation of takeovers is translated into prices, Jarrell and Poulsen (1989), formally examine the contribution of different types of publicly available information to the share price run-up. In a study of 172 US takeovers provided by the SEC, the authors show that the pre-bid price run-up in takeover targets was not significantly different between those firms that experienced prosecuted illegal insider trading and those that did not. This evidence runs contrary to the arguments put forward by Keown and Pinkerton (1981). Instead, the authors find that the primary predictors of pre-bid run-up are news-media rumours and the existence of toeholds greater than 50%. The importance of the news-media speculation as a mechanism by which private information becomes public is similarly shown in studies such as Sanders and Zdanowicz (1992), Pound and Zeckhauser (1990) and Aitken and Czernkowski (1992).

Sanders and Zdanowicz (1992) identify 30 takeovers from 1978 to 1986 where the news of the takeover appeared prior to the public announcement. The authors find evidence for both the insider trading hypothesis of Keown and Pinkerton (1981) and the market anticipation hypothesis of Jensen and Ruback (1983), with one quarter of the pre-bid run-up attributable to insiders and a further half of the pre-bid run-up explained by the news announcement of the firm being “in play”.

Pound and Zeckhauser (1990) find evidence for the market anticipation hypothesis by analysing rumours of takeovers rather than takeovers themselves. They find that

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[3] Merger waves or “bubbles of financial activity” as referred to by Brealey and Myers (1996) are depicted in a broad sample of studies across different regions. This can be a source of profit for arbitrageurs and other sophisticated investors if there are perceived trends (Mitchell and Pulvino (2001)).

such rumours are preceded by significant pre-announcement run-up. The authors also find no significant causal link between these rumours and actual takeover activity, with 18 out of the 42 firms receiving takeover bids in the twelve months subsequent to the takeover rumour. They identify this evidence as consistent with the collection and analysis of publicly available information, as they surmise that rumours based on private information would be shortly followed by takeovers.

Aitken and Czernkowski (1992) examine the impact of news-adjusting the announcement date of the takeover. This involves identifying the first news-media speculation of the target and bidder as a potential combination - the news-adjusted date is then taken as the earlier of the speculation and public announcement date. By reconstructing the abnormal returns over the period, the authors find that rumours in the news media account for over 30% of the documented pre-bid run-up.

2.2.3 Toe-Hold Acquisitions

Previous theoretical (Bris, 2002) and empirical (Jarrell and Poulsen, 1989; Aitken and Czernkowski, 1992, Betton, Eckbo and Thorburn, 2008b) studies suggest that toehold acquisitions prior to takeovers may have the capacity to generate pre-bid run-up. To date, however, there has been little success in documenting this effect. Preliminary efforts have found conflicting evidence. Betton and Eckbo (2000) construct and test a theoretical model of the outcomes of sequential bidding for targets. They find that greater pre-bid toeholds reduce the probability of competition and target resistance, lowering both bid premiums and price run-ups. Jarrell and Poulsen (1989), however, examine the determinants of the pre-bid price run-up prior to 172 tender offers in the 1980's and show a significant and positive relationship between toeholds and the price run-up. They examine five "large" toeholds (in excess of 40%) that have been held for greater than six months separately, and find these have no impact on the run-up. The authors argue that the increased run-up is a result of sophisticated informed traders identifying the purchasing activity and trading on this information. The lack of consensus regarding the impact of toeholds on pre-bid run-up is driven by the absence of information regarding the accumulation of target shares by the bidder, a problem acknowledged in both these previous studies.

Further empirical evidence supporting the market anticipation theory is provided by Barclay and Holderness (1991) and Akhigbe et al. (2007), who find significant positive abnormal returns around the purchase of toehold stakes greater than 5%. These positive returns are found to be greater in firms for whom the ex-ante probability of a takeover is larger.[4] Bris (2002) provides theoretical evidence that the acquisition of a toehold stake produces an information flow that can result in share price movements ahead of takeover announcements. This is consistent with the theoretical model of Ravid and Spiegel (1999) which shows that toehold purchases create rumours of an imminent takeover bid, resulting in run-up in the targets share price.

One potential reason for the inconsistencies observed around the impact of toehold acquisitions on pre-bid run-up is the lack of attention drawn to the timing of these toehold acquisitions. Previous studies have not differentiated between toeholds held for significant periods of time and those established shortly prior to the acquisition. Differences in the mix of both short and long-term toeholds could result in the differences in the findings on the impact of toeholds on run-up, as noted in a recent study by Betton et al. (2008). This study analyses the implications on the price paid by the acquirer for toeholds taken within 40 days of the bid, with the authors finding that targets receiving bids in this short pre-period experience a run-up of 15%, significantly higher than the 5% for all other takeovers.

If Bris' (2002) argument that toeholds signal an increased probability of receiving a takeover bid to the market is to hold, then the timing of such an acquisition will be a significant determinant of the run-up. The literature contains several explanations for this. Stulz (1988) argues that the upward sloping supply curve for target shares will result in an increase in the targets share price due to the purchasing pressure of the bidder. This effect will be especially pronounced for less liquid targets. Evidence from Jarrell and Poulsen (1989) and Aitken and Czernkowski (1992) indicate that rumours

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[4] The ex-ante probability of a takeover is constructed using a probit model including information known about the bidders stake (type of bidder, proportion of targets shares acquired in this block, total portion owned by bidder) as well as financial information about the target (including stock-price return, cash-flow and leverage ratios, firm-size and institutional ownership levels).

have a significant impact on the pre-bid run-up. Betton et al. (2008) argue that one explanation for this is that large unexplained trades trigger speculation that the firm will soon become a takeover target. Furthermore, the information contained in substantial shareholder notices may also signal the intentions of the bidder to the market, triggering buying in anticipation of a takeover premium (Mikkelson and Ruback, 1985; Holderness and Sheehan, 1985; Choi, 1991). Akhigbe et al. (2007) argue that toeholds bought immediately prior to the bid should have a larger signalling impact on the pre-bid run-up as compared to those toeholds which have been held for a longer period of time. These long-term toeholds will have incorporated information about the probability of a future takeover at the time of the toehold acquisition. As such it is expected that the price run-up immediately prior to the announcement will be insignificantly different from the case where the acquirer chooses not to purchase a toehold.

The current literature offers a range of competing explanations for the well-documented abnormal price reactions to takeover announcements: insider trading, market anticipation and the existence of rumours. Chapter 3 combines the news-adjustment criteria developed by Aitken and Czernkowski (1992) and the toehold ideas of Akhigbe et al. (2007) and Betton et al. (2008) to examine whether pre-bid acquisition stakes help to explain target stock price run-ups in an informationally transparent market framework. By utilising a unique database containing changes in substantial shareholdings prior to the takeover event, this dissertation seeks to shed empirical light on the causes of the run-up witnessed in the lead up to a takeover.

2.3 High-Frequency Trading

There is a growing body of literature on the influence of high-frequency trading (HFT) in the global marketplace. The literature to date has had to grapple with the difficulties of defining and identifying high-frequency traders, as well as teasing out the potentially endogenous nature of their conduct on the efficiency of the market. For example, high-frequency traders prefer more liquid securities, making their impact on market quality difficult to disentangle. The distinction between algorithmic traders, news traders, statistical arbitrageurs and market makers is also blurred by the aggregated nature of the data that is presently available. These difficulties have hindered efforts to provide evidence on how the increase in the speed of trading has impacted the efficiency and integrity of global securities markets. Contrasting conclusions from a range of theoretical and empirical works leave open the current debate as to the relative desirability or otherwise of high-frequency trading.

Cvitanic and Kirilenko (2010) provide some of the earliest theoretical work on HFT. The authors argue that the introduction of HFT reduces the average trade value and dampens fluctuations in prices, resulting in reduced volatility as market-making algorithms update their information in response to news announcements. Their model incorporates an electronic limit order book in which both high- and low-frequency (human) traders participate.

Jovanovic and Menkveld (2011) construct and test a theoretical model that does not assume a Kyle (1985) style market maker, in which high-frequency traders are uninformed. Rather, they model high-frequency traders as both faster and more informed than their counterparts, and with these assumptions their findings for market efficiency are mixed. Their theoretical model suggests that high-frequency traders may cause welfare gains, as they are able to update their information faster than a traditional market maker. This allows the high-frequency market makers to reduce their exposure to adverse selection, consequently increasing efficiency through reduced spreads. Furthermore, the ability of the average high-frequency trader to dynamically update their information set minimises the inventory holding costs, reducing the total cost for the provision of liquidity, reducing spreads and avoiding stale orders. The overall result of this is increased market efficiency.

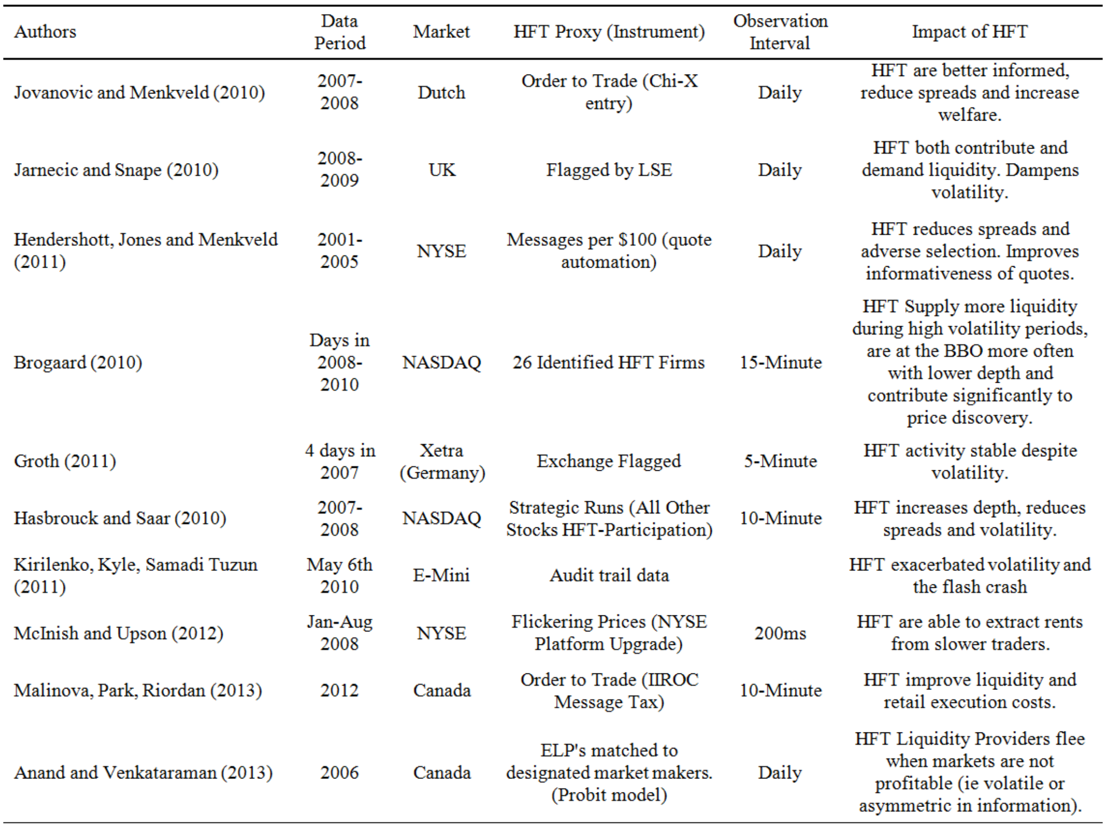
Jovanovic and Menkveld (2011), on the other hand, warn that if no adverse selection problem exists to begin with, the ability of high-frequency traders to update their information set faster than human traders may cause new adverse selection problems. These problems would stem from their ability to react to rapidly changing limit order information, reducing the willingness of human participants to enter the market for fear of trading with a better informed high-frequency trader. The authors theorise that such a situation could widen spreads and thereby reduce market efficiency.In their empirical analysis, Jovanovic and Menkveld (2011) investigate the introduction of Chi-X, which they use as an instrument for the escalation of HFT. Examining 77 trading days of Dutch index stocks between 2007 and 2008, Jovanovic et al. (2010) find that high-frequency traders are better informed about news and the state of the limit order book than the average trader, making them better able to avoid adverse selection, reduce spreads and overall effect a marginal increase in total welfare.

These largely positive theoretical market quality findings are supported by the majority of empirical papers that deal with HFT, finding a predominantly positive overall impact of the practice. The predictions made by Cvitanic and Kirilenko (2010) of reductions in volatility, trade value, and trade volume are empirically supported by the work of a number of studies, as documented in Table 2.2.

Jarnecic and Snape (2010) examine the equity market in the UK, using proprietary data provided by the LSE. They find that high-frequency traders contribute and demand liquidity in almost even proportions, and that their activity is more likely to dampen rather than increase volatility.

The question as to how HFT impacts on informational asymmetry costs, as modelled theoretically and empirically by Jovanovic and Menkveld (2011), is also empirically addressed by Hendershott et al. (2011). These authors use the volume of message traffic, normalised by the number of trades, as a proxy for HFT. Their five year sample period straddles the staggered introduction of the automation of quote dissemination on the NYSE in 2003. The authors show that algorithmic trading, of which HFT is a subset, significantly reduces both quoted and effective spreads finding that this narrowing of the spreads is the result of a decline in adverse selection. Their results also show that the presence of HFT has resulted in more of the permanent price discovery information being disseminated through quotes as opposed to trades. Hendershott et al. (2011) also find that the introduction of algorithmic trading increases the profits to liquidity providers through increased realised spreads consistent with the results of McInish and Upson (2012).

Table 2.2: High-Frequency Trading Literature Summary



Authors	Data Period	Market	HFT Proxy (Instrument)	Observation Interval	Impact of HFT
Jovanovic and Menkveld (2010)	2007-2008	Dutch	Order to Trade (Chi-X entry)	Daily	HFT are better informed, reduce spreads and increase welfare.
Jarnecic and Snape (2010)	2008-2009	UK	Flagged by LSE	Daily	HFT both contribute and demand liquidity. Dampens volatility.
Hendershott, Jones and Menkveld (2011)	2001-2005	NYSE	Messages per $100 (quote automation)	Daily	HFT reduces spreads and adverse selection. Improves informativeness of quotes.
Brogaard (2010)	Days in 2008-2010	NASDAQ	26 Identified HFT Firms	15-Minute	HFT Supply more liquidity during high volatility periods, are at the BBO more often with lower depth and contribute significantly to price discovery.
Groth (2011)	4 days in 2007	Xetra (Germany)	Exchange Flagged	5-Minute	HFT activity stable despite volatility.
Hasbrouck and Saar (2010)	2007-2008	NASDAQ	Strategic Runs (All Other Stocks HFT-Participation)	10-Minute	HFT increases depth, reduces spreads and volatility.
Kirilenko, Kyle, Samadi Tuzun (2011)	May 6th 2010	E-Mini	Audit trail data		HFT exacerbated volatility and the flash crash
McInish and Upson (2012)	Jan-Aug 2008	NYSE	Flickering Prices (NYSE Platform Upgrade)	200ms	HFT are able to extract rents from slower traders.
Malinova, Park, Riordan (2013)	2012	Canada	Order to Trade (IIROC Message Tax)	10-Minute	HFT improve liquidity and retail execution costs.
Anand and Venkataraman (2013)	2006	Canada	ELP's matched to designated market makers. (Probit model)	Daily	HFT Liquidity Providers flee when markets are not profitable (ie volatile or asymmetric in information).

Using a data set provided by NASDAQ that directly identifies 26 HFT traders over periods during 2008, 2009 and 2010, Brogaard (2010) investigates the trading patterns of high-frequency traders during times of heightened volatility. To identify these periods of high volatility, he divides the trading day into 15-minute intervals and finds that when prices fluctuate more than normal, high-frequency traders supply more liquidity and thus demand less liquidity. Brogaard (2010) concludes that high-frequency traders are unlikely to exacerbate volatility, consistent with the findings of Jarnecic and Snape (2010). Brogaard (2010) also analyses the liquidity provision of high-frequency traders by looking at the depth and time spent by each trader type at the national best bid and offer (NBBO). His findings indicate that while high-frequency traders spend more time at the NBBO, they provide less depth than their non-high-frequency trader counterparts. Additionally, high-frequency traders are found to be better able to avoid trading with insiders than non high-frequency traders, consistent with the theoretical findings of Jovanovic and Menkveld (2011).

One of the most comprehensive data sets analysed to date is that compiled by Groth (2011). The data set covers trading in German stocks on Xetra. Due to a rebate scheme applied to algorithmic traders, a flag is applied to every trade identifying whether it arises from a human or an algorithmic source. Groth (2011) takes data from four trading days during 2007 and analyses the conduct of high-frequency traders during times of high and low volatility, splitting the days into 5 minute intervals and then identifying the level of volatility in each. His findings indicate that high-frequency traders are not sensitive to changes in volatility and do not alter their trading patterns in response to shifts in such criteria. Groth (2011) also finds that there is no evidence of market withdrawal by high-frequency traders during periods of increased volatility.

One of the more unique proxies for HFT used in the literature is described by Hasbrouck and Saar (2013), where the authors use trade and quote data in a millisecond environment to identify strategic runs of trades, observing interactions between traders separated by as little as three milliseconds. These strategic runs are used to create a proxy for the level of HFT. Hasbrouck and Saar (2013) analyse the trading activity on the NASDAQ for one month chosen from 2007 and one from 2008, which unlike studies such as Groth (2011) and Jarnecic and Snape (2010), allows them to analyse HFT during a period of high market stress. Hasbrouck and Saar (2013) divide the day into 10 minute intervals and uniquely apply a two-stage simultaneous equation for each market quality metric, allowing for a potentially endogenous relationship between HFT and their market quality indicators of volatility, depth, and spreads. Their findings show that higher levels of HFT increase the quoted depth, narrow quoted bid-ask spreads, and reduce volatility, even during periods of market stress.

While the proxies for HFT differ, all but one of these empirical studies document a positive impact on market efficiency. Overall, the evidence provided suggests that increased levels of HFT specifically result in narrower bid-ask spreads, increased depth and reduced volatility.

The empirical evidence on the prevalence of HFT in the market is relatively sparse and relies primarily on noisy proxies. Perhaps, as a result, the estimates that have been provided in the literature for the proportion of HFT in the market vary widely. Using a

2009 sample for LSE, Jarnecic and Snape (2010) find that 40%-64% of trades included a high-frequency trader on at least one side. In their 2010 response to the Committee of European Securities Regulators (CESR) call for evidence, the LSE gave their internal estimates of HFT as between 32%-33% of total UK equities trading for 2010. In a similar submission, NYSE Euronext calculated that in the overall European market there was a 5% market share for high-frequency traders in the first quarter of 2007, increasing to 23% of total traded value in the first quarter of 2010.

Empirical studies of the US market support these findings. Brogaard's (2010) analysis, which focuses on U.S equities, finds that 60%-80% of all NASDAQ trades involve a high-frequency trader on at least one side. Ito and Lyden (2012) construct an undisclosed measure of HFT for the largest 15 stocks traded on NASDAQ, NYSE and BATS in the US and show that high-frequency traders participate on one side of trades between 87%-92% of the time.

Several studies, including Brogaard (2010), Jarnecic and Snape (2010) and Ito and Lyden (2012) find that high-frequency traders are more active in larger stocks than smaller stocks, and are comparatively more active towards the end of the day. These results are found to be indicative of the market making nature of the high-frequency traders, seeking to close the day with zero inventory positions.

Kirilenko et al. (2011) provide one of the few papers that is critical of the role of HFT in the market. The authors analyse a set of metrics including holding periods, inventories and trade directions around the May 6th, 2010 "Flash Crash". The authors find that high-frequency traders, after providing some initial liquidity to fundamental sellers, contributed to the significant selling pressure that precipitated the flash crash. While Kirilenko et al. (2011) do not go so far as to blame this incident on high-frequency traders, they determine that their presence in the market exacerbated the volatility present during this period of extreme market stress. The authors use audit trail data for the E-mini S&P 500 futures contracts on the day of the flash crash to identify high-frequency traders. Their designation relies on trade frequency and size, which the authors use to determine that 16 accounts out of a total of 15,422 belonged to high-frequency traders on that day.

Brogaard (2010) takes a different approach to the identification of HFT participants, examining the actual trades of high-frequency traders during the four days in September 2008 on which the news regarding the collapse of Lehman brothers became public. Brogaard (2010) finds that high-frequency traders did not significantly increase their demand for liquidity during this period, but significantly increased their liquidity supply. This analysis, and an examination of HFT following earnings announcements with similar findings, leads Brogaard (2010) to conclude that high-frequency traders do not remove liquidity from the market, even in times of severe market stress.

Malinova et al. (2013) analyse the impact of the introduction of the IIROC messaging tax in the Canadian market. This cost recovery program allocated IIROC's infrastructure costs amongst brokers proportional to their fraction of messaging traffic. As HFT participants typically have high order-to-trade ratios (See Hendershott et al., 2011), Malinova et al. (2013) argue that this messaging tax will increase the cost of HFT strategies. As a result, the tax is expected to result in a significant reduction in the number of orders being entered to the Canadian market. The authors address this question using a proprietary TSX order-level data set to identify high-frequency traders, marking them as those traders whose order-to-trade ratio and absolute number of submitted messages are both in the top 5% of traders. They find that as HFT activity reduces, spreads widen and depth narrows. This reduction in liquidity is found to increase the execution costs of retail participants, showing that HFT may provide a valuable service to "slow" traders.

The current literature on high-frequency trading is analytical in nature and focuses on the implications for market efficiency. The findings suggest that HFT participants make better market makers, by providing liquidity quickly and in smaller buckets. In doing so, they are less prone to adverse selection than existing liquidity providers, and are, in aggregate, therefore able to quote narrower spreads. Contrary to popular belief, it does not appear that these HFT participants "flee" the market during periods of heightened volatility. This dissertation tests the assertions of the literature over a much longer time frame, across multiple markets. Additionally, instead of focusing only on efficiency, the interaction *between* efficiency and integrity is examined, allowing for the possibility that there is an endogenous relationship between the two elements of market quality.

2.4 Market Manipulation

Closing price manipulation is a concern for both regulators and market participants, as it affects pricing accuracy and liquidity. Empirical evidence from Comerton-Forde and Putnins (2011) and Hillion (2004) has demonstrated that closing price manipulation is associated with increases in bid-ask spreads, reductions in depth, and mispricings. These mispricings occur both at the close of the day of manipulation and on the open the following day. Comerton-Forde and Putnins (2011) argue that these impact negatively on markets increasing the costs of trading for market participants and potentially increasing the cost of capital for firms. This may lead to capital flight away from markets that are perceived to have high levels of closing price manipulation.

The widespread use of closing prices to value portfolios and close out financial contracts such as options and futures contracts makes closing prices a particularly attractive target for manipulators. For example, a mutual fund's net asset values and performance are typically measured based on closing prices. Since the performance of a fund determines both its rankings compared to other funds and manager remuneration, it is unsurprising that studies such as Carhart et al. (2002) and Bernhardt and Davies (2009) find that returns are significantly positively skewed on the last days of reporting periods (such as month- and quarter-end). This type of stock price clustering is also documented by Ni, Xiaoyan Ni et al. (2005) around options expiry dates. The authors argue such clustering is evidence of the manipulation of closing prices for profit. Kumar and Seppi (1992) describe in detail the process by which profit can be made through closing price manipulation.

Comerton-Forde and Putnins (2011) provide the first examination of prosecuted cases of closing price manipulations. Analysing 184 instances of closing price manipulation that occurred on the NYSE, AMEX TSX and TSX-V between 1997 and 2009, the authors develop an index for identifying the closing price manipulation. The authors document that closing price manipulation results in increased returns in the last minutes of trading, followed by price reversals at the open on the following trading day. Closing price manipulation is also associated with more frequent trades in the final minutes of trading, tighter spreads and larger trades.

Comerton-Forde and Putnins (2013) use this index to estimate the level of closing price manipulation in the presence of undetected, unobservable manipulation. They document that approximately one percent of closing prices are manipulated, with manipulation more likely in stocks with high levels of information asymmetry and mid-to-low levels of liquidity. Consistent with the findings of Carhart et al (2001) and Bernhardt and Davies (2009), these manipulations are more frequent amongst stocks with higher levels of institutional ownership and on month/quarter end days. This dissertation combines measures of insider trading and market manipulation to analyse the joint impact of high-frequency trading on both efficiency and integrity.

2.5 Dark Pools

The emergence of dark pools, which allow trading without pre-trade transparency, has been met with much scepticism. While dark pool operators argue that their venues provide protection for large traders from front-running and price impact, opponents argue that they create a two-tiered market and damage the price discovery process.[5] As trade activity on dark pools has increased, both regulators and market participants have become concerned about their impact.

The recent emergence of this type of trading combined with the necessary lack of transparency has hindered the study of the market quality impacts of dark pools. This relatively underdeveloped area of literature has resulted in a lack of consensus regarding the desirability of dark trading. This dissertation sheds light on the impact of dark pools using unique natural experiments and data sets.

2.5.1 Theoretical Evidence on the Introduction of Dark Pools

Several theoretical papers have assessed the impact of the introduction of a dark trading venue alongside a traditional "lit" marketplace. These theoretical works primarily focus on how informed traders will use these new non-transparent venues for trade execution,

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[5] For a more detailed discussion of the pros and cons of dark pools see the comments received in response to the Dark Pool regulations proposed by IIROC at
www.iiroc.ca/SitePages/Comments-Received.aspx?linkid=794

as it is the informed trader that generates price discovery, while also focussing on the impact that the introduction of the dark venue will have on market makers, spreads, the selection of order-types, and the price discovery process. The varying assumptions of these models have led to a range of contradictory findings indicating that the addition of dark pools is both beneficial or detrimental to market quality.

Degryse et al. (2009) develop a theoretical model that seeks to explain the impact of a crossing network (a particular type of dark pool) on order flow. In their model, a crossing network competes with a traditional dealer market for order flow in a simplified two period consumption trading situation. This crossing network has only time priority and takes its price as the midpoint of the current bid and ask in the underlying dealer market (assumed to be competitively priced at one tick). They analyse both order submission strategies and overall trader (and dealer) welfare in situations where the traders are able to observe quotes on either; both venues, only the dealer market, or on neither venue. They find that regardless of opacity, the introduction of a crossing network alongside a dealer market generates additional orders, as price sensitive traders who would refrain from trading in a dealer market are attracted to the lower spreads on the new venue.

Whilst the addition of a crossing network increases total liquidity, there are two opposing effects impacting on crossing network traders. The addition of liquidity on one side of the orderbook increases the probability of execution on the contra side. Such an addition of crossing network liquidity encourages new traders to the market. At the same time, however, as the crossing network uses only time priority, it is possible that "low-willingness" traders (those who are less eager to transact) submitting earlier in the day can crowd out "high-willingness" traders (those who must receive an execution on that day), such that the increased liquidity in the crossing network actually *reduces* the overall execution probability.

Analysing total trader and dealer welfare, Degryse et al. (2009) find that the addition of a transparent crossing network improves welfare as additional trade is generated. This welfare benefit is reduced, however, as markets become more opaque and uncertainty regarding execution increases. Degryse et al. (2009) also offer two empirically testable hypotheses. The first is that the probability of observing a crossing network order at the same side of the market will be smallest after such an order has just been executed. They also predict directional informational flows between the markets, with a buy order on the crossing network lowering the probability of a dealer selling and increasing the probability that the dealer will also buy. As the order flow of the crossing network becomes less transparent, however, these information flows are reversed, with the dealers' trades influencing the order imbalance in the dark. These informational flows between the dark pool and the lit market are found to be one way that dark pools may contribute to the price discovery process, especially in situations of partial transparency, where *executed* orders are visible but *unexecuted* orders remain opaque.

While Degryse et al. (2009) provide insight into how the opacity of a dark pool may affect order flow and trader welfare, the authors do so in an environment that is quite different to that of current equities markets. Ye (2011) uses an extension of the Kyle (1985) model which more closely resembles current equity market trading conditions. The author models a market where a crossing network sits beside the traditional exchange and informed traders have the choice of either sending their order to the traditional exchange, the opaque crossing network, or splitting their orders between the two. Ye (2011) proposes a two-period model in which there are three agents: an informed trader; liquidity traders whose trading decision is exogenous; and a designated market maker who sets prices at the exchange. In the first period, the market maker observes the combined order flow on the exchange which has come from both informed and liquidity traders. Based on this order flow and his belief regarding the informed trader's strategic choice between the exchange and the crossing network, he sets his price on the exchange. In the second period, orders which have been placed in the crossing network are executed based on the price determined in the exchange in the first period. If an order imbalance exists on the crossing network, orders on the more populous side are only partially filled. The informed trader in this model is now forced to trade-off the cost of non-execution against the risk of generating a price impact. While execution is guaranteed on the exchange, the informed traders order flow may adversely move the price. Alternately, trades in the the crossing network do not have any impact on price, however the probability of execution decreases as order size increases.

In order to balance these risks, Ye (2011) identifies that the informed trader's optimal strategy is to split his orders between the crossing network and the exchange. The removal of some of these informed orders from the market is shown to reduce both price discovery and volatility. These impacts are likely to be larger for those stocks that have greater uncertainty surrounding their true value; as the informed agent's information is more valuable, he has a greater incentive to hide his information by using the crossing network. While Ye's (2011) model is closer to reality than that of Degryse et al. (2009), many dark pools both anti-gaming techniques and employ exclusive access in order to try to limit the ability of informed traders to access their venue, thereby limiting the generalisability of this model.

The idea of increased dark pool liquidity resulting in lower execution probability is extended by Zhu (2011). Unlike Ye (2011), who treats the choice to trade in the dark as exogenous, Zhu (2011) allows this choice to be endogenous to the trader's information set and the liquidity of the security. While dark pools execute at the midpoint of the best bid and ask, the need to find a counterparty in the dark renders execution uncertain, depending on the availability of counterparties.

He argues that informed traders will tend to cluster on the same side of the order book, reducing their probability of execution. Given non-execution in the dark, the informed traders will need to execute the remainder of their order with the exchange market maker at prices *inferior* to those prevailing at the time of their dark order. Due to this non-execution risk, informed traders will exhibit a preference for lit venues, while liquidity traders will prefer to execute their trades in the dark. Zhu (2011) argues that this "cream-skimming" of uninformed traders by dark pools will concentrate price-relevant information onto the lit exchange. Consequently, Zhu (2011) theorises that the addition of a dark pool will improve overall price discovery.

Zhu (2011) also separately models dark venues as either opaque crossing networks, where trades are executed at the midpoint of the bid and ask, or as opaque limit order books in which price priority can be gained. While both models predict that dark pools expose the informed trader to a greater risk of non-execution, informed traders will prefer opaque limit order books as they can reduce the non-execution risk by submitting aggressive hidden orders. This theoretical prediction fits well with the structure of actual dark pools in both Canada and the US, as most offer traders the ability to vary the level of price improvement offered, with priority given to orders offering prices closer to the midpoint.

Kratz and Schoeneborn (2011) examine the implications of non-execution on the optimal intra-day submission of orders. Their theoretical model finds that in the presence of a dark pool the optimal trader will initially delay lit market executions in favour of seeking less revealing dark executions. If no dark executions are found, either due to a lack of traders or due to a prevalence of traders also seeking executions on that same side, these traders are forced to increase the speed of their lit market executions in order to ensure the liquidation of their positions. The authors document the existence of adverse selection in dark pools - the possibility that latent liquidity in the dark indicates impending favourable price movements in the lit market. The addition of adverse selection risk to the model increases dark execution costs and discourages the usage of the dark pool.

Kratz and Schoeneborn (2011) also model conditions under which manipulation in the dark will be unprofitable. The authors suggest that buy orders submitted in the lit market can be profitably sold in the dark market without incurring a price impact “penalty”. Kratz and Schoeneborn (2011) argue that the profitability of such manipulative strategies can be eliminated by imposing constraints on the amount of liquidity available in the dark as well as by introducing adverse selection into the dark market.

Buti et al. (2011a) model the interaction between a lit order book and a dark pool. Similar to Zhu (2011), the dark pool is modelled as a crossing network that allows traders to enter opaque orders that will be crossed at the midpoint of the best bid and ask. Unlike Ye (2011) and Zhu (2011) who analyse the effects on informed order flow, Buti et al. (2011a) provide evidence on the drivers of dark pool activity, as well as documenting the effects on the lit market of the introduction of the dark market. The authors show that dark pool activity will increase when the lit limit order book is deep, the tick size is large and the stock is trading at the minimum tick. Given these situations, a trader can either place their order at the end of the limit order book queue or cross the spread to gain priority. The dark order at the midpoint offers preferential execution at half the cost of a market order. Dark pool activity is theorised to decrease as spreads widen, representing the uncertainty around the value of the security.

Buti et al. (2011a) also provide mixed predictions on the impact of dark pools on market quality. While the introduction of a dark pool will cause some lit order flow to migrate to the dark, the introduction of a dark pool will also encourage more price-sensitive traders to enter the market, and thus increase total liquidity, a finding similar to that of Degryse et al. (2009).

Boulatov and George (2013) develop a further theoretical model on the order flow implications of the introduction of dark markets. They model the choice to trade with the existence of either a combination of lit and dark markets, or a lit market only - these situations are the closest to the market structures observed in most equity trading venues. The authors find that hidden liquidity has a favourable impact on market quality, as it increases the competition between liquidity suppliers, and forces informed agents to actively provide liquidity, though this competition does involve a trade-off between certainty of execution and the leakage of information. As liquidity providers are able to extract "rents" from their information (of the true value of a security) by buying when underpriced and selling when overpriced, the addition of a dark venue allows them to extract this rent without exposing their value information to the market as a whole. They are therefore encouraged to act as liquidity providers, narrowing spreads and improving the efficiency of the market. Boulatov and George (2013) argue that these agents will trade less aggressively when only lit liquidity is available. As executing market orders will tend to reveal their information, liquidity providers will seek to extract rents from their information by instead using limit orders. The authors argue that this reduction in competition between liquidity suppliers to extract informational rents will result in wider bid-ask spreads and decreased informational efficiency. The implications of Boulatov and George's (2013) work are empirically testable, as they are directly observable on the lit market.

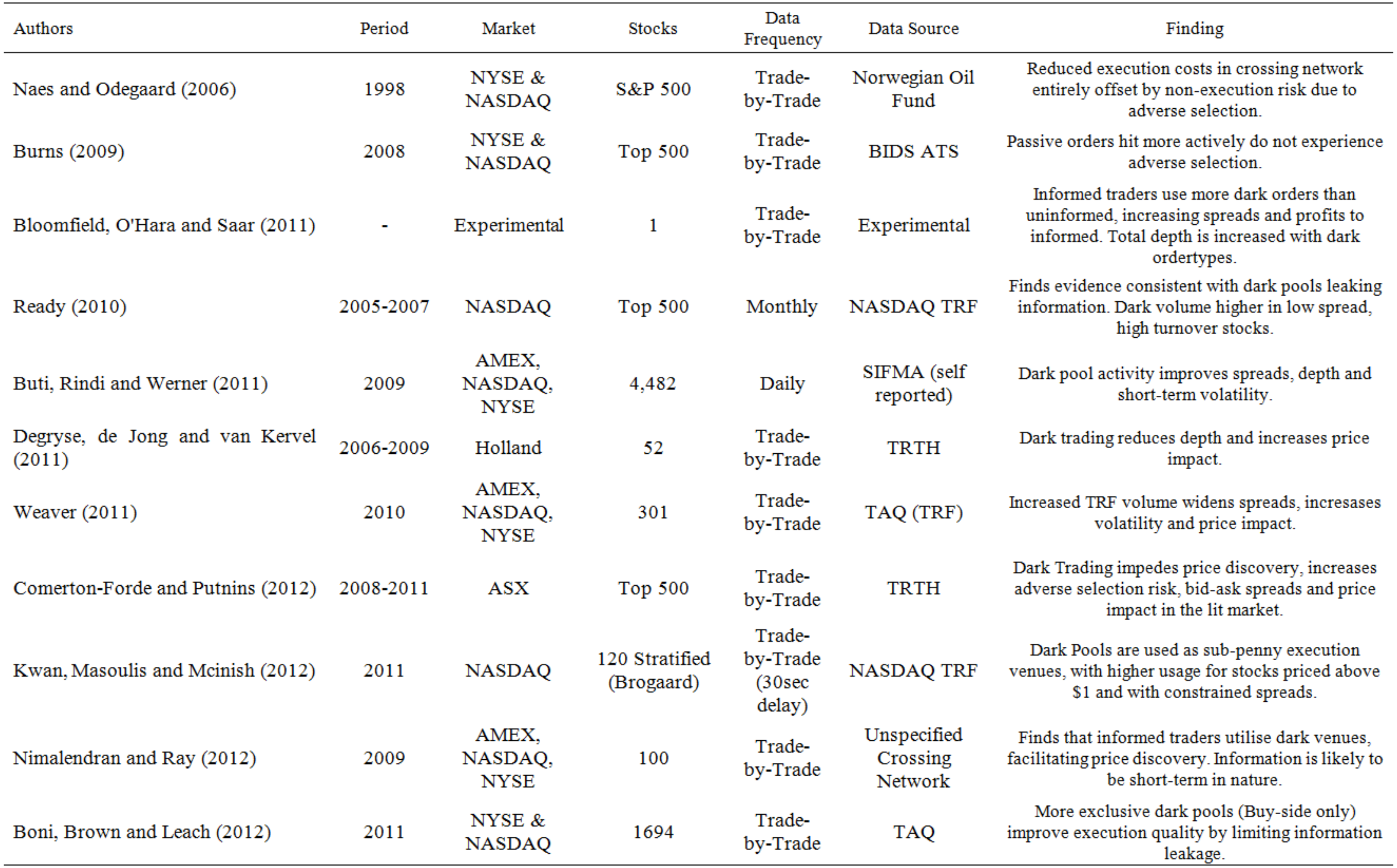
The theoretical evidence reviewed above has developed a variety of competing views. Bloomfield et al. (2011) use an experimental market framework to provide additional evidence for these theoretical models. They show that both informed and uninformed traders substitute their lit market orders for dark-market orders when dark markets are available. In the presence of dark markets, *informed* traders tend to convert a larger portion of their lit market trades relative to *uninformed* participants, consistent with the theoretical findings of Ye (2011) that when informed traders are able to trade in the dark, they become less aggressive in their trading. Bloomfield et al. (2011) attribute this to the lack of information leakage through visible order books. This minimises the extent to which informed traders compete amongst themselves for order flow.

This line of argument contrasts to the position adopted in Boulatov and George (2013). Using their experimental framework the authors show that the profits of informed traders are significantly higher when they have the ability to use dark order types, providing supporting evidence as to why informed traders may prefer dark markets. The authors also find that the introduction of hidden order types increases total depth in the market whilst simultaneously reducing the amount of visible depth. The "true" spread (that is, the spread taking into account both hidden and visible limit orders) does not significantly differ between the visible and opaque markets. However, the "visible" spread (equivalent to the lit market spread) is almost twice as high in the presence of hidden orders. These results may be less applicable to market structures that do not allow dark limit orders, such as those based on midpoint pricing. The authors find that the introduction of dark orders does not create any differences in the volume traded, nor in the informational efficiency of the marketplace.

2.5.2 Empirical Evidence on the Introduction of Dark Pools

The development of empirical literature dealing with the introduction of dark pools is hindered by three particular issues. The first is the necessary opacity of these markets. The removal of pre-trade transparency is necessary to maintain the integrity of the dark pool, however it significantly increases the difficulty of measuring microstructure changes such as non-transparent depths or buy/sell imbalances. This has led the literature to rely primarily on (often incomplete) proprietary data sets. The second impediment to assessing the impact of the introduction of dark pools is that not all traders begin to use these dark order types as soon as they are introduced. Without a critical mass of users, the introduction of dark pools may in itself be a non-event, and in such a case, it will not be until months or even years subsequent to the introduction that trading in these instruments is sufficiently large as to cause an effect. This renders typical event-study methodologies ineffective. The final challenge for the study of dark pools is the likely endogenous relationship between market conditions and dark pool usage. Low spreads may encourage dark trading, however if dark trading causes low spreads the causality of these two events is difficult to disentangle. Table 2.3 provides a summary of the previous empirical works on the market quality impact of the introduction of dark pools.

Table 2.3: Dark Trading Literature Summary



Authors	Period	Market	Stocks	Data Frequency	Data Source	Finding
Naes and Odegaard (2006)	1998	NYSE & NASDAQ	S&P 500	Trade-by-Trade	Norwegian Oil Fund	Reduced execution costs in crossing network entirely offset by non-execution risk due to adverse selection.
Burns (2009)	2008	NYSE & NASDAQ	Top 500	Trade-by-Trade	BIDS ATS	Passive orders hit more actively do not experience adverse selection.
Bloomfield, O'Hara and Saar (2011)	-	Experimental	1	Trade-by-Trade	Experimental	Informed traders use more dark orders than uninformed, increasing spreads and profits to informed. Total depth is increased with dark ordertypes.
Ready (2010)	2005-2007	NASDAQ	Top 500	Monthly	NASDAQ TRF	Finds evidence consistent with dark pools leaking information. Dark volume higher in low spread, high turnover stocks.
Buti, Rindi and Werner (2011)	2009	AMEX, NASDAQ, NYSE	4,482	Daily	SIFMA (self reported)	Dark pool activity improves spreads, depth and short-term volatility.
Degryse, de Jong and van Kervel (2011)	2006-2009	Holland	52	Trade-by-Trade	TRTH	Dark trading reduces depth and increases price impact.
Weaver (2011)	2010	AMEX, NASDAQ, NYSE	301	Trade-by-Trade	TAQ (TRF)	Increased TRF volume widens spreads, incresases volatility and price impact.
Comerton-Forde and Putnins (2012)	2008-2011	ASX	Top 500	Trade-by-Trade	TRTH	Dark Trading impedes price discovery, increases adverse selection risk, bid-ask spreads and price impact in the lit market.
Kwan, Masoulis and Mcinish (2012)	2011	NASDAQ	120 Stratified (Brogaard)	Trade-by-Trade (30sec delay)	NASDAQ TRF	Dark Pools are used as sub-penny execution venues, with higher usage for stocks priced above $1 and with constrained spreads.
Nimalendran and Ray (2012)	2009	AMEX, NASDAQ, NYSE	100	Trade-by-Trade	Unspecified Crossing Network	Finds that informed traders utilise dark venues, facilitating price discovery. Information is likely to be short-term in nature.
Boni, Brown and Leach (2012)	2011	NYSE & NASDAQ	1694	Trade-by-Trade	TAQ	More exclusive dark pools (Buy-side only) improve execution quality by limiting information leakage.

The established literature documenting the impacts of partial pre-trade opacity (otherwise known as iceberg orders) can supplement the literature on dark pool orders. Anand and Weaver (2004) examine the impact of the removal and subsequent re-instatement of iceberg orders on the TSX in 1996 and 2002, respectively. The authors find that although lit market depth is reduced by the decision to allow iceberg orders, this reduction in depth does not affect total traded volume. Anand and Weaver (2004) (as well as Burns (2009)) argue that this finding implies market orders are substituted for the non-visible portion of iceberg orders, while also showing that informed traders use hidden limit orders to minimise their price impact, especially when the probability of non-execution is small. This addition of hidden limit orders can increase the combined lit and dark order books, consistent with the experimental findings of Bloomfield et al. (2011).

One of the first examinations of the performance of executions in dark pools is undertaken by Naes and Odegaard (2006). Using a data set constructed from the executions around the establishment of the Norwegian oil fund, the authors find that institutional orders sent *first* to dark pools and *then* to the lit market obtain lower realised execution costs for the dark component, but not necessarily for the entire order. Consistent with the theoretical arguments about same-side clustering by informed traders, the authors find that these lower explicit dark pool trading costs are offset fully by the increased implicit costs of non-execution caused by adverse selection in the dark pool.

Some of the earliest works to examine dark trading utilise the US trade reporting facility (TRF) as a proxy for dark pool activity. The TRF is a problematic proxy for dark pool activity because it includes trades occurring in a range of venues, including dark pools, crossing networks, retail market makers and broker internalisers. This inability of the TRF to capture dark pool activity prohibits these studies from *directly* identifying dark pool activity, though they may still provide useful insights into dark trading generally.

O'Hara and Ye (2011) use TRF volumes to proxy for the degree of dark fragmentation at the stock-day level, concluding that dark fragmentation does not harm market quality. Using a sample of 2,754 NYSE and NASDAQ listed securities over a six month period in 2008, the authors are able to show that dark trading reduces average effective spreads and improves the speed with which orders are executed. While short-term volatility is found to increase with dark fragmentation, prices are generally found to be more efficient. This improvement in market quality is most pronounced for smaller stocks, suggesting that dark fragmentation increases competition for stocks that have traditionally been less liquid.

Weaver's (2011) method of analysis is very similar to that of O'Hara and Ye (2011) except that the data set used is from 2010 rather than 2008. Weaver (2011) argues that this change is important as the TRF data used by O'Hara and Ye (2011) contained trades reported from two crossing networks which became exchanges shortly after their sample period, and so are not present in Weaver's (2011) sample.

Contrary to the findings of O'Hara and Ye (2011), Weaver (2011) finds that dark fragmentation harms market quality. Five measures of market quality are used: quoted spreads, effective spreads, realised spreads, Amihud (2002)'s illiquidity metric, and the volatility of midpoint returns. Weaver (2011) finds that absolute quoted spreads increase by approximately one half of a percent for every ten percent of volume that is transacted off-exchange. Similarly, relative quoted spreads, realised spreads and effective spreads on the lit market are all found to increase as TRF trading increases. Furthermore, this work also finds that dark fragmentation is associated with increased illiquidity and volatility. These results contradict those found by O'Hara and Ye (2011), though the differences may be due to the inclusion of the crossing networks in the earlier TRF data. While Weaver (2011) is unable to directly attribute his findings to dark pools, the study's conclusions are consistent with the theoretical findings of Zhu (2011), that informed traders will continue to use the primary lit market in the presence of opaque alternatives.

Neither O'Hara and Ye (2011) nor Weaver (2011) attempt to differentiate between the market quality impacts of *lit* market fragmentation as compared to *dark* fragmentation. Degryse et al. (2011) and Gresse (2013) fill this gap in the literature by using the Herfindahl index to account for the level of fragmentation in European lit markets. The introduction of the Markets in Financial Instruments Directive (MiFID) on the 1st of November 2007 resulted in the establishment of a number of multilateral trading facilities

(MTFs), both lit and dark in nature, causing significant fragmentation across European equity markets.

Degryse et al. (2011) examine the market quality impacts of the fragmentation of liquidity to dark and lit venues. To achieve this, the authors analyse trading in 52 large Dutch stocks between 2006 and 2009, using the Herfindahl index as a proxy for fragmentation in the lit markets. These stocks are able to be traded in three types of venues: regulated market, MTFs with visible liquidity, and MTFs with hidden liquidity. Regulated markets are those market centres that existed prior to the introduction of MiFID. MTFs with visible liquidity are analogous to the alternative trading systems that exist in Canada, the US and Australia and include Chi-X, Turquoise, Bats Europe and Nasdaq OMX. MTFs with dark liquidity include regular dark pools, broker-dealer systematic internalisers and over-the-counter transactions. The authors find that lit market fragmentation reduces quoted, realised, and effective spreads, consistent with the reduced explicit costs and increased competition between liquidity suppliers across venues. This relationship between liquidity and lit market fragmentation is found to be quadratic in nature, with liquidity improving as lit market fragmentation increases up to 35%, and decreasing as fragmentation exceeds 35%.

Dark trading, however, is found to significantly *reduce* quoted depth and *increase* the price impact of trades. The authors propose that this effect may be due to uninformed traders preferring the dark venue, leaving relatively more informed traders in the lit market. This relative increase in informed traders usage of the lit market results in reduced liquidity and increased adverse selection in the lit venues, consistent with the theoretical findings of Zhu (2011).

Gresse (2013) analyses the FTSE 100, CAC 40 and SBF 120 in a similar way to Degryse et al. (2011), using a pre-MiFID period from October 2007 and a post-MiFID period from 2009. Consistent with Degryse et al. (2011), the author finds that lit market fragmentation reduces realised, quoted and effective spreads, with dark fragmentation not having any significant impact on market quality.

While both Degryse et al. (2011) and Gresse (2013) are able to account for the difference between dark and lit fragmentation, their measure combines dark pool trading with other types of internalisation, similar to the TRF in the US. This complicates the interpretation of the findings of these studies, reducing their applicability to *specific* dark pool activity.

2.5.2.1 Empirical Studies of Dark Pools Using Proprietary Data

Several studies obtain proprietary data sets to examine the impact of dark pool activity on market quality directly. These include: Ready (2010), who uses trading volume from three dark crossing networks; Nimalendran and Ray (2014) who use trade level data from an unspecified dark pool; Buti et al. (2011b) who use daily volumes that are self reported by a small selection of US dark pools; and Comerton-Forde and Putnins (2012) who use transaction data from the dark pool operated by the Australian Stock Exchange (ASX).

Ready (2010) studies the determinants of dark pool volume using monthly data at the stock level from three dark pools: Liquidnet, POSIT, and Pipeline, between June 2005 and September 2007. Dark pool volumes are higher in stocks that are liquid, have low bid-ask spreads, and have high daily turnover. Stocks that exhibit *higher* levels of information asymmetry (determined by high institutional holdings as reported in 13F filings) are found to have *less* dark pool activity, consistent with the findings of Zhu (2011) that informed traders will self-select the lit market due to low execution probability in the dark.

Nimalendran and Ray (2014) examine the information flows between dark and lit venues using a proprietary trade-by-trade data set from an unspecified US crossing network. The authors show that bid-ask spreads are *higher* immediately after dark executions, with more pronounced effects for less liquid stocks. This impact on liquidity is also found using Amihud's (2002) price impact measure, with price impact increasing in the ten minutes following dark trades. Nimalendran and Ray (2014) interpret this as evidence of information-based trading occurring in the dark venues, and to test this hypothesis, the returns to dark trades are constructed. They find economically and statistically significant half-hour returns to signed dark trades of 8.6 basis points, indicating that dark participants have some short-term informational advantage. Nimalendran and

Ray (2014) further divide these returns into three types of trade counterparties: trades with the firm's proprietary desk; manually negotiated trades between two large traders; and trades between crossing network members and an external (electronic) liquidity provider. Informed trading is concentrated in those trades initiated by electronic liquidity providers against crossing network members.

To further examine the information flows between the dark and lit markets, Nimalendran and Ray (2014) test the order flow imbalances on the lit exchange around dark transactions. They find that there is a preponderance of signed lit market order flow in the same direction as the signed dark orders immediately around the dark transactions. This provides evidence for their hypothesis that there is concurrent informed trading occurring on both dark *and* lit venues, revealing a channel by which information may be disseminated across both venues.

To test the type of information dark traders possess, Nimalendran and Ray (2014) examine dark executions around earnings announcements. They find that there is no significant difference between dark executions that occur on earnings and non-earnings announcement days. Nimalendran and Ray (2014) argue that this indicates that the information possessed by those traders operating in the dark is likely based on short-term, technical information, rather than only long-term fundamental information.

Buti et al. (2011b) use data self reported by dark pools to the Securities Industry in Financial Markets Association (SIFMA) in 2009 to provide empirical evidence on the determinants of dark pool participation. The authors consider this data superior to that of Ready (2010) as it is recorded daily rather than monthly. Due to the voluntary nature of the data, however, the authors only have information from approximately one third of dark pools active in the US market during their sample period. Their cross-sectional results show that dark pool activity is greater for stocks with low spreads, low volatility, and high liquidity, consistent with the findings of Ready (2010). Additionally, the authors find that days with low order imbalances and days with small absolute returns each tend to exhibit greater dark pool participation.

Using a time-series analysis, Buti et al. (2011b) show that dark pool activity is greater on days with higher turnover, narrower quoted spreads, greater bid-depth and lower volatility. The authors argue these results have desirable explanations. Higher turnover results in higher execution probabilities in the dark. Narrower spreads make dark pools attractive to traders as they are able to compete in sub-penny increments in the dark and are indicative of lower adverse selection costs. Greater bid-depth makes it harder to receive executions on the lit market, making dark venues more attractive. Low volatility indicates there is no buyer or seller imbalance in the market, making dark-executions more likely.

To account for the potentially endogenous nature of dark pool trading and market quality outcomes, Buti et al. (2011b) use a two-stage least squares estimation to infer the direction of causality between dark trading and market quality outcomes. Similar to Hasbrouck and Saar's (2010) HFT instrument, they use the percentage of dark trading on all stocks *except* for the stock in question as an instrument for the level of dark trading on the stock of interest. The authors find that the impact of dark pool activity on market quality is mixed. While spreads, bid-depth and volatility are all *improved*, dark activity appears to *reduce* total market volume and *reduce* pricing efficiency.

Comerton-Forde and Putnins (2012) use dark orders executed on the ASX between 2008 and 2011 to investigate the informativeness of dark trades using the information leadership share technique introduced by Yan and Zivot (2010). The authors show that the order flow that initially migrates to dark venues tends to be *less* informed than that which is left behind in the lit exchange. This, in turn, leads to an *increase* in adverse selection, bid-ask spreads and price impact in the lit market, and generally negatively impacting pricing efficiency. The authors identify that the loss of pre-trade transparency to the dark pool renders quotes less informative, resulting in a negative relationship between dark volume and price discovery.

This finding that dark pools hinder the price discovery process provides initial support for the concerns of regulators that dark pools do harm the overall efficiency of marketplaces. In light of their finding that block-trades do not harm price efficiency, the authors suggest that one potential solution to this problem is the introduction of minimum trade sizes for trade orders.

Kwan et al. (2013) provide evidence that informed traders may not determine the usage of dark orders. Rather it may be the discretion of dark pools (at least in the US) to price in sub-penny increments that makes them attractive to traders. To examine the role of dark pools in facilitating sub-penny pricing regimes in the US market, the authors use NASDAQ data from the TRF. They find that dark trading in stocks that are constrained to the minimum tick size in the lit market is significantly higher as compared to stocks that are unconstrained. Kwan et al. (2013) test the robustness of this finding by analysing the change in dark trading for stocks that cross the tick-size threshold of \$1. The authors show that stocks that increase in price from below \$1 to above \$1 (which increases the tick size from \$0.0001 to \$0.01) experience significant increases in dark volume at the time of crossing, and vice versa for stocks reducing to prices below \$1.

This empirical evidence is consistent with the theoretical predictions of Buti et al. (2011b) that constrained spreads will drive order flow to sub-penny venues that offer reduced transaction costs. Their work indicates that it may be the demand for finer trading increments that is driving liquidity to the dark, and thus that the harmonisation of pricing grids between dark and lit markets (as proposed by the Ontario Securities Commission (OSC) and the Investment Industry Regulatory Organization of Canada (IIROC)) would be likely to reduce the incentive to trade shares in dark markets.

Given the opaque nature of dark pools, and the possibility that traders in the dark are informed, it is not surprising that the "leakage" of dark-traders demand for liquidity is valuable information. Boni et al. (2012) find that the heterogeneity present in the variety of dark pools offerings have an impact on the execution quality of orders sent to these venues. They argue that "more exclusive" dark pools (that is, those that attempt to cater to buy-side traders by excluding high-frequency traders), provide better execution quality than those that provide access to all traders. Using Liquidnet Classic as one example of an exclusive dark pool, the authors compare the trade executions in this venue to those of other less "exclusive" dark pools, as well as to lit market executions for large orders (those greater than 50,000 shares). The authors' evidence suggests that *more* exclusive dark pools exhibit *less* serial return correlation, *less* pre-trade volume increases, *fewer* volatility increases, and *more* trade clustering across days.

These findings are consistent with less exploitation of the information contained within the order-flow data, resulting from less information leakage in the more exclusive venue.

The current literature suggests that an optimal dark pool is one with a pricing grid harmonised to the lit market and with restrictions around the type of participants that have access to the dark market and minimum trade sizes for dark executions. It is unsurprising, therefore, that regulations in countries such as Canada and Australia around dark pools have introduced limits to the pricing grid that can be used and the minimum quantities of shares that are allowable for dark transactions. This dissertation examines the introduction of one of these rules - the minimum price improvement legislation in Canada - with the aim of providing evidence as to the impact of this rule on efficiency and liquidity of dark trading. Additionally, the introduction of dark orders to the lit market of the Toronto Stock Exchange (TSX) is examined to identify the desirability of dark pools for market quality.

Chapter 3

Does Insider Trading Explain Price Run-Up Ahead of Takeover Announcements?

3.1 Introduction

This chapter analyses the extent to which toehold[6] acquisition prior to a takeover event can account for the observed pre-bid run-up. The ability to explain pre-bid price run-up has two main contributions. The first of these is the quantification of the impact of both toehold acquisition and timing on the pre-bid run-up. The second is the examination of the combined ability of rumours, information announcements and toehold timing to explain the pre-bid run-up.

A considerable body of empirical evidence has accumulated over the last few decades showing a persistent and substantial target stock price run-up prior to the announcement of a takeover bid (Dodd, 1980; Jarrell and Poulsen, 1989; Betton and Eckbo, 2000 and Bris, 2005). This effect is robust across different time periods and financial market structures, but whilst there is considerable consensus regarding the nature and magnitude of the run-up, its cause is less clear. Whilst anecdotal Australian evidence

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[6] Toeholds are pre-bid acquisition stakes.

suggests that unchecked illegal insider trading[7] is the cause, several other explanations have been suggested in the academic literature.[8] These suggested explanations include the actions of illegal insider traders (Meulbroek, 1992); market speculation of industry dynamics, that is perpetuated by market anticipators (Jensen and Ruback, 1983); or the incorporation of takeover rumours based on market information such as those related to toehold acquisitions (Jarrell and Poulson, 1989).

The causes of the run-ups observed in the lead up to takeover events are empirically examined using a uniquely constructed database containing the changes in substantial shareholdings prior to each takeover. The findings show that the timing of toehold positions is a non-trivial cause of the price-run up, and that in combination with market rumours and information announcements the vast majority of the pre-bid run-up is able to be explained. This pre-bid run-up has been used in several studies as evidence of illegal insider trading. If toehold timing has the capacity to drive significant pre-bid run-up, these previous findings may need revisiting.

In addition to bidder toehold information, the operation of continuous disclosure rules in the Australian market means that information events not associated with the takeover announcement can be identified and removed from the examination of takeover wealth effects.[9] Not only does the continuous disclosure framework require the immediate release of potentially price sensitive announcements to the market, each of these announcements are subsequently flagged as either price or non-price sensitive. The ability to control for price sensitive announcements provides further clarity on the causes of pre-bid price reactions by allowing potentially confounding events to be removed from the data set. Disclosure requirements, such as those in Australia exist in many developed markets globally, including the UK, New Zealand and Canada. This potentially allows for the extension of this research method to other developed markets, though it should be noted that the Australian disclosure regime differs significantly from the Fair Disclosure regulations of the US, which mandates only periodic reporting, with additional intervening news releases submitted voluntarily.

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[7] Illegal insider trading, is defined by section 1002G(2) of the Corporations Act as the "profitable trading in securities by a person with material non-public information".

[8] "Insider Trading Rife in Australia", The Australian, 20th February, 2008, Michael Sainsbury

[9] These regulations mandate that any price-sensitive information be released to the market as soon as companies become aware of it.

As regulators seek to become more "evidence based"[10] in their approach to policy making, this work quantifies the impacts of rumours, news announcements and toehold acquisitions as sources of pre-bid run-up. This has implications for regulators interested in identifying and limiting the causes of information leakage. It also reveals potential impacts of toehold acquisition timing to market participants, particularly bidders considering acquiring a pre-announcement stake in a target company.

3.2 Data

The data set of takeover bids is obtained from the Reuters Connect4 database, which provides a record of all deals involving Australian Securities Exchange (ASX) listed public companies from January 2000 to December 2009. Data collected from Connect 4 includes deal values, deal types and break fees, as well as other relevant acquisition and accounting information. This raw data set contains 852 takeover bids for 668 unique target companies.

Stock trading information and firm level data are collected via the Reuters intra-day interface provided by the Securities Institute Research Centre of Asia Pacific (SIRCA). This data is captured in real time from the ASX Integrated Trading System (ITS).

Toehold information is collected manually from bidder statements, s.603 "Becoming a Substantial Shareholder" notifications, or form 671B "Change in substantial shareholding" notices, which are analogous to the US 13D filings. As soon as an investor has beneficial ownership of greater than 5% of a publicly listed company, they are required to complete one of these notices within two business days of the acquisition.[11] A database comprising over 10,000 such changes has been constructed manually for the period 1999 - 2010. Given the dependence of this study on the timeliness of these filings, the "reporting lag" of the sample was determined, with an average of 0.53 days.

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[10] See, for example, the Foresight Driver Review being undertaken by the Financial Services Authority in the UK.

[11] This prompt disclosure differs significantly from the comparable US Schedule 13D filings which are required to be submitted within 10 days, with acquirers able to continue purchasing shares during this 10 day period.

This lag is consistent with both the reporting requirements[12] and the prompt reporting documented by da Silva Rosa et al. (2005).[13]

As investors are not required to report holdings smaller than 5%, toeholds below this threshold level are not captured in the data set.[14] Of the target firms subject to takeover offers, 38% contain pre-announcement purchases by the acquirer. News releases used to adjust announcement dates are manually collected from the Factiva database and cross referenced with ASX announcements. In order for an announcement date to be adjusted, both the acquirer and target must be named in the same release as a potential business combination. In such cases, the event date is brought forward to reflect the earlier release of the takeover rumour.

To ensure the integrity of the analysis, certain exclusions needed to be made to the initial set of 852 takeovers identified in the database. Firstly, any deal that represents a secondary bid for the same target firm, (either a competing or revised bid), is excluded from the sample in order to isolate the run-up effects of the first bid, with 184 deals excluded in this manner. A further 30 bids are removed as the bidder has pre-existing majority control via a toehold that is greater than 50%. Bids with more than 50 missing observations in the period (-250,0) are removed due to the paucity of such data excluding an additional 56 bids. Finally, any bid with an announcement flagged by the ASX as price sensitive in the 30 days prior to the adjusted announcement date is also removed so as to narrow the possibility of confounding effects in the price run-up.[15] This process results in the removal of an additional 132 observations. The final sample adjusted for missing data, multiple bids, existing control and sensitive announcements contains 450 takeover offers.

Table 3.1 describes the final sample of 450 target firms. Information regarding the share price, deal value, deal premium, market to book ratio, earnings and the news adjustment

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[12] The Financial Services Reform Act, 2001 (Cth), effective as of the 11th of March, 2002, imposes significant penalties for non-compliance with the continuous disclosure regime.

[13] In a sample of 5,213 substantial shareholding notices between 1996 and 1999 a mean lag of 2.4 calendar days was documented. This is consistent with two business days (given the potential of weekends and public-holidays) and was also prior to the introduction of the continuous disclosure regulations.

[14] There were twelve such observations in the data set, with toeholds ranging between 0.43% and 4.9%.

[15] An additional robustness test is performed to identify the possibility that the announcement effect may not be due to the toehold but rather to the release of the price-sensitive news by constructing dummy variables capturing the release of news 2, 5, 10, and 30 days prior to the takeover event. The results are qualitatively similar to those reported.

process are all provided. The mean (median) value of the sample of deals is $AU1.28 billion ($AU113 million) indicating that a sizeable fraction of the deals announced are for small-to-medium tier capitalisation firms. Figures reporting the profitability of the sample of firms show average (median) earnings of approximately $AU62.38 million ($AU4.24 million) for takeover targets. The average premium of approximately 18% over the defined sample period is broadly consistent with the 18% found by King (2009) in Canada and the 28% found by Jarrell and Poulsen (1989) in the US.

The pre-bid run-up caused by rumours of the bid is controlled using an adjustment process implemented by both Aitken et al. (1992) and King (2009). This process searches news sources for any rumour of an impending transaction that is publicly disclosed and includes the names of both the eventual acquirer and target. When such a rumour is identified, the event date is set to be the earlier of the official announcement date and the date of the first rumour to reflect the dissemination of this information. The Factiva database is then searched for publications regarding the listed takeovers in the sample up to one calendar year prior to the official announcement date. Of 450 announcements, the mean number of calendar days between the news-adjusted and formal announcement dates is 68.69 days across those announcements. This is a similar adjustment period to the 58 days reported by King (2009) for deals conducted on the Toronto Stock Exchange and the 59.21 days reported by Aitken et al. (1992) on the ASX.

Table 3.1: Characteristics of Target Firms

This table provides descriptive statistics for the 450 target firms that form our final sample. Share price is reported as at 20 days prior to the takeover announcement. Deal value is the offer price multiplied by the number of shares to be purchased. Premium is the difference between the bid price and the price 20 days prior to the announcement of the bid. Market to book is a financial ratio comparing the deal value to the book value of net assets. EBIT is the earnings before interest and taxes and is taken from the last available annual report. Days news adjusted reports the number of days that the announcement date has been modified due to rumours of a potential merger in the news media mentioning both the bidder and target.

Variable	Mean	Median	Standard Deviation
Share Price ($)	2.73	0.94	7.50
Deal Value ($ millions)	1,281.90	113.45	8,497.31
Premium (%)	18.28	16.10	23.98
Market to Book	3.03	1.83	4.10
EBIT ($millions)	62.38	4.24	547.74
Days News Adjusted	68.69	11.00	176.23

Table 3.2 displays information about the acquisition patterns of toeholds in Australian deals between the years 2000 and 2009. The deals are divided into two categories: short-term toeholds, which occur when the bidder acquires an incremental toehold stake within 30 days of the official announcement date; and long-term toeholds, which represent all toeholds taken outside 30 days after the official announcement date. An acquirer that has an existing long term toehold and increases their stake within 30 days of making a bid is treated as a short-term toehold, due to the additional information provided by the increased purchase of shares.[16]

Short-term toeholds are purchased on average up to 10 days prior to the bid, although the median of 1 day is evidence of frequent buying activity on the day before the formal announcement. In purchasing one day prior to the bid, acquirers are able to delay reporting their stake until after the bid has been made public. This deprives potential rivals of sufficient time to prepare competing bids, allowing firms to minimise the transmission of their intentions to the market. Long-term toeholds are held on average for just over a year. The mean of 404 days implies that these toeholds are often acquired with the intention of making a bid in the near future, either as an investment, to deter

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[16] There are 24 such takeovers in the data set that have been categorised as “short-term”.

Table 3.2: Toehold Characteristics

This table contains descriptive statistics relating to both the average time that toeholds are held for and the average deal size. Short Term toeholds are defined as those that are purchased within 30 days of the official announcement of the takeover bid. Long Term toeholds are defined as those that are purchased outside of 30 days of the announcement of a takeover bid. Observations is the number of short or long-term toeholds in our sample of 450 firms.

Holding Period	Observations	Mean	Median	Standard Deviation
Short Term (Days)	52	10.26	1	55.65
Long Term (Days)	118	404.95	367	373.46
Deal Size	**Observations**	**Mean**	**Median**	**Standard Deviation**
Short Term ($M)	52	1419.06	104.00	3848.13
Long Term ($M)	118	489.07	71.83	1252.35
No Toehold ($M)	280	1541.86	135.57	10378.00

rival merger activity or as an option over anticipated future acquisition (Betton, Eckbo and Thorburn, 2009).

Table 3.2 shows that there are more than twice as many long-term toehold acquisitions than short-term toeholds in the sample. This finding may reflect the common use of standstill agreements at the start of negotiations, which prevents bidders from acquiring a stake during the period prior to the formal announcement (Bruner, 2004). The descriptive data on deal size presented in Table 3.1 illustrates that acquirers avoid toeholds in the largest companies. This is likely due to the costly nature of such a shareholding, and the risks associated with the disposition of such a stake in the event of deal failure (Betton, Eckbo and Thorbun, 2009).

Table 3.3 reports the distribution of takeover bids through time. It shows that over the ten year sample 38% of deals include an acquirer held pre-bid toehold stake. This figure is marginally higher than comparative empirical studies, however the relative decline observed through time is consistent with the findings of Betton et al. (2009) in the United States.[17] The literature describes several advantages to acquiring a toehold, including; cost advantages (Bishop, 1991); avoiding the free-rider problem (Shleifer and Vishny, 1986); reducing price impact (Walkling, 1985); and the potential to deter rivals (Bulow, Huang and Klemperer, 1999). Despite these documented benefits to toehold acquisition, the results in Table 3.3 show that the majority of Australian acquirers do not purchase a toehold prior to their formal bid. One potential explanation for this is that the risks to deal negotiations stemming from the market activity involved in purchasing the common stock may overshadow the potential benefits.

To date, only one other study has examined the timing of toehold purchases. Betton, et al. (2008) examine the impact of short-term toeholds on final acquisition price, with 90% of their toehold sample being acquired over a period greater than six months prior to the launching of a bid. The proportion of acquirers taking toeholds in Betton et al. (2008) is significantly lower than reported in this study. Additionally, in this study long-term acquisitions are found to account for over 69% of all toehold activity. The apparent reluctance of firms to establish toeholds shortly prior to an acquisition across both samples highlights the perceived costs of such activity.[18]

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[17] Jarrell and Poulsen (1989) report that 58% of US bidders take toeholds, Betton, et al. (2009) report 13% in a later sample, and King (2009) finds 19% in Canada.

[18] Bris (2002) argues that short-term toeholds act as a signal to the market of the impending bid, increasing the eventual takeover premium.

Table 3.3: Toehold Time Series Distribution

This table documents the number and distribution of toehold bids within our sample on an annual basis. Bids is the number of takeover bids that were launched in each year. Short-term toeholds is the proportion of bids for that year where a toehold was acquired within 30 days of the announcement of the bid. Long-term toeholds is the proportion of bids in which a toehold stake was acquired more than 30 days prior to the announcement of the bid. Toeholds is the proportion of bids that had a non-zero toehold prior to the announcement of the bid.

Year	Bids	Short-Term (%)	Long-Term (%)	Toeholds (%)
2000	50	16.0	32.0	48.0
2001	52	9.6	34.6	44.2
2002	30	23.3	23.3	46.6
2003	44	9.1	38.6	47.7
2004	36	13.9	27.7	41.6
2005	34	11.7	14.7	26.4
2006	64	12.5	18.7	31.2
2007	64	6.2	28.1	34.3
2008	33	12.1	30.3	42.4
2009	43	7.0	11.6	18.6
Average	45	12.1	26.0	38.1

Table 3.4: Toeholds by Size and Type

Table 4 provides a breakdown of the size of toehold positions held by bidders in the sample. Short-term is the number of toeholds acquired in each size range within the 30 days prior to the takeover bid. Long-term is the number of toeholds acquired outside of 30 days from the announcement date.

Toehold (%)	Short-term	Long-term
0 - 5%	8	4
5 - 10%	6	9
10 - 15%	10	19
15 - 20%	23	31
20 – 25%	2	13
25 – 50%	3	42
Total	52	118

Table 3.4 provides a breakdown of the size of toehold positions held by bidders. The majority of toehold positions held by short-term acquirers are clustered around 15-20% of outstanding share capital. This clustering reflects regulations prohibiting firms from acquiring toeholds greater than 20% without formally announcing a takeover to the

market.[19] In the US market, where such “fair price” provisions do not exist, Betton, et al. (2009) report a clustering of both short-term and long-term toeholds around the 10% level. The comparatively smaller size of short-term toeholds can also be partially attributed to the upward sloping-supply curve encountered by acquirers, increasing costs with toehold size (Walkling, 1985). Long-term toeholds are on average larger, with 46% of long term toeholds exceeding 20% of outstanding equity. The tendency for long-term toeholds to be greater than 20% is likely associated with the need to acquire a significant enough position to deter rivals (Bulow et al. (1999)).

3.3 Research Design

Standard event study methodology is used to examine whether timing of the toehold placement has an impact on the pre-bid price run-up. In order to limit the upward bias in the run-up driven by trading on rumours of the deal in the financial press, the event date is adjusted to reflect the earlier of the public announcement of the takeover, or any rumour mentioning both the takeover target and the acquirer as a potential combination. Though the announcement of a toehold will not of itself necessitate an adjustment, it is possible that a toehold reported to the exchange results in a rumour of the potential takeover on the following day. In these cases, the toehold is considered “short-term”, whereas if the toehold is taken after the first rumour, it is classified as a “no-toehold” event. The determination of the toehold classification is only possible ex-post, with uninformed market participants unable to determine ex-ante if a toehold acquisition is going to be long-term or short-term in nature. This classification process is consistent with the previous work of Aitken et al. (1992) and Sanders and Zdanowicz (1992).

Abnormal returns are calculated for a window around the adjusted announcement date for all the firms in the sample. To calculate the pre-bid run-up, the daily excess returns

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[19] Section 615 of the Corporations Act 2001 (Cth) prohibits an individual or company from exceeding 20% share ownership without launching a full takeover bid for all remaining shares. Section 618 provides an exception for “creeping” takeovers, whereby an acquirer may increase their shareholding above the 20% level in 3% increments every six months without launching a full takeover bid.

from 30 days prior to the announcement to the day before the announcement are aggregated. Equation 3.1 is used to compute the cumulative abnormal return per stock (CAR):

$$Runup_i = CAR_{i,(-30,-1)} = \sum_{-30}^{-1} AR_i. \tag{3.1}$$

Figure 3.1 plots the CARs for the official announcement date, the news adjusted date and the announcement adjusted data set. The news adjusted date considers the earlier of the rumour or announcement date as the event date. Also removed from the announcement adjusted set are takeovers that have a market sensitive announcement within the 30 days prior to the bid. Consistent with Aitken et al. (1992), media-published rumours are shown to account for over 20% of the observed pre-bid run-up. Prior to any adjustment, the run-up begins up to twenty-three days prior to the official release of the takeover, reaching almost 6% on day -1.

Once rumours in the market are controlled for, CARs become uniformly lower, amounting to just under 4.5% on day -1. A further source of potential bias in the run-up is from price sensitive announcements unrelated to the takeover. The additional removal of these from the sample accounts for a further 10% of the observed pre-bid run-up. The pre-announcement run-up of 4%-6% is consistent with the reported pre-bid run-up in studies such as Sanders and Zdanowicz (1992) and King (2009) of 7.4% - 8.1%.

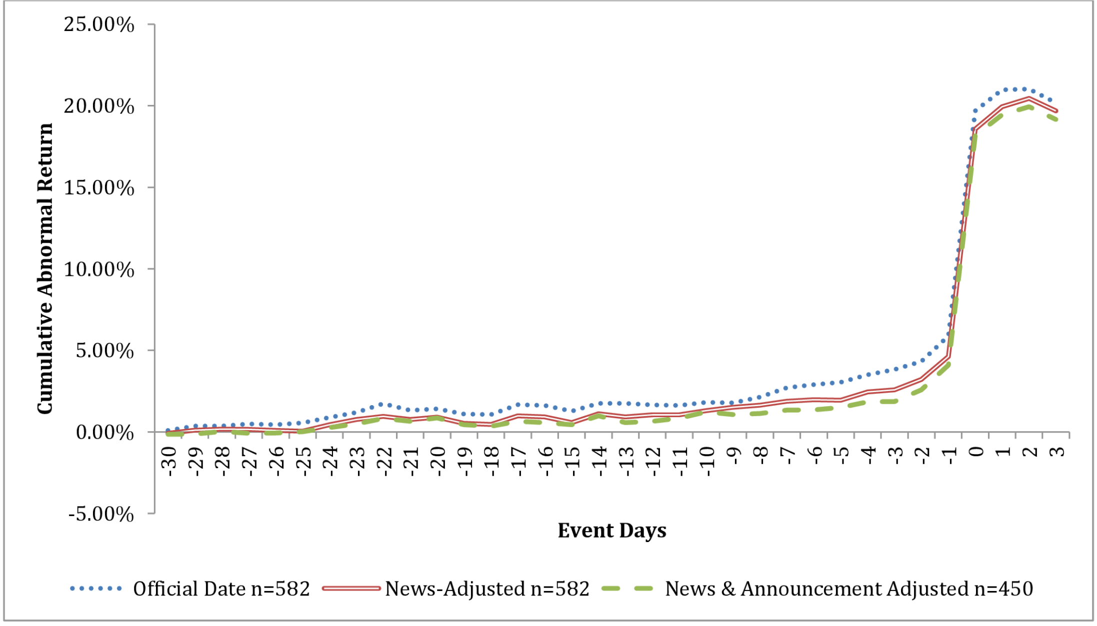
This analysis uses the news and announcement adjusted event dates to assess the impact of toehold timing on the pre-bid run-up. The impact of toeholds and their placement strategies are determined using the regression analysis documented in equation 3.2:

$$\begin{aligned} Runup_i = \alpha_i + \beta Toehold_i + \gamma LT_i + \delta ST_i + \sigma ln(value_i) + \theta Turnover_i + \\ \kappa ThirdParty_i + \omega LT_i * Toehold_i + \mu ST_i * Toehold_i + \epsilon_i, \end{aligned} \tag{3.2}$$

where; Run-up is the CAR of stock i between day -30 and -1; Toehold is the proportion of the targets shares held by the acquirer immediately prior to the takeover bid; LT is a dummy variable that takes the value 1 if a long-term toehold was acquired in stock i and 0 otherwise; and ST is a dummy variable that takes the value 1 if a short-term toehold

Figure 3.1: News Adjusted Returns

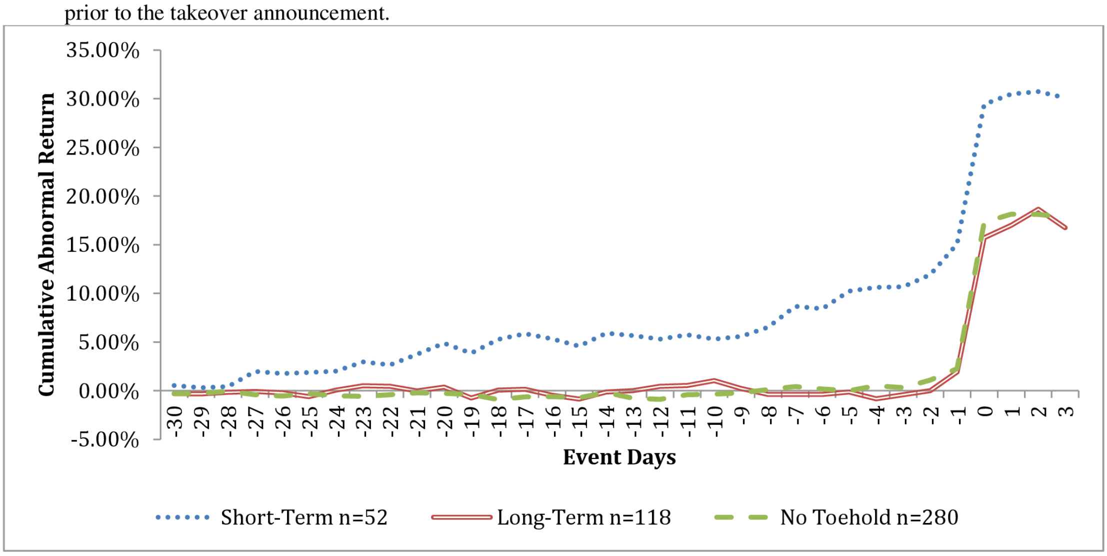
Figure 1 displays the cumulative average abnormal returns for the entire sample. Official date indicates the event time relative to the public announcement of the bid. News-adjusted indicates the returns relative to the news adjusted announcement date. News & Announcement adjusted reports the returns relative to the news adjusted date after the removal of targets that had a price sensitive news announcement in the 30 days prior to the announcement date.



was acquired and 0 otherwise; ln(Value) is a control variable for the target firm, being the natural log of stock *i's* market cap twenty days prior to day "0"; Turnover is the cumulative abnormal turnover in stock *i*, defined as the cumulative average daily volume for each target as a percent of turnover in the benchmark period (-250,-100); Third Party is a dummy variable that takes 1 if a third party other than the bidder increases their substantial shareholding in stock *i* in the 30 days prior to the announcement, and 0 otherwise; ST*Toehold and LT*Toehold are interaction terms of the timing and size of the toehold. A fixed effects model is used to capture the industry and time variation in the sample. These results are reported in Table 3.5. Whilst a large body of empirical literature documents the post-takeover announcement effects of bid characteristics (such as whether the offer is in cash or stock, if the bidder is a public or private company, and whether the bid was subsequently consummated) these characteristics will only become public knowledge *after* the announcement of the bid. As only the run-up *prior* to the takeover announcement is of interest, only factors contemporaneous with the period prior to the takeover bid have been considered.

Figure 3.2: Toehold Adjusted Returns

Figure 2 outlines the cumulative average abnormal returns by toehold type. Day 0 is the news and announcement adjusted event date. Long-term indicates stocks where a toehold was acquired more than 30 days prior to the announcement. Short-term indicates toeholds that were acquired within 30 days of the takeover announcement. No toehold indicates those targets where the bidder did not acquire any shares prior to the takeover announcement.



3.4 Results

The results presented in Figure 3.2 show the target run-up after controlling for toehold timing. These results provide preliminary evidence that a significant proportion of the target run-up can be explained by considering the recent acquisition of toehold shares. Figure 3.2 shows that takeovers with established long-term toeholds without confounding information announcements have on average a 2.25% run-up in the thirty days prior to the first rumour or announcement of a bid. This is found to be statistically insignificant from zero at the 5% level.[20] Choi (1991) argues that the acquisition of a toehold, which results in a positive valuation effect, reflects investors' perception of an increased probability of a subsequent takeover. Since the control premium is largely impounded at the time of the acquisition of the toehold, the insignificant run-up observed in this period is consistent with minimal leakage prior to the announcement of the bid.

Figure 3.2 additionally shows a significant run-up for short-term toeholds in the 30 days prior to the first rumour or announcement of a takeover bid. This run-up of approximately 15% is found to be statistically significant at the 1% level. Consistent

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[20] Tests for significance have been omitted for brevity.

with the theoretical predictions of Bris (2002), these results provide preliminary evidence that the acquisition of a toehold in the target is associated with increased abnormal returns. It is not possible to disentangle the effects of market anticipation and the market impact costs of the toehold acquisition - the the two are intrinsically related. Market participants attempting to identify takeover targets may use unusual price and volume movements to inform their purchasing behaviour (Choi, 1991). If this is the case, large trading volume will drive market anticipation, which will in turn drive additional trading volume. This circularity describes the mechanism by which toehold activity can cause prices to anticipate takeovers. Table 3.5 presents the results of the regression analysis using various model specifications. There are two interesting results. Firstly, Model 1 shows that the size of the toehold alone cannot explain the variation in the run-up. This is consistent with the lack of consensus in the empirical literature regarding the impact of toehold size on the pre-bid run-up. Secondly, Models 2 - 5 demonstrate that the acquisition of toeholds shortly prior to the announcement of a takeover are associated with significantly increased price run-up.[21] Consistent with the findings of Betton et al. (2008), short-term toeholds are associated with larger pre-takeover run-ups relative to long-term and no toehold positions. This increased run-up provides support for the theoretical predictions of Bris (2002) that toehold activity can signal a bid to the market, thus generating market anticipation. While short-term toeholds have a significant and positive impact on the run-up, the presence of existing long term toeholds is not significantly related to run-up. If the acquisition of toeholds causes investors to revise their expectations of a takeover, then the run-up may have already occurred around the placement of the toehold. Evidence consistent with this proposition is presented in the following section.

Examining the control variables, the measure of abnormal turnover reported in Table 3.5 is positive and significant across all model specifications. This finding suggests a positive association between increased market activity and abnormal pre-bid price increases. The market anticipation hypothesis proposed by Jensen and Ruback (1983) posits that traders predicting a takeover bid will buy in anticipation of receiving the takeover premium. Such buying activity will also increase the volume of shares traded,

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[21] The inclusion of a thin-trading bias variable, as constructed in Fidrmuc et al. (2006) does not significantly alter the results presented.

TABLE 3.5: Regression results: The determinants of pre-bid run-up

This table presents results of a standard regression analysis used to examine the determinants of price run-up prior to the announcement of a takeover bid. The dependent variable, Run-up, is the average CAR between day -30 and -1; Toehold is the proportion of target shares held by the acquirer immediately prior to the takeover bid; Long-Term Dummy and Short-Term Dummy are dummy variables that take 1 if a long-term (short-term toehold) was acquired in stock i and 0 otherwise. The base case is no-toehold; Value defined as the natural logarithm of the market capitalization of stock i one day prior to the official takeover bid announcement; Turnover is the cumulative abnormal turnover in stock i as a % of "clean period" (-250,-100) turnover; Third Party is a dummy variable that takes 1 if a third party increases their substantial shareholding in stock i in the 30 days prior to the announcement and 0 otherwise; Long-Term*Toehold and Short-Term*Toehold are variables that indicate the percentage of stock i shares owned by the bidder on the date of announcement. Standard Errors are reported in brackets. *** represents significance at the 1% level, ** at 5% and * at 10%.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.038***	0.033***	0.030*	-0.113	-0.151
	(0.011)	(0.010)	(0.011)	(0.078)	(0.086)
Toehold	0.018	-	0.047	-	-0.024
	(0.043)	-	(0.047)	-	(0.031)
Long-Term	-	-0.021	-0.033	-0.029	-0.103
	-	(0.026)	(0.023)	(0.030)	(0.040)
Short-Term	-	0.116***	0.113***	0.104***	0.103**
	-	(0.017)	(0.027)	(0.039)	(0.040)
Value	-	-	-	0.008*	0.010**
	-	-	-	(0.004)	(0.004)
Turnover	-	-	-	0.015***	0.014***
	-	-	-	(0.005)	(0.005)
Third Party	-	-	-	-0.001	-0.001
	-	-	-	(0.080)	(0.018)
Long-Term*Toehold	-	-	-	0.051	0.032
	-	-	-	(0.690)	(0.099)
Short-Term*Toehold	-	-	-	0.012	0.007
	-	-	-	(0.070)	(0.171)
Sample Size, N	450	450	450	450	450
Adjusted R-Squared	0.018	0.043	.058	0.078	0.093
Yearly Fixed Effects	-	-	-	-	Yes

which is supported by the results. Consistent with previous studies, the coefficient on the deal size variable is positive and significant, demonstrating that larger target firms have a greater pre-bid share price run-up. Finally, the interaction terms in Table 3.5 show that the size of the toehold, with respect to the proximity of its placement to the announcement date, does not have a statistically significant impact on the size of the run-up. This result demonstrates that the impact toeholds have on the run-up arises not from their size, but rather from the information conveyed by their purchase. This

Table 3.6: Matched Sample Descriptives

Table 6 outlines the cumulative average abnormal returns for a sample of 52 matched toehold acquisitions. Each short-term toehold in our sample was matched by firm size and toehold size to another change in substantial shareholding that was not followed by a takeover bid within the subsequent year. The event day is the public announcement of the acquisition of the toehold stake. All results are reported in %. *, ** and *** represent significance at the 10%, 5% and 1% level respectively.

Sample Period	Short-Term Toeholds	Matched Sample	Difference
CAR (-30,0)	0.0649	0.0766	0.0117
CAR (-15,0)	0.0584	0.0549	-0.0035
CAR (-10,0)	0.0569	0.0393	-0.0176
CAR (-5,0)	0.0286	0.0405	0.0119

finding provides an interesting and novel explanation to reconcile the lack of consensus that exists in the literature regarding the impact of toehold size on the run-up.

3.5 Robustness Test - The Impact of Toehold Acquisitions

Not all acquisitions of toeholds or increases in sizes of existing toeholds are followed by a takeover bid. By constructing a matched sample of toehold stakes that are not followed by takeover bids, the pre-bid price run-ups can be assessed to determine whether they were a function of insiders profiting from their privileged position, or an average market reaction to the establishment of a toehold. This allows for the impact of the toehold acquisition to be directly observed, free of the look-ahead bias inherent in only analysing takeover bids. A matched sample stock is identified for each of the short-term toehold acquisitions in the sample by minimising *Distance* in Equation 3.3,

$$Distance = min \sum_{i=1}^{2} \frac{|factor_i^{ST} - factor_i^{Match}|}{\left(\frac{factor_i^{ST} + factor_i^{Match}}{2}\right)}. \tag{3.3}$$

To construct the *Distance* measure, the absolute difference of either the market value or toehold size is computed for the run-up sample stock and each potential match. This difference is then divided by the average of the matched factors. Each matched stock is chosen without replacement by minimizing the sum of these two factors.

Table 3.6 documents the difference in market value and toehold size between the short-term toehold stocks and their matched samples. Significance tests confirm that there is no significant difference between the samples based on the matching criteria. The matching of the size of the toehold is considered especially important due to the unusually large size of the toehold acquisitions, as reported in Table 3.4.

The regression analysis used to examine the determinants of the reactions to the toehold acquisitions is documented in equation 3.4 below:

$$CAR_i(x,y) = \alpha_i + \beta_i ln(value_i) + \gamma Toehold_i + \delta Turnover_i + \mu Matched_i + \epsilon_i, \quad (3.4)$$

where CAR(x,y) is the cumulative abnormal return of stock i between x and y days; value refers to the market value of firm *i's* shares; Toehold indicates the size of the toehold; Turnover is the cumulative abnormal turnover of stock *i* between x and y days; and *Matched* is a dummy variable that takes a value of 1 to indicate that the stock is part of the matched sample, and 0 if it is part of the short-term toehold sample.

Table 3.7 reports the returns around toehold acquisitions prior to the announcement of a takeover, vis-a-vis the returns with no resulting takeover announcement. As the median short-term holding period is only one day before the takeover announcement (as reported in Table 3.1) the returns up until the public announcement of the toehold are specifically considered. This exercise isolates the run-up and announcement period from the confounding impacts of the takeover announcement itself.

Table 3.7 compares the CARs for the short-term and matched samples. Both samples exhibit similar pre-announcement patterns, with positive pre-event CARs of 6.5-7.5% for the 30-day window preceding the acquisition of the toehold. The difference reported between the short-term toeholds and the matched sample are not significant at the 5% level for any of the event windows examined. Furthermore, the size of the observed abnormal return is comparable to results presented in Akhigbe et al. (2007), with toehold targets which were not subject to takeovers exhibiting returns of 2.5%, while targets acquired within one year experienced returns of 9.5%, over a comparable 20-day period.

Table 3.7: Matched Sample Toehold Returns

Table 7 outlines the cumulative average abnormal returns for a sample of 52 matched toehold acquisitions. Each short-term toehold in our sample was matched by firm size and toehold size to another change in substantial shareholding that was *not* followed by a takeover bid within the subsequent year. The event day is the public announcement of the acquisition of the toehold stake. All results are reported in %. *, ** and *** represent significance at the 10%, 5% and 1% level respectively.

Sample Period	Short-Term Toeholds	Matched Sample	Difference
CAR (-30,0)	0.0649	0.0766	0.0117
CAR (-15,0)	0.0584	0.0549	-0.0035
CAR (-10,0)	0.0569	0.0393	-0.0176
CAR (-5,0)	0.0286	0.0405	0.0119

To further examine the significance of the previous result a regression analysis is performed across the two samples. The results reported in Table 3.8 show that the “matched” dummy variable is insignificantly different from zero in all specifications. This suggests that run-ups in a target’s share price (where short-term toeholds have been established) are not the result of insiders using their position to trade ahead of the takeover announcement, but rather due to the price discovery that occurs around the acquisition of toeholds. The fact that the returns between the matched samples are statistically indistinguishable means that prior conclusions attributing the run-up to insiders may be an overstated concern.

Table 3.8: Matched Sample Toehold Regressions

Table 8 provides the results of a standard regression analysis for a matched sample of 52 toehold acquisitions. Each short-term toehold was matched by firm size, toehold size and share price to another change in substantial shareholding that was *not* followed by a takeover bid within the subsequent year. The dependent variable is the average CAR between day *x* and *y*; *Value* defined as the natural logarithm of the market capitalization of stock *i* one day prior to the official takeover bid announcement; *Turnover* is the cumulative abnormal turnover in stock *i* as a % of "clean period" (-250,-100) turnover; *Toehold* is the proportion of shares acquired in the present notification, in % of shares outstanding; *Matched Sample* is a dummy variable that takes 1 if the observation is part of the matched sample and 0 if the observation is part of the short-term toehold sample. Standard errors are reported in brackets. *** represents significance at the 1% level, ** at 5% and * at 10%.

Variable	CAR(-30,0)	CAR(-15,0)	CAR(-10,0)	CAR(-5,0)
Intercept	0.3259	0.2404	0.2837*	0.2080**
	-0.2736	(0.2145)	(0.1437)	(0.1031)
Value	-0.0153	-0.0124	-0.0126*	-0.0108**
	(0.0141)	(0.0110)	(0.0074)	(0.0053)
Toehold	0.0026	0.0040	0.0015	0.0023
	(0.0039)	(0.0030)	(0.0020)	(0.0015)
Turnover	0.0011	0.0013**	0.0004	0.0001
	(0.0008)	(0.0006)	(0.0004)	(0.0003)
Matched Sample	-0.0073	-0.0063	-0.0307	0.0144
	(0.0604)	(0.0472)	(0.0317)	(0.0228)
Sample Size, N	104	104	104	104
Adjusted R-Square	0.0487	0.0903	0.0665	0.0934

3.6 Conclusions

This chapter presents an analysis that finds that the purchase of a toehold immediately prior to the announcement of a takeover induces a significant price run-up. The existing literature is extended by identifying and controlling for three potential causes of pre-bid run-up: media speculation, price sensitive announcements and toehold acquisitions by the bidder. As this chapter shows, the activity generated from these three areas explains a significant proportion of the pre bid share price run-up. The impact of the timing of the acquisition of a toehold stake is specifically analysed to ascertain the affects on the share price run-up, finding that takeover bids with toeholds acquired shortly before the takeover announcement are associated with significantly larger share price run-ups. Share-price run-ups documented for the short-term targets also exist for other toehold acquisitions that are *not* followed by takeover announcements, which suggests they are driven by the toehold acquisition process itself. New evidence is provided on the impact of the toehold timing decision, potentially resolving previous inconsistencies in the literature regarding the impact of toeholds on pre-bid run-up. This evidence further suggests the timing of the toehold significantly affects the pre-bid price behaviour in the target firm: an absence of any such toehold is associated with no significant run-up. In light of this evidence, previous studies attributing the price run-up to cases of insider trading appear to over-state the case, as this study shows that the existence of insider traders is not necessary to induce an increase in the target's share price, as has been previously claimed. Insider trading is by nature surreptitious, and it is not possible to rule out arguments such as that proposed by Chakravarty (2001) - that insiders' trade stealthily to conceal their trades. If insiders do actively try to conceal their trades for fear of prosecution, it is possible that they trade more frequently when they observe abnormal price and volume movements generated by toehold acquisitions or by market rumours. Without data describing the trades of prosecuted insiders, however it is extremely difficult to ascertain if this behaviour is occurring. Despite this potential limitation, this research suggests that almost all of the pre-bid run-up which has previously been attributed to insider trading can be explained by legal factors associated with market anticipation.

Chapter 4

Assessing the Impact of HFT on Market Efficiency and Integrity

4.0.1 Introduction

This chapter investigates the impact of high-frequency trading (HFT) on efficiency and integrity in the LSE and Euronext Paris markets. Much of the current academic literature has focused on the impact HFT has on efficiency, with no empirical evidence presented that attempts to identify the relationship between HFT and market integrity. This chapter analyses the impact of HFT on two distinct aspects of market integrity - using both trade and information-based measures of market manipulation.

This focus on integrity is important for two reasons. The first is that the integrity of the market is one of the key mandates of regulators when assessing any regulatory changes, of which HFT is one. The second reason integrity is important is that theoretical finance models (as far back as those of Kyle (1985)) demonstrate a relationship between adverse selection and market efficiency. This interrelationship between market efficiency, integrity, and the level of HFT poses a potential endogeneity problem: spreads may be narrow due to the prevalence of HFT market makers, or narrow spreads may *encourage* the participation of HFT market makers. To allow for such endogeneity, a three-stage least squares (3SLS) method is used to simultaneously estimate the determinants of efficiency, integrity and HFT. Using this technique, HFT participation is shown to have had a significant impact on both the cost of trading (a proxy for efficiency) and the frequency of end-of-day price dislocation[22] (a proxy for market integrity), both of which have improved as the degree of HFT participation has increased.

4.1 Institutional Detail

Regulatory framework changes have both encouraged and restricted the practice of high-frequency trading. As an increasing number of firms enter this space seeking to carve out niches for themselves, regulators have had to regulate HFT without fully understanding how it impacts on market fairness and efficiency. This section provides a broad examination of the major structural changes at both the market and exchange level that have facilitated the expansion of HFT participation.

4.1.1 Structural Changes at the Market Level

Following a similar transformation in U.S. financial markets some years prior, the implementation of the Markets in Financial Instruments Directive (MiFID) in 2007 transformed the European equity market landscape. An unintended outcome of this variation in the rules regarding best execution, market transparency, and market organisation is the promotion of HFT. According to a statement from the Committee of European Securities Regulator (CESR): "...one of the primary objectives of MiFID was to introduce competition among trading venues and thereby reduce transaction costs for the benefit of both the final investors and issuers. These results were meant to be achieved, among others, by removing the concentration rule and, at the same time, introducing specific pre- and post-trade transparency for listed shares coupled with a detailed best execution regime for investment firms which execute clients' orders."[23] It is this competition that has facilitated the increasing rate of HFT in Europe.

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[22] This practice is also often referred to as "marking the close".

[23] Committee of European Securities Regulator - 24th April 2006.

MiFID specifically introduced four key changes with clear implications for HFT. These changes included the abolishment of the "concentration rule", the introduction of "best-execution" obligations for brokers, the promotion of greater pre- and post-trade transparency rules, and the introduction of "passporting". The requirement of best-execution to ensure all market prices are taken into consideration, as well as the passporting rule which allows securities listed anywhere in Europe to be traded on any other venue have significantly fragmented the trading of European securities. This fragmentation has provided a fertile field within which HFT has blossomed.

Prior to MiFID, the concentration rule required all trades in a single stock to go through one, centralised exchange (typically the national incumbent exchange). The abolition of this rule meant that trades were simply required to go through a regulated exchange, allowing for greater competition amongst trading venues in Europe. Provisions in MiFID allowed the introduction of competing structures, such as multilateral trading facilities (MTFs) and systematic internalises (SIs), which saw traditional incumbent exchanges being challenged by more aggressive entrants who were supported by the introduction of a principles-based best-execution regime.[24]

This change created an incentive for the incumbent exchanges to compete on cost. Market operators, looking to attract order flow, began to offer alternative fee structures that were asymmetric in nature, so called "maker-taker" pricing models. Under such conditions, market participants that provided liquidity enjoyed a lower fee (and in some circumstances a rebate) relative to those participants that demanded liquidity from the market.[25] This differed substantially from the typically symmetric explicit pricing regime that had existed pre-MiFID.

This change was expected to deliver a market environment that was characterised by lower trading costs. Evidence provided by Gomber et al. (2011) suggests that the delivery of this fragmented marketplace resulted in lower explicit costs for market participants. Given the acute sensitivity of HFT to the cost of trading, regulatory changes which have allowed both implicit and explicit trading costs to fall have also encouraged HFT participants to be more involved in equity markets.

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[24] This was subsequently amended in MiFID II bringing it in line with the U.S. regulatory regime.

[25] These market operators would be able to offset some of the cost of the rebate from "tape-revenue".

The fragmentation of trading away from a monopolistic primary market into a variety of smaller venues also opens up the potential for inter-market arbitrage, as well as "fee-arbitrage", whereby electronic liquidity providers seek to capture these explicit rebates by posting limit orders on both sides of the market.

In the aftermath of the changes introduced by MiFID, the CESR's second version, MiFID II imposes a variety of future challenges to the practice of HFT. In a bid to safeguard against potential systemic risks, the directive warned that there was now a greater potential for "overloading of trading venues systems", "duplicative or erroneous orders", and "overreaction to other market events".[26] These risks are still the subject of much contention, as any proposal that would require entities who engage in HFT to employ greater risk mitigation practices may produce a whole range of unintended consequences.[27] To avoid such unintended consequences, it is important to understand the impact of the practice of HFT on market efficiency and integrity.

4.1.2 Changes at the Exchange Level

Whilst changes at the market level have been partly responsible for driving the growth in HFT participation at the exchange level, a number of other initiatives have also supported this dramatic increase. For example, in June 2007, the London Stock Exchange (LSE) introduced a system called TradElect, which promised to deliver an average 10 millisecond latency from order submission to order confirmation.[28]

This system was subsequently replaced by MillenniumIT, which went live in 2011, delivering average latency of less than 120 microseconds, and making the LSE one of the fastest trading venues in the world. Unlike the initial MiFID directives. The LSE also introduced Direct Market Access (DMA) in 2007 (under the name Member Authorised Connection MAC) - a direct, low latency connectivity solution allowing non-member firms to access the Exchange's central clearing engine using an authorised member firm's trading account. This increased investment in market infrastructure was geared *towards* capturing a greater share of the HFT order flow.

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[26] MiFID II - Committee of European Securities Regulator (CESR)

[27] HFT is also being scrutinised at the national level, with a recent proposal in France requiring a tax of 0.1% on firms that cancel more than 50% of their automated orders per day be implemented.

[28] Equivalently accommodating 3000 orders per second.

Despite adopting and abandoning a maker-taker fee structure in 2008 the LSE, responding to pressures from competing trading platforms such as Chi-X and Bats Europe, introduced an amended tiered pricing facility based on trade turnover. With exchanges and MTFs encouraging and implementing low latency access, lower explicit trading costs, and direct market access, HFT will continue to feature prominently across European markets.

4.2 Definition of HFT

Though attempts have been made by regulators, academics, and practitioners to define HFT, most statements in circulation seem only to highlight the fact that HFT is a tool employed by professional traders.[29] More recent and earnest efforts to understand and define HFT have recognised the multifaceted nature of the activity, and these can be used to produce a more accurate and thoughtful explanations.

One source of confusion in many open debates is the relationship between HFT and another prevalent trading activity - algorithmic trading. The two, though possessing some similarities, are not synonyms. Rather, HFT is generally viewed as a subset of algorithmic trading (see Brogaard, 2010) where trading decisions are normally pre-designed and submissions are automated and executed without human intervention. While algorithmic trading is employed in agency trading to achieve particular outcomes such as stealthily capturing liquidity, engaging in block trading in a manner that minimises information leakage, or simply minimising implementation shortfall, HFT is specific to proprietary traders.[30]

More explicitly, HFT is characterised by rapid order submissions and cancellations, and these are normally accommodated by exchanges offering co-location services (thereby facilitating low latency). Furthermore, HFT participants hold little to no over-night positions. This minimum inventory position characteristic adds some insight to the core business model used by those that engage in HFT. HFT traders realise profits from

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[29] For a comprehensive list of definitions see Gomber et al. (2011)

[30] Proprietary traders (or "prop traders") utilise their own capital for trading activities to create profit.

small deviations in prices across hundreds if not thousands of transactions throughout the day, and is therefore a low margin, high turnover trading practice.

Similar to algorithmic trading, HFT is characterised by a broad range of active strategies employed by a diverse group of trading participants. With participants ranging from proprietary market making firms to quantitative hedge funds, and trading strategies that can include both pseudo market-making and statistical arbitrage trading, there is no clear profile to either HFT participants or their trading strategies. HFT is distinguished instead by technological changes; though many HFT trading approaches derive from strategies that have long existed in markets, it is only in recent years that they have been able to be implemented as such high speeds and low costs.[31] With these changes delivering significant competitive advantages to HFT participants, the dramatic growth in HFT over such a short time horizon is not unexpected.

The proxy used for HFT in this chapter is the cancel-to-trade ratio. This ratio is versatile, as it can be constructed from public full orderbook data, and is also highly correlated with HFT given the intensity of the enter and cancellation messages that are necessary to execute this kind of trading. This measure is the most commonly used in the literature, being implemented in papers such as Jovanovic and Menkveld (2011), Hendershott et al. (2011) and Malinova et al. (2013).

4.3 Data

The data used in this chapter relates to all listed securities on the LSE and Euronext-Paris between 2003 and 2011 for which level 10 depth data is available. The 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). In relation to the fields obtained, information is acquired on bid and ask quotes (time-stamped to the nearest millisecond) for up to ten levels of the order book. Intra-day information on market prices, volume, number of level 1 orders/trades, and all changes to the level 10 order book is also collected.

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[31] Whilst the nature of trading strategies employed has not significantly changed over time, the mix of participants organising and executing HFT strategies has fundamentally evolved over this period.

To construct the information leakage metric, company news announcements from the Reuters News Announcement feed (RNA) are used. As these announcements only became available after 2003, the analysis is restricted to the period 2003 - 2011, inclusive.

In order to determine the number of order cancellations, it is necessary to match each trade execution against the limit order book immediately prior to the trade. To match these trade executions, the methodology employed by Hasbrouck and Saar (2013) is used. This involves the assumption that the dominant economic event is the arrival of a marketable limit order. Similar to their data set, when an incoming marketable order executes against more than one standing limit order, multiple messages are generated - one for each limit order that it is executed against. Thus, order executions that carry the same millisecond timestamp and direction and are unbroken by any non-execution message are combined to define a single marketable order.

The cancellations data used in this study are generated by analysing the combination of trade records and level 10 quote data. Any decrease in quoted depth is caused by either an execution against an incoming marketable order or a cancellation or amendment request. All trades and quotes are matched by time and price to account for all quoted depth reductions resulting from trade executions. Changes in the quoted depth are then analysed for the remaining quote updates, with each categorised according to the following rules:

1. If the new quote update increases depth from the previous quote at any of the 10 levels , then it is considered to be due to the addition of a limit order.
2. If the quote update contains additions to depth at some levels and reductions in depth at others, this is considered to be an amendment.
3. If the quote update contains 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.

The number of cancellations is then compared to the number of trades to arrive at the Cancel-to-Trade ratio, which is used to identify the rate of HFT participation. A cancellation ratio has been used in previous empirical works (such as Hendershott et al.

(2011)) to identify the level of HFT participation, and is found to be highly correlated with explicit measures of HFT due to the high rate of order submissions and cancellations necessary to conduct a HFT strategy.

4.4 Metrics of Market Efficiency and Market Integrity

The following section describes the metrics used in the empirical analysis. This section also describes the rationale for the proxies adopted as well as the methods used to construct them.

4.4.1 Market Quality Metrics

The academic literature to date has largely focused on the impact of HFT on those elements of market quality that relate to efficiency: spreads, depth, volatility and to a lesser extent, price discovery. While these elements are fundamental to the operation of efficient markets, the mandate of national regulatory agencies and exchanges alike is to promote both *efficient* and *fair* marketplaces. This study seeks to address the impact of HFT participation on both of these market quality outcomes. Empirical evidence indicates that increasing HFT participation has resulted in increased efficiency. Ideally, this increase in efficiency would occur without harming the integrity of the market. Indeed, one of the main criticisms raised by other market participants against HFT is the impact of HFT on the fairness and transparency of the marketplace. Two integrity metrics are used to address this question, with each of the metrics detailed below.

4.4.2 Market Efficiency

Ideal market efficiency is defined as the minimisation of transaction costs with a maximisation of price discovery; the lower the cost of trading, and the more quickly information is impounded into price, the more efficient the market. Thus, measures of transaction costs and price discovery are useful proxies for market efficiency. Three explicit elements of transaction costs that can be measured in a marketplace include quoted, effective, and realised spreads.

4.4.3 Effective Spreads

Transaction costs are measured using the volume-weighted effective spread calculated on a per-trade basis as in Venkataraman (2001)[32] and averaged across the month. This spread is transformed into a percentage of the share price to arrive at the final statistic as in Equation 4.1

$$RES_{i,t} = 200 \times D_t \times \frac{Price_{i,t} - Mid_{i,t}}{Mid_{i,t}}, \tag{4.1}$$

where; D is the direction of trade t in stock i, and is given a value of 1 for a buyer initiated trade and a value of -1 for a seller initiated trade; *Price* is the traded price of stock i; and *Mid* is the midpoint of the best bid and ask prevailing at the time of the trade.

This metric is separately constructed for every execution in every 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 for each trade. This stock-day 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. In order to reach the monthly-market wide effective spread utilised in this report, the daily-market-wide effective spread is then averaged over every trading day in the month.

To determine the direction of trades, the Lee and Ready (1991) algorithm is used. Specifically, all trades that occur above the prevailing midpoint of the best bid and ask price are classified as buyer initiated and all trades occurring below the midpoint are classified as seller initiated. While Ellis et al. (2000) and Chakrabarty et al. (2007) document that the Lee and Ready (1991) algorithm may misclassify trades at the midpoint, we exclude dark transactions from our sample, relying instead only on lit market transactions. This will limit the impact of misclassifying within-spread executions, as lit transactions will occur either at the bid or ask. Trades occurring at the midpoint are

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[32] Venkataraman, K., 2001, Automated versus Floor Trading: An analysis of execution costs on the Paris and New York Exchanges, Journal of Finance, Vol. 56, No. 4, pg. 1445-1885.

dealt with using the "tick-test", whereby, if the trade immediately prior to the last trade was seller initiated, the last trade will be classified as seller initiated and vice-versa for buyer initiated trades.

There are two alternative measures of transaction costs: realised spreads and quoted spreads. Realised spreads measure the benefits associated with supplying liquidity to a market, as opposed to demanding it. Quoted spreads measure the average cost of demanding liquidity *throughout* the day, as opposed to at the point in time at which trades *actually* occurred. Due to the high degree of correlation between realised, effective and quoted spreads, effective spreads are preferred in this study due to their reflection of the actual conditions that generated each trade.

4.5 Market Integrity

Market integrity is defined as the extent to which market participants engage in prohibited trading behaviours. These prohibited conducts can be categorised as either information-based (such as insider trading) or trade-based (such as market manipulation and front-running). While none of these prohibited actions are directly measurable, there are proxies which are highly correlated with such conduct. The two proxies used for the purpose of this analysis are: information leakage - an indirect measure of the level of insider trading; and dislocation of the end-of-day price - an indirect assessment of the degree of market manipulation.

4.5.1 Information Leakage

Information leakage relates to the dissemination of non-public, price sensitive information prior to the public transmission of the news. The measure of information leakage used here calculates the proportion of public announcements that exhibit leakage. As such, a lower measure implies fewer potential violations of market integrity.

The theoretical and empirical findings of Jovanovic and Menkveld (2011) suggest that it is possible for HFT participants to be better informed than other market participants.

There are several reasons that this could occur. One possibility is that informed traders are trading on private information, resulting in an order imbalance that the HFT participants are able to identify and trade on. Whilst this type of conduct is not directly attributable to the HFT participants, their role in exaggerating the trades of informed participants may exacerbate information leakage, leading to larger pre-announcement run-ups. Kirilenko et al. (2010) find evidence consistent with this theory surrounding the flash crash of 2010.

A second reason HFT participation may exaggerate the appearance of information leakage is related to the ability of mechanical processes to almost instantaneously incorporate changes to public information. With information providers such as Reuters and Bloomberg now selling RSS (Rich Site Summary) feeds in a format that is friendly to mechanical analysis, HFT participants may simply be able to impound the impacts of new information quicker than non-HFT participants.

A third possibility is, in the worst case, HFT participants' informational advantage could be based on their operators (illegal) inside information.

While the true level of insider trading is not directly measurable, the concept of information leakage can be used to estimate it. Both the level of insider trading and the proxy of information leakage seek to measure the extent to which price sensitive information ends up in the hands of a privileged few rather than the market as a whole. Insider trading is the subset of information leakage cases where such conduct is illegal. A proxy for information leakage gives an idea of the extent of the practice and can be considered an upper bound for the incidence of illegal insider trading in a market.

The proxy for information leakage is constructed by measuring the extent of unusual price and volume behaviour prior to price sensitive announcements. The leakage metric is calculated using abnormal price returns relative to a market index.

$$Abnormal\ Return_{i,t} = Return_{i,t} - \beta_i(Return_{m,t}), \tag{4.2}$$

where; $Return_i, t$ is the daily return for stock i on day t, β_i is the stock-specific correlation with the market return constructed during the benchmarking period, and

$Return_m, t$ is the day t market return. This measure is constructed to detect prohibited trading behaviour in equities markets and uses both a market model and a "clean" event window (similar to the measure constructed by Dubow and Monteiro, 2006). The information leakage metric is constructed using a subset of all announcements, those that are price sensitive. An announcement is regarded as price-sensitive when the return of the underlying security between days t-6 and t+2 is more than three standard deviations (σ_i) away from the average seven-day abnormal return ($\overline{sevendayreturn_i}$), which is constructed using a bootstrap procedure over the 250 trading day benchmark period ending at t-10. The bootstrap procedure computes the average return across nine randomly drawn days from the benchmark period 1,000 times, with replacement. The use of period which includes pre- and post-announcement returns allows for sensitive announcements to be captured even if there is substantial price anticipation of the event.

$$\sum_{t=-6}^{t=+2} Abnormal\ Return_{i,t} > \overline{sevendayreturn_i} + 3\sigma_i. \tag{4.3}$$

For an announcement to be included in the sample, it must also occur within a "clean" event window, that is, where there are no other stock-specific announcements within the six day pre-event window. By only investigating announcements from clean events, any price reaction can only be associated with one single announcement. Where the company has more than one announcement within a clean event day, only the first announcement is considered, with the second announcement discarded. A case of suspected leakage is defined as an event where there is an abnormal price movement on one or more days in the t-6 to t-1 pre-announcement period in the same direction as the overall announcement return. An example is given below in equation 4.4 for a positive announcement.

$$\begin{gathered}\overline{AR_i} = \frac{1}{250}\sum_{t=-10}^{-260} AbnormalReturn_{i,t} \\ \text{Information Leakage if any} \textit{Abnormal Return}_{i,t} > \overline{AR_i} + 3\sigma_i \\ \text{Where day t occurs between event day -6 and -1} \\ \text{and there are no days in which } \textit{Abnormal Return}_{i,t} < \overline{AR_i} - 3\sigma_i \\ \text{for any day in the pre-event window (-6 to -1).}\end{gathered} \tag{4.4}$$

A daily price movement is considered abnormal if it is at least 3 standard deviations ($3\sigma_i$) away from the mean abnormal return over the 250 day benchmarking period ending on day t-10. In the case of positive price sensitive announcements, at least one pre-event return must exceed three standard deviations above the mean, where none of the other pre-announcement day's exhibit abnormal returns lower than three standard deviations below the mean.

A measure of information leakage that increases as a market becomes more "leaky" is constructed by examining the ratio of suspected information leakages to clean event windows, as follows in Equation 4.5:

$$\textit{\%Information Leakage} = \frac{\text{\# of information leakages}}{\text{\# of clean event windows}} \tag{4.5}$$

4.5.2 Market Manipulation

Trade-based manipulation is the creation of a false or misleading representation of either price or volume with the intent to affect the market price. Such manipulation reduces the average, long-run informational efficiency of stock prices and degrades overall market quality. There are many types of trade-based market manipulation, and distinctions need to be drawn between actual market manipulations and activities that may merely look like manipulations, such as temporary liquidity imbalances.

Brogaard (2010) and Jarnecic and Snape (2010) both find that HFT participants are inclined to end the trading day in a stock-neutral position. This results in elevated HFT participation towards the end of the trading day. This, coupled with Brogaard's (2010) finding that the trading patterns of HFT's are similarly correlated, could create a false impression that markets are being manipulated.

In this chapter, market manipulation is proxied by examining the number of suspected instances of dislocation of the end-of-day price. Dislocating the end-of-day price involves influencing closing prices so that they no longer represent the true forces of supply and demand. Closing price manipulation affects both the pricing accuracy and liquidity of equities markets, and may, in the long-run, discourage participation in equity markets that exhibit such undesirable conduct. Given the globalised nature of equity trading, any negative impact on liquidity has the potential to increase the cost of capital, discouraging firms from listing on markets known for manipulation. Closing price manipulation also impairs the price discovery process by reducing order flow and distorting prices away from their natural levels. This has the potential to adversely impact the role of market prices in efficiently allocating scarce capital (Goldstein and Guembel, 2008).

There are many reasons that participants may try to manipulate closing prices. These include profiting from derivatives positions on the underlying stock (Kumar and Seppi, 1992), and brokers gaming their clients' perception of their execution ability (Hillion and Suominen, 2004). There may also be an incentive for pension fund managers to manipulate closing prices, as a pension fund's net asset value and performance are often calculated using closing prices, and may be used to determine the ranking between funds as well as the remuneration of the funds' management team. The clustering of such "high-closing" events is documented empirically by both Carhart et al. (2002) and Bernhardt and Davies (2009).

Nevertheless, not all abnormal closing prices are the result of deceitful trading strategies. Stock prices may naturally close at unusual levels if there are announcements towards the end of the day, if brokers needing to fill unexecuted positions become aggressive in their trading, if participants unwilling to hold positions overnight clear their inventory or if large orders are entered towards the end-of-day without considering the liquidity available. It is therefore important to categorise and distinguish between different types of abnormal end-of-day prices.

Distinguishing between the various forms of abnormal end-of-day prices is a challenging task. Following the method established by Comerton-Forde and Putnins (2011), attempts to mark the close are measured as abnormally large end-of-day price changes which exceed predetermined 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, over the previous 30 trading days. The calculation of end-of-day movement and the average distribution of end-of-day movements are shown in equation 4.6.

$$\begin{aligned} \triangle EOD_{i,t} &= \frac{P_{eod,i,t} - P_{eod-15m,i,t}}{P_{eod-15m,}} \\ \overline{\triangle EOD_i} &= \frac{1}{30} \sum_{t=-31}^{t=-1} \triangle EOD_{i,t}, \end{aligned} \tag{4.6}$$

where; $\triangle EOD_{i,t}$ is the return between the closing price and the price 15 minutes prior to the close, $\overline{\triangle EOD_i}$ is the average return over a rolling window of thirty trading days prior to the day being analysed, and σ_i is the standard deviation of $\triangle EOD_i$ 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 over the past 30 days.

There is potential positive price manipulation if $R_{i,t} > \overline{\triangle EOD_i} + 3\sigma_i$

And potential negative price manipulation if $R_{i,t} < \overline{\triangle EOD_i} - 3\sigma_i$

Comerton-Forde and Putnins (2013) show that prosecuted cases of end-of-day manipulation are likely to exhibit next-day price reversion. Instances of abnormal end-of-day price changes which 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”. Without this reversion, the abnormal change in the end-of-day price could be due to changes in the true supply and demand for the stock. In the absence of this reversion, manipulation is not considered to have occurred.

4.6 Research Design

To study the cross-sectional determinants of HFT participation, it is necessary to include variables that are publically available over a long time series. The structural model used accounts for the fact that quoted spreads and measures of market integrity are likely to be endogenously related. Higher levels of suspected cases of market manipulation raise volatility and reduce order aggressiveness, and overall lead to higher bid-ask spreads. At the same time, however, quoted spreads are a non-trivial execution cost of market manipulation. Higher quoted spreads, therefore, are expected to reduce the incidence of manipulation, ceteris paribus.

Market integrity, efficiency, and the level of high-frequency trading are also likely to be simultaneously determined. Both lower costs of trading and improved market integrity increase the level of high-frequency trading. High-frequency trading itself has the potential to lead to lower bid-ask spreads if it leads to a more competitive market environment, characterised by improved market integrity. A three-stage least squares (3SLS) method is adopted to account for the fact that efficiency (spreads), integrity (EOD manipulation or Information leakage) and HFT participation residual errors will likely be cross-equation correlated.

The empirical model is a simultaneous set of three structural equations describing integrity violations alert incidence (Integrity), the effective spread (Spread), and HFT participation (HFT). These are set out in equations 4.7, 4.8 and 4.9 below:

Integrity Eqn:

$$Integrity_{i,t} = \widehat{Spread} + \widehat{HFT} + \text{Control variables + Market Design Changes + Fixed effects,} \tag{4.7}$$

Efficiency Eqn:

$$Spread_{i,t} = \widehat{Integrity} + \widehat{HFT} + \text{Control variables} + \text{Market Design Changes} + \text{Fixed effects} \ , \tag{4.8}$$

HFT Eqn:

$$HFT_{i,t} = \widehat{Integrity} + \widehat{Spread} + \text{Control variables} + \text{Market Design Changes}, \tag{4.9}$$

where: $Integrity_{i,t}$ is a constructed variable including the number of suspected cases of insider trading ("Insider") and market manipulation ("MTC") in market i for month t; $Spread_{i,t}$ is a constructed variable of effective spreads, measuring the cost of a round trip transaction in market i for month t; $HFT_{i,t}$ is a variable that is constructed to proxy the level of HFT participation in market i for month t using the order-to-trade and cancel-to-trade ratios;[33] and market design changes is a variable that takes into account whether the period is pre- or post-MiFID.

The instrumental variables for the endogenously determined items (Spreads, integrity and HFT) are based on reduced-form equations of all the exogenous and predetermined regressors; hat symbols signify these simultaneously determined predicted values. As each of the endogenous variables could in principle, affect each other, the order condition for identification is ensured by excluding from each equation two control variables present elsewhere in the system. For each equation, 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.

Equation 4.10 presents the regression relationships between the level of integrity of a single exchange (proxied by either the percentage of suspected cases of insider trading or the level of marking around the close) and a range of explanatory variables described below:

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[33] The order condition for identification is satisfied in the following ways: Integrity is identified through the exclusion of the Yearly Fixed Effects and Price variables; Efficiency is identified through the exclusion of the End of Quarter Effects and market return, whilst HFT is identified by excluding the End of Quarter Effects, the Yearly Fixed Effects and total Price.

$$\begin{aligned} AI_t = \alpha + \beta_1 \widehat{Spread}_t + \beta_2 \widehat{HFT_t} + \beta_3 Std_t + \beta_4 Return_t + \beta_5 Volume_t \\ + \beta_6 Integrity_(t-1) + \beta_7 MiFID + \beta_8 Quarter + \tilde{\epsilon_t}'. \end{aligned} \tag{4.10}$$

Equation 4.11 describes the level of market efficiency (proxied by the size of the quoted spread):

$$\begin{aligned} Spread_t = \alpha' + \beta_9 \widehat{Integrity}_t + \beta_{10} \widehat{HFT_t} + \beta_{11} Price_t + \beta_{12} Volume_t \\ + \beta_{13} Std_t + \beta_{14} Spread_{(t-1)} + Yearly + \tilde{\epsilon_t}''. \end{aligned} \tag{4.11}$$

While equation 4.12 describes the determinants of HFT participation:

$$\begin{aligned} HFT_t = \alpha'' + \beta_{15} \widehat{Integrity_t}) + \beta_{16} \widehat{HFT_t} + \beta_{17} Std_t + \beta_{18} Volume_t \\ + \beta_{19} HFT_{(t-1)} + \beta_{20} HFT_{(t-2)} + \tilde{\epsilon}''', \end{aligned} \tag{4.12}$$

where: Std_t is the mean standard deviation of daily returns in time period t; Ret_t is the mean daily return in time period t; $Volume_t$ is the mean turnover in time period t; MiFID is a dummy variable for the introduction of MiFID taking a value of 0 prior to November, 2007, and 1 thereafter; Quarter is a dummy variable which accounts for the end of each financial quarter (taking a value of 1 for March, June, September and December, and 0 for all other months); $Price_t$ is the mean price in time period t; Yearly represents yearly fixed effects which are applied to the constructed regressions; and $\tilde{\epsilon}', \tilde{\epsilon}''$ and $\tilde{\epsilon}'''$ represent the residual error terms.

The specifications are modelled separately for all LSE and Euronext-Paris listed securities. Beyond accounting for the potential simultaneity bias in the multiple-equation results, the potential cross-equation correlation of the error terms is addressed by using the three-stage least squares estimation.[34]

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[34] Lindleys paradox identifies that large data sets can result in inflated levels of significance. Robustness tests were conducted clustering the errors so as to account for this phenomenon. The results of these tests are qualitatively similar to those reported in this thesis

4.6.1 Stationarity of the estimates and adjustment for Autocorrelation

Durbin-Watson tests indicated the presence of autocorrelation. In order to assess the optimal lag structure, general to specific F-tests were used, starting with six lags. The optimal lag structure was found to be 1 month for the Spread, Insider Trading and Marking the Close metrics. The HFT proxy was found to exhibit a two month lag structure. The regression analyses have used these optimal lag structures to minimise the presence of autocorrelation, with reported Durbin-Watson statistics for each regression found to be insignificant at the 5% level. The parameters themselves are adjusted for possible auto-correlated disturbances by adopting Newey-West standard errors.

4.7 Descriptive Statistics

For each of the metrics used as dependent variables in equations 4.7, 4.8 and 4.9, descriptive data is presented in Table 4.1. These descriptive statistics are separated both by market and time periods (that is, pre- and post- the introduction of MiFID). This distinction has been made due to the significant structural changes MiFID initiated, including the fragmentation of the European equities market.

The introduction of MiFID appears to have reduced the prevalence of marking the close violations on the LSE significantly, with smaller reductions also observed on Euronext. The impact of MiFID on the amount of information leakage is less clear, with minor reductions observed on the LSE but minor increases observed on Euronext. The proxy for market efficiency, effective spreads, exhibits significant reductions in the post-MiFID period across both markets. This is likely driven by the increased fragmentation observed in the market subsequent to the introduction of MiFID. The proxy used for HFT, the cancel to trade ratio, exhibits a marked increase subsequent to the introduction of MiFID, increasing by over 5 times its pre-MiFID levels for both the LSE and Euronext.

Table 4.1: Dependent Variable Descriptive Statistics by Market

This table reports descriptive statistics on market-wide efficiency and integrity measures during the periods pre- and post-MiFID (January 2003 – November 2007 and November 2007 – December 2011) for both the Euronext Paris and LSE markets. The marking the close measure identifies the number of suspected end-of-day manipulations occurring per year. The information leakage measure is the fraction of price sensitive announcements that exhibited information leakage per year. The effective spread is the market-wide average monthly spread per market in basis points. The cancel to trade ratio is the number of cancellations in a given year across all securities divided by the number of transactions in that year. The mean, median and standard deviation are calculated at the same frequency as the observations.

	Minimum	Mean	Median	Maximum	Std. Deviation	T-Test
Panel A - LSE						
Marking the Close						
- Pre-MiFID	4	31.85	24	139	22.95	-24.3***
- Post-MiFID	2	7.55	7	27	4.62	(-8.25)
Information Leakage						
- Pre-MiFID	0	24.47	25	60	31.56	-3.73
- Post-MiFID	3.77	20.74	17.86	60	13.52	(-1.58)
Effective Spread						
- Pre-MiFID	10.31	17.43	14.84	33.31	6.07	-6.61***
- Post-MiFID	8.13	10.82	10.69	16.45	2.11	(-7.46)
Cancel to Trade						
- Pre-MiFID	0.52	3.07	3.2	6.53	1.39	14.84***
- Post-MiFID	2.2	17.91	15.68	39.5	11.13	(9.37)
Panel B - Euronext-Paris						
Marking the Close						
- Pre-MiFID	13	39.34	37	91	14.34	-7.53*
- Post-MiFID	9	31.81	27	108	18.72	(-2.02)
Information Leakage						
- Pre-MiFID	0	25.35	24.5	100	23.54	3.49
- Post-MiFID	0	28.84	26.09	100	18.04	(0.84)
Effective Spread						
- Pre-MiFID	5.91	11.71	11.26	21.33	3.12	-4.03***
- Post-MiFID	5.28	7.68	7.53	12.23	1.71	(-6.67)
Cancel to Trade						
- Pre-MiFID	0.91	1.42	1.31	2.79	0.32	6.59***
- Post-MiFID	1.7	8.01	6.17	25.93	6.28	(7.92)

4.7.1 HFT Influence on Periodicities

In their analysis of NASDAQ trade and quote data, Hasbrouck and Saar (2013) identify periodicities in their 2008 and 2009 data. These periodicities exist in “wall-clock” time - that is taking timestamps which define milliseconds since midnight. This deconstructs each second into 1000 equally sized buckets, and analyses the arrival rate of orders based upon the part of the second in which they were entered. If there were no patterns to order entry, approximately 1/1000th of orders would exist within every millisecond. Instead, Hasbrouck and Saar (2013) identified very frequent order entries immediately following the start of the second, and less strong, though prevalent, order entries immediately following the half-second barrier.

Hasbrouck and Saar (2013) attribute these peaks in order entry activity to automated trading systems that periodically access the market near the second and half-second boundaries. They further find that these periodicities are on much longer intervals than the minimum latency within which HFT participants are able to react to orders, which they find to be in the sub 20 millisecond range. This leads Hasbrouck and Saar (2013) to identify two subsets of HFT participants, those that are programmed to access and revisit the market periodically, potentially in order to “slice and dice” an institutional order, and those that react to information events. The seminal work of Admati and Pfleiderer (1988) shows that where liquidity is demanded, both informed and discretionary uninformed traders will congregate. It appears that these longstanding theories are also applicable to the millisecond environment.

Figures 4.1 and 4.2 document the millisecond level order entry characteristics of each market during 2003, when little HFT is likely to be present in the respective markets. Figures 4.3 and 4.4 document the order entry patterns at the millisecond level in late 2011, when there was considerably more HFT participation in the markets.

Figure 4.1 considers the month of February 2003 for the Euronext Paris market, with an approximately equal incidence of order arrivals reported throughout the second. This is close to the situation which would be expected with truly random order arrival, that is a uniform distribution at 0.1% (ie, $\frac{1}{1000}$ * 100%). Whilst Figure 4.2 reveals a bulge in

Figure 4.1: Euronext Millisecond Remainders February 2003

This figure displays the distribution of millisecond remainders on all orders entered onto the Euronext-Paris exchange during February 2003.

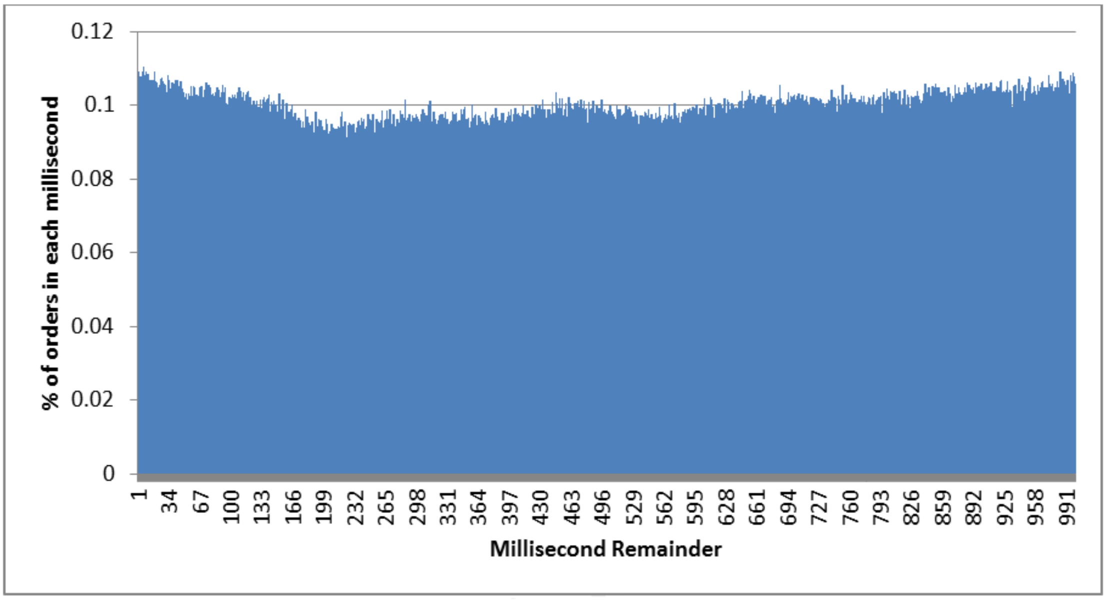
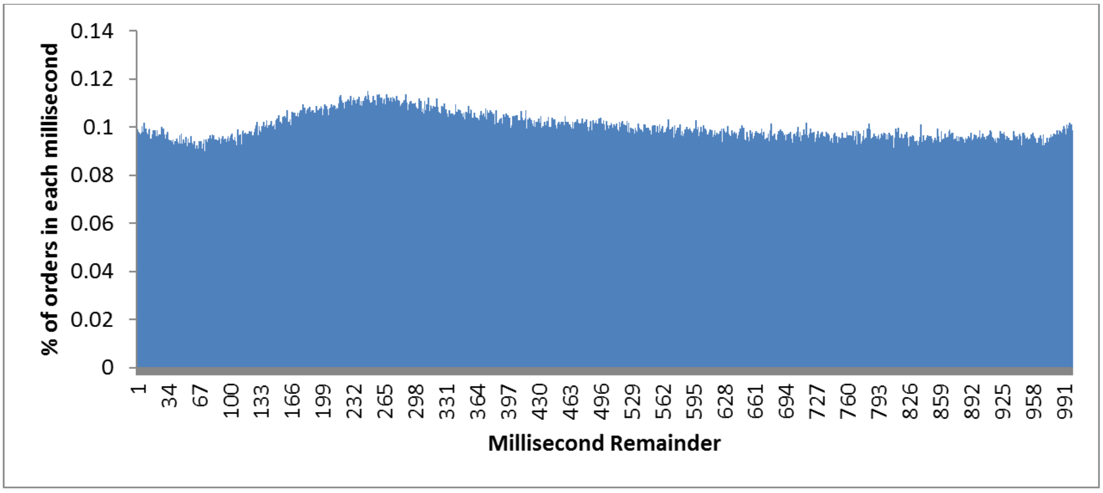


Figure 4.2: LSE Millisecond Remainders February 2003

This figure displays the distribution of millisecond remainders on all orders entered onto the LSE during February 2003.

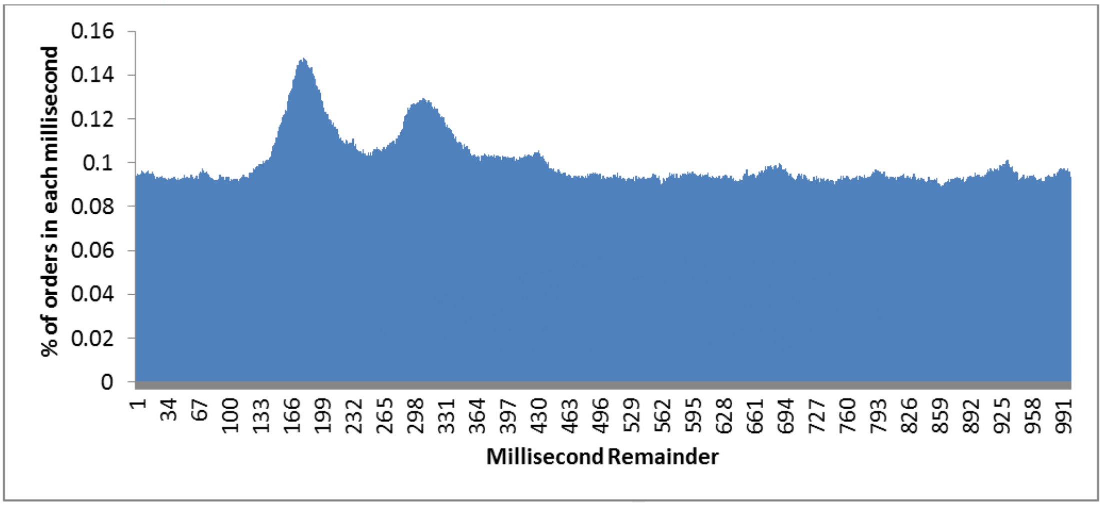


order entries for the LSE between 100 and 300ms, neither market exhibit any particular deviation from the relatively uniform distribution across each millisecond bucket.

Figure 4.3 shows the millisecond order and trade entry pattern for Euronext in December 2011. Euronext exhibits very marked periodicities around 150ms and 300ms. The shape of these periodicities is similar in nature to the double peak observed by Hasbrouck

Figure 4.3: Euronext Millisecond Remainders December 2011

This figure displays the distribution of millisecond remainders on all orders entered onto the Euronext-Paris exchange during December 2011.



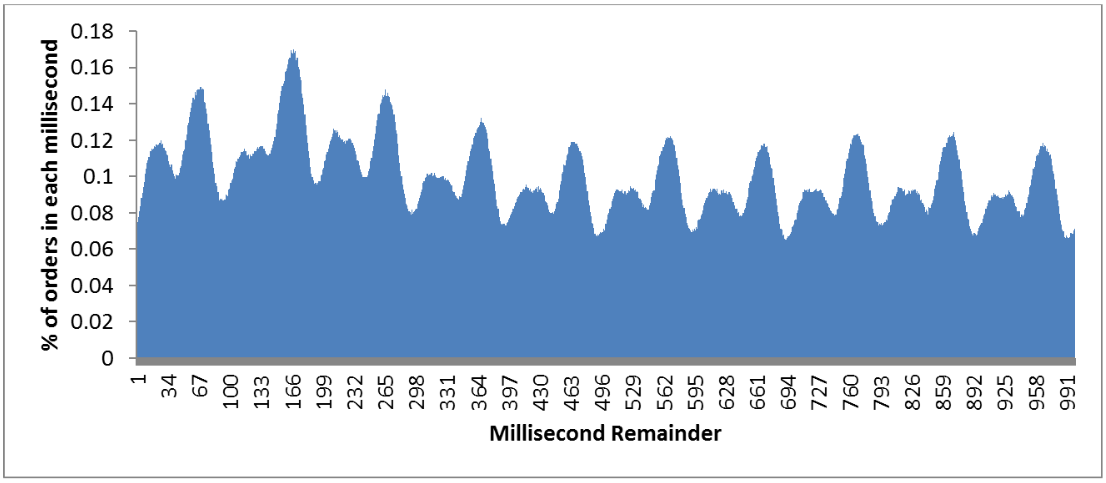
and Saar (2013) in their NASDAQ data for the periods 2008 and 2009. Hasbrouck and Saar (2013) attribute this double peak to either clustering in transmission time (due to geographic latency, with co-located orders arriving at the exchange more quickly than non-co-located orders) or to other potential technological challenges associated with handling large volumes at the firm level.

Figure 4.4 indicates an even more striking periodicity for the LSE during December 2011. There are ten double peaks, offset from the second boundary by approximately 20ms, with each of the second peaks approximately 50ms away from the first. These ten double peaks appear to occur just after the 100ms boundary. This appears to be evidence of the same kind of algorithmic approach to trading found on the NASDAQ and LSE, but occurring every 100ms. As in the Hasbrouck and Saar (2013) 10-second analysis, there appears to be a heightened order submission rate around the first, second and third 100ms periods.

The contrasting appearance of millisecond remainders between 2003 and 2011 confirms that there now exist high-frequency trading patterns that did not exist at the beginning of 2003. This evidence is consistent with the empirical findings of Brogaard (2010) and Jarnecic and Snape (2010), who find significant levels of HFT participation in the LSE market using data from 2009 and 2010.

Figure 4.4: LSE Millisecond Remainders December 2011

This figure displays the distribution of millisecond remainders on all orders entered onto the LSE during December 2011.



4.8 Regression Results

4.8.1 Market Efficiency

Table 4.2 presents the results of the 3SLS estimation described in the research design. Specifically, the determinants of effective bid-ask spreads are examined for the LSE and Euronext-Paris.[35] The percentage of potential insider trading violations (the proxy for market integrity) is found to be positively and statistically significant across both the LSE and Euronext markets, which suggests that a deterioration in market integrity is associated with higher trading costs. This result is consistent with the premise that market efficiency can be improved with appropriate controls and supervision of the trading behaviour of market participants. Whilst this first measure of market integrity is significant for both Euronext and the LSE, the measure of the dislocation of end-of-day prices is only weakly associated with bid-ask spreads on the LSE. Furthermore, it does not have a significant impact on bid-ask spreads on Euronext. This result is consistent with Comerton-Forde and Putnins (2011) who show the bid-ask spread is likely to be *lower* on days where end-of-day manipulation is present, but *higher* the following day as market participants react to the possibility of market manipulation.

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[35] Note that due to the restricted availability of announcement data from January 2003 specifications have been run with only 2003-2011 data. Unreported specifications using the MTC proxy were run over the period 2001 - 2011 with similar results.

Table 4.2: Determinants of the Effective Spread

This table reports the results of the 3SLS regression equation for the determinants of the effective spread for both the Euronext Paris and LSE markets. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. The information leakage measure is the fraction of price sensitive announcements that exhibited information leakage per month. The number of successful MTC identifies the number of suspected end-of-day manipulations occurring per month. Price is the natural log of the average price of all listed securities. Traded volume records the total number of shares traded in the month. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. Lag(spread) represents the 1-month lag of the dependent variable. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext		LSE	
Intercept	-0.217	-0.118	1.269***	0.523**
	(0.147)	(0.159)	(0.278)	(0.200)
Number Successful MTC	0.000	-	0.001*	-
	(0.000)	-	(0.000)	-
Information Leakage	-	0.047**	-	0.117***
	-	(0.019)	-	(0.011)
Price	-0.034***	-0.042***	-0.119***	-0.082***
	(0.007)	(0.008)	(0.021)	(0.011)
Traded Volume	0.019**	0.018**	-0.010	0.001
	(0.007)	(0.007)	(0.009)	(0.008)
Volatility	0.003	0.008**	0.012***	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
HFT	-0.009**	-0.014***	-0.045***	-0.012**
	(0.004)	(0.004)	(0.006)	(0.003)
MiFID	-0.004	-0.005	0.0318**	0.001
	(0.005)	(0.010)	(0.013)	(0.007)
Lag(Spread)	0.632***	0.470***	-0.004	0.288***
	(0.091)	(0.072)	(0.085)	(0.073)
N	105	105	105	105
Durbin-Watson	1.69	1.76	1.84	1.62
Adjusted R-Squared	0.805	0.787	0.864	0.86
Year Fixed Effects	Yes	Yes	Yes	Yes

Results from the regression analysis suggest that HFT participation has a negative and significant impact on bid-ask spreads for both LSE and Euronext-Paris listed securities. This result is foreshadowed by the intense competition for order-flow and market-making revenues documented in the literature. The introduction of MiFID, which, largely through the increase in HFT activity, has increased competition for incumbent exchanges, has thus resulted in lower trading costs for market participants.

The opposing signs on the coefficients for MiFID, whilst initially a curious result, may be explained by the differences in market structures prior to 2007. The introduction of the passporting rule by MiFID allowed stocks listed in any EU country to be traded in any of the venues also regulated by an EU country. It thus provided for significant competition in the trading of securities which is likely to have had a larger impact on Euronext-Paris than the LSE market because the UK market was not previously subject to the concentration rule.

The control variables for price behave as predicted, with higher priced securities reducing the spread across all specifications. The results for traded volume are positive and significant for the Euronext sample. This is likely driven by the market-wide nature of the estimation, with larger traded volume during points of market stress, such as the GFC. Where volatility is found to be significant it increases spreads, as anticipated.

Included year fixed effects are found to be significant and negative, reflecting the deterministic downward trend in spreads through the estimation period that is attributable to both MTFs (such as Instinet-Europe) and MiFID-triggered competition for order flow across exchanges.

Finally, the lag of the bid-ask spread is found to be positive and significant in three of the four specifications. This result is driven by the presence of first-order autocorrelation. The Durbin-Watson statistics ranging from 1.62 - 1.84 are not found to be statistically different from 2 at the 5% level, indicating that the inclusion of the first order lag has accounted for the detected autocorrelation of the residuals.

4.8.2 Market Integrity

Table 4.3 presents the results of the 3SLS estimation for market integrity described in equation 4.10, with the determinants of market integrity specifically examined for the LSE and Euronext-Paris. The results firstly indicate that HFT participation is negatively and significantly related to market integrity, meaning fewer integrity breaches occur as HFT activity increases. This suggests that HFT has not only created a more competitive market environment resulting in lower trading costs, but has also improved the integrity of the operating environment.

The coefficient on the effective spread variable is positive and significantly related to the number of integrity violations in three of the four specifications. This indicates a strong association between attempted market manipulations and bid-ask spreads. This relationship is documented by studies such as Glosten and Milgrom (1985), Copeland and Galai (1983), Meulbroek (1992) and Chung and Charoenwong (1998) as a result of traders and/or market makers identifying the existence of asymmetric information and consequently becoming less willing to trade.

As in the other specifications, MiFID is found to have had differing impacts on the LSE and Euronext. These differences are likely to do with the level of enforcement and regulation existing in each market. In discussions as recent as March 2012, the Economic and Monetary Affairs Committee Rapporteur Arlene McCarthy argued that the fragmentation which MiFID has fostered makes it more difficult to detect instances of manipulation or misconduct.[36] The increased fragmentation in Paris from a single venue to multiple venues may have increased the difficulty of enforcement in Paris. In contrast, due to the UK's higher existing levels of fragmentation, the introduction of MiFID may not have caused any change in the difficulty of regulatory enforcement. The fragmentation of markets leads to a greater ability of manipulators to hide their conduct amongst the crowd of multiple markets. This difficulty of cross-market manipulation may be one of the unintended consequences of the fragmentation caused by MiFID, and bears further scrutiny in its own right.

An additional potential explanation is provided by Cumming et al. (2011). The authors analyse the impact of the introduction of MiFID on US cross-listed ADR's and find that MiFID actually leads to a *reduction* in the European trading of these securities. They attribute this to the complexity of the newly introduced regulations. Such increased complexity may further complicate the role of enforcement agencies within Europe.

The end of quarter fixed effects are found to have a positive relationship with the level of integrity violations. This evidence explains in part the initial non-stationarity of the integrity results prior to inclusion of this deterministic trend variable. This is entirely consistent with the findings of Carhart et al. (2002) - that the incentives for individuals

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[36] European Parliament News Release - 12th of April, 2012.

Table 4.3: Determinants of Market Integrity

This table reports the results of the 3SLS regression equation for the determinants of the market integrity variables for both the Euronext Paris and LSE markets. The information leakage (Insider) measure is the fraction of price sensitive announcements that exhibited information leakage per month. The number of successful end of day manipulations (MTC) identifies the number of suspected end-of-day manipulations occurring per month. Price is the natural log of the average price of all listed securities. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. Return is the average monthly return across all listed securities. Traded volume records the total number of shares traded in the month. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. One month lags of the dependent variables are included to account for autocorrelation. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext MTC	Euronext Insider	LSE MTC	LSE Insider
Intercept	-1.942	-0.438	-596.282***	-490.450***
	(2.248)	(2.454)	(192.204)	(136.297)
Volatility	0.005	-0.082	0.962	10.120***
	(0.035)	(0.057)	(3.223)	(3.119)
Return	-0.118	-0.609	-27.244	-131.842***
	(0.216)	(0.424)	(27.548)	(26.118)
Traded Volume	0.116	0.051	24.585***	23.688***
	(0.091)	(0.108)	(7.949)	(6.055)
HFT	-0.011	-0.097***	-1.002	-5.774***
	(0.020)	(0.032)	(2.368)	(2.092)
Spread	0.386***	0.307***	-0.958	14.221**
	(0.092)	(0.094)	(8.412)	(5.495)
MiFID	0.096*	0.323***	-8.021	-8.864*
	(0.056)	(0.078)	(5.555)	(4.478)
End of Quarter Fixed Effect	-0.000	0.077***	1.946	3.536*
	(0.016)	(0.023)	(2.229)	(1.891)
Lag(Marking the Close)	0.001***	-	0.568***	-
	(0.000)	-	(0.071)	-
Lag(Insider Trading)	-	0.003***	-	-0.032
		(0.001)		(0.061)
N	105	105	105	105
Durbin-Watson	1.73	1.89	2.24	1.87
Adjusted R-Squared	0.252	0.265	0.667	0.579
Year Fixed Effects	No	No	No	No

to commit integrity violations are greater at the end of the quarter due to the calculation of listed fund returns.

Similar to the trading cost specifications, the other control variables behave in the expected fashion. The lag of the MTC and Insider variables are found to be positive and significant in three of the four specifications a result driven by the presence of first-order autocorrelation. The Durbin-Watson statistics ranging between 1.87 and 2.24, after inclusion of the lagged terms, are not found to be statistically different from 2 at the 5% level.

4.8.3 High-Frequency Trading

Table 4.4 presents the HFT results of the 3SLS specification described in the research design section. Specifically, the determinants of HFT participation are examined for the LSE and Euronext-Paris. The proxies for market manipulation (both marking the close and information leakage) are found to be negatively associated with the degree of market participation by high-frequency traders. This result indicates that high-frequency traders either avoid trading in venues that are characterised by lower levels of market integrity or, more likely, that their presence in the market *inhibits* the practice, particularly with respect to closing price manipulation.

The instrument for trading costs shows that as it becomes more expensive to trade, there is a negative impact on the level of HFT activity. This reflects the high degree of sensitivity that high-frequency traders have to the cost of trading, due to the frequency with which they are required to trade. HFT participation does not appear to be significantly related to the total amount of volume in the market. This lack of a significant relationship, despite empirical evidence of HFT participants preferring larger stocks, is likely due to the market-level aggregation conducted.

4.9 Robustness Test - Top Decile

To explore the sensitivity of the results in the previous section, a subset of the initial sample is chosen to reflect the securities which are most likely to be traded by HFT

Table 4.4: Determinants of HFT Participation

This table reports the results of the 3SLS regression equation for the determinants of HFT participation for both the Euronext Paris and LSE markets. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. Return is the average monthly return across all listed securities. Traded volume records the total number of shares traded in the month. The number of successful MTC identifies the number of suspected end-of-day manipulations occurring per month. The information leakage measure is the fraction of price sensitive announcements that exhibited information leakage per month. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. Traded volume records the total number of shares traded in the month. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. One and two month lags of the dependent variables are included to account for autocorrelation. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext		LSE	
Intercept	-115.016***	-27.037	39.762	126.759
	(40.714)	(41.695)	(33.882)	(129.012)
Ln(Volatility)	2.452***	-0.898	0.872*	4.845**
	(0.798)	(0.928)	(0.522)	(1.998)
Ln(Return)	-33.674***	-9.170	0.34	18.999
	(8.761)	(7.716)	(4.817)	(18.647)
Number of successful MTC	-0.258***	-	-0.013	-
	(0.048)	-	(0.017)	-
Information Leakage	-	-20.523***	-	-27.459***
	-	(3.579)	-	(9.620)
Spread	-4.611***	4.037**	-2.641**	-18.553***
	(1.469)	(1.601)	(1.294)	(5.043)
Volume	5.473***	1.776	-1.657	-5.531
	(1.855)	(1.857)	(1.403)	(5.259)
MiFID	-2.859**	4.874***	-0.421	4.326
	(1.193)	(1.180)	(0.974)	(2.802)
Lag(HFT)	1.169***	0.894***	1.293***	1.318***
	(0.109)	(0.108)	(0.085)	(0.097)
Second Lag(HFT)	-0.440***	-0.262***	-0.400***	-0.415***
	(0.104)	(0.097)	(0.084)	(0.100)
N	105	105	105	105
Durbin-Watson	1.82	1.86	2.04	2.07
Adjusted R-Squared	0.806	0.726	0.856	0.849
Year Fixed Effects	No	No	No	No

participants.[37] The securities chosen are from the top traded quintile and are rebalanced on an annual basis. This results in a sample of approximately 570 stocks on the LSE and 220 on Euronext. This sample reflects the most liquid securities in the market so as to be consistent with previous empirical studies such as Brogaard (2010) and Jarnecic and Snape (2010), that show HFT participation exists primarily in large, liquid stocks. As a result, the relationships between HFT activity and the efficiency and integrity metrics are expected to be stronger in this subset than when assessing the market in aggregate.

4.9.1 Market Efficiency

Table 4.5 displays results similar to those of Table 4.2. Spreads are found to increase as the level of information leakage increases, consistent with the findings of Dubow and Monteiro (2006) that reduced market integrity leads to an increase in transaction costs. Attempts to manipulate the closing price do not appear to have an impact on spreads in the most liquid securities. This result is indicative of the difficulty of manipulating the closing price of highly liquid securities. Indeed, the work of Comerton-Forde and Putnins (2011) finds that prosecuted closing price manipulations occur only in low-medium liquidity securities. Therefore it is unsurprising that closing price manipulation does not appear to have an impact on the spreads of the largest listed securities.

high-frequency trading is found to significantly reduce spreads amongst the highest decile of stocks on both the LSE and Euronext markets. This reduction is found to be significant at the 1% level in all specifications. The strength of this result confirms that the market making activity of HFT participants has a stronger impact on reducing spreads amongst the most liquid securities, as compared to all securities.

Consistent with Table 4.2, reductions in spreads due to MiFID are found to be largest for securities listed on Euronext-Paris, demonstrating the significant impact of the concentration rule in introducing competition for European listed securities.

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[37] Unfortunately, due to the limited number of monthly observations, an analysis of a shorter time period is unlikely to provide stable estimates.

Table 4.5: Top Traded Quintile - Determinants of the Effective Spread

This table reports the results of the 3SLS regression equation for the determinants of the effective spread for the top decile of stocks traded on the Euronext Paris and LSE markets. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. The information leakage measure is the fraction of price sensitive announcements that exhibited information leakage per month. The number of successful MTC identifies the number of suspected end-of-day manipulations occurring per month. Price is the natural log of the average price of all listed securities. Traded volume records the total number of shares traded in the month. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. Lag(spread) represents the 1-month lag of the dependent variable. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext		LSE	
Intercept	5.503	17.105**	0.717	-1.363***
	(3.778)	(7.417)	(0.499)	(0.463)
Number Successful MTC	0.012	-	0.000	-
	(0.008)	-	(0.001)	-
Information Leakage	-	3.430***	-	0.367***
	-	(0.610)	-	(0.103)
Price	-0.010	-0.267	-0.014	-0.012
	(0.242)	(0.254)	(0.012)	(0.013)
Traded Volume	-0.250	0.770**	-0.020	0.056***
	(0.170)	(0.324)	(0.019)	(0.018)
Volatility	-0.073	-0.172	0.043***	-0.001
	(0.090)	(0.166)	(0.010)	(0.010)
HFT	-0.351***	-0.477***	-0.031**	-0.083***
	(0.106)	(0.144)	(0.014)	(0.020)
MiFID	-0.198	-1.584***	-0.038	0.015
	(0.237)	(0.325)	(0.028)	(0.028)
Lag(Spread)	0.428***	-0.055	0.822***	0.795***
	(0.100)	(0.110)	(0.047)	(0.085)
N	105	105	105	105
Durbin-Watson	1.51	1.49	2.26	1.91
Adjusted R-Squared	0.462	0.436	0.866	0.747
Year Fixed Effects	Yes	Yes	Yes	Yes

4.9.2 Market Integrity

Table 4.6 documents the determinants of the market integrity metrics. As in Table 4.3, there is a strong and negative relationship between integrity violations and the level of HFT. The presence of high levels of HFT provides competition between electronic market makers, resulting in more efficient prices. Trade-based manipulation, such as trying to influence the closing price, moves prices against their fundamentals. Such attempts at manipulation, if market makers can identify them, provide an opportunity for profit. As manipulators attempt to inflate prices through buying pressure, market makers can sell stock back to the manipulators at these inflated prices, thwarting their attempt to manipulate while also profiting from this attempted manipulation.

Similarly, the ability of HFT to rapidly impound information may allow high-frequency traders to identify, and trade upon, order imbalances generated by insiders. This would result in a rapid movement towards the new, equilibrium price, minimising the profitability of insider trading and so discouraging its' existence. Given the attention paid to large securities by HFT participants, it is unsurprising that this negative relationship exists between market misconduct and HFT.

Similar to the results presented in Table 4.3, Table 4.6 also shows that as integrity violations induce uncertainty around the true value of the security, traded spreads become *wider*. In general, because of the greater degree of certainty around the fair value of larger securities, bid-ask spreads for these set of firms are on average *lower*. Due to this low base, however, integrity violations tend to result in much larger increases in spread, with the positive co-efficient on the integrity variables found to be more significant than those reported in Table 4.3. Taken together, these results imply that there is no significant difference between the estimated specification and the top decile. In fact, the results themselves are stronger in the top decile than what is observed market wide.

4.9.3 High-Frequency Trading

Table 4.7 documents the determinants of HFT participation. As in table 4.4, there is a strong negative relationship between HFT and both measures of market misconduct. As expected, these results are stronger amongst the top decile stocks than in the main sample, reflecting both the scrutiny of these stocks by market participants and the difficulty of manipulating larger securities.

While the relationship between HFT and spreads is found to be negative and significant, the magnitude is not as large for the top decile stocks as it is for the main sample. This is likely due to the fact that many stocks amongst the top decile are already have their spread constrained by the minimum tick size.

Table 4.6: Top Traded Quintile - Determinants of Market Integrity

This table reports the results of the 3SLS regression equation for the determinants of the market integrity variables for the top decile of stocks traded on the Euronext Paris and LSE markets. The information leakage (Insider) measure is the fraction of price sensitive announcements that exhibited information leakage per month. The number of successful end of day manipulations (MTC) identifies the number of suspected end-of-day manipulations occurring per month. Price is the natural log of the average price of all listed securities. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. Return is the average monthly return across all listed securities. Traded volume records the total number of shares traded in the month. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. One month lags of the dependent variables are included to account for autocorrelation. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext MTC	Euronext Insider	LSE MTC	LSE Insider
Intercept	-151.893**	-2.723	47.460	0.772
	(74.006)	(2.122)	(73.018)	(1.638)
Volatility	5.181***	0.030	1.295	0.013
	(1.716)	(0.049)	(1.979)	(0.042)
Return	-56.257***	0.066	-25.874*	-0.283
	(15.109)	(0.162)	(13.809)	(0.276)
Traded Volume	8.407**	0.143	-1.685	-0.023
	(3.312)	(0.094)	(3.006)	(0.066)
HFT	-6.546***	-0.202***	-6.264**	-0.218***
	(1.100)	(0.035)	(2.503)	(0.027)
Spread	6.722***	0.191**	9.490***	-0.063
	(1.503)	(0.025)	(2.962)	(0.053)
MiFID	6.830***	0.393***	-13.926***	0.133*
	(2.337)	(0.071)	(4.264)	(0.073)
End of Quarter Fixed Effect	0.844	0.032**	0.054	0.034***
	(0.575)	(0.012)	(1.414)	(0.010)
Lag(Marking the Close)	0.029	-	0.411***	-
	(0.034)	-	(0.085)	-
Lag(Insider Trading)	-	0.004***	-	0.002***
	-	(0.001)	-	(0.001)
N	105	105	105	105
Durbin-Watson	1.66	1.65	2	2.05
Adjusted R-Squared	0.464	0.155	0.577	0.17
Year Fixed Effects	No	No	No	No

The findings amongst the top decile are qualitatively similar to the results presented in the full sample, with increased levels of HFT associated with lower spreads and fewer integrity violations. Consistent with the findings of previous empirical works, both the significance and magnitude of the impact of HFT on spreads is greater than in the primary sample. In the integrity equations, the HFT variable exhibits the same negative correlation with both insider trading and marking the close that was observed in Table 4.4; however, in the restricted sample these coefficients become highly significant, likely due to the increased attention given to these larger stocks by HFT participants.

Table 4.7: Top Traded Quintile - Determinants of HFT Participation

This table reports the results of the 3SLS regression equation for the determinants of HFT participation for the top decile of stocks traded on the Euronext Paris and LSE markets. HFT represents the number of cancellations in a given month across all securities divided by the number of transactions in that month. Volatility is the standard deviation of 5-minute returns, averaged at the daily level per-stock and then at the monthly level across stocks. Return is the average monthly return across all listed securities. Traded volume records the total number of shares traded in the month. The number of successful MTC identifies the number of suspected end-of-day manipulations occurring per month. The information leakage measure is the fraction of price sensitive announcements that exhibited information leakage per month. The effective spread is constructed as the value-weighted effective spread per stock-day, averaged across all stocks for each day and then averaged monthly across the market and is reported in basis points. Traded volume records the total number of shares traded in the month. MiFID is a dummy variable that takes 0 prior to the introduction in December 2007 and 1 subsequently. One and two month lags of the dependent variables are included to account for autocorrelation. T-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Euronext		LSE	
Intercept	-54.396**	-27.467	33.076***	2.541
	(22.008)	(18.461)	(9.516)	(27.068)
Ln(Volatility)	2.058***	0.638	0.329	0.590
	(0.518)	(0.398)	(0.250)	(0.693)
Ln(Return)	-20.832***	-3.012	0.003	-3.154
	(5.512)	(2.122)	(1.814)	(4.587)
Number of successful MTC	-0.382***	-	-0.035	-
	(0.051)	-	(0.022)	-
Information Leakage	-	-10.047***	-	-20.429***
	-	(1.763)	-	(2.362)
Spread	-2.271***	-1.942***	-1.189***	-1.709*
	(0.444)	(0.297)	(0.359)	(0.886)
Volume	3.097***	1.535	-1.326***	-0.124
	(1.012)	(0.833)	(0.391)	(1.102)
MiFID	1.252**	3.045***	-1.039	0.205
	(0.575)	(0.501)	(0.716)	(1.161)
Lag(HFT)	-0.028	0.151*	0.405***	0.037
	(0.091)	(0.084)	(0.082)	(0.087)
Second Lag(HFT)	0.359***	0.232***	0.221**	0.114
	(0.091)	(0.084)	(0.086)	(0.077)
N	105	105	105	105
Durbin-Watson	1.79	1.72	1.96	1.98
Adjusted R-Squared	0.596	0.655	0.83	0.569
Year Fixed Effects	No	No	No	No

4.10 Conclusion

This study examines the impact of HFT activity on the efficiency and integrity of the Euronext-Paris and LSE marketplaces. While a number of academic studies have shown that HFT participation has a negative impact on market efficiency (as proxied by both realised and effective spreads), none of these studies have examined the impact of HFT on integrity, nor have any examined the interaction between the multiple dimensions of market quality and HFT.

In order to understand the impact of HFT participation on the LSE and Euronext markets, a range of key market metrics are examined over a nine year period - from 2003 to 2011. The results indicate that there has been significant structural change in the two markets during this period. The average trade size and value have reduced significantly as have average bid-ask spreads. This evidence directly coincides with the introduction of HFT activity, whose participants have been empirically shown to trade in smaller packages. The results further show significant increases in both the order to trade and cancel to trade ratios, following the introduction of HFT participants, whose strategies require frequent order entry and cancellation. The results also identify significant changes in the millisecond periodicities in each of the two markets between 2003 and 2011. In particular, there are heightened levels of activity observed at a frequency of 100ms for the LSE. Collectively, this evidence indicates a significant and rapid acceleration of HFT activity in both marketplaces.

The reduction in spreads observed over the sample period in this chapter is consistent with the theoretical predictions of Jovanovic and Menkveld (2011), which suggest that because HFT participants are better able to update their information sets relative to other market participants, they incur lower adverse selection and inventory holding costs as compared to traditional market makers.

In order to examine the impact of this increased HFT activity, the cancellation to trade ratio is utilised as a proxy for HFT - as commonly used in the academic literature. Relative effective spreads are used as a proxy for efficiency, and two measures are constructed to proxy for the level of integrity in the market - one for insider trading and the other for end-of-day manipulation. These metrics are integrated in a three-stage simultaneous regression framework, which allows for the endogenous relationships that may exist between each of the dependent variables while also controlling for fixed effects arising from the regulatory environment and other external variations through time.

The results of the simultaneous equations regression framework indicate that the increasing level of HFT participation on the LSE and Euronext-Paris markets have unambiguously increased market efficiency by reducing bid-ask spreads. This result is consistent with both the observed decrease in spreads through time and the theoretical and empirical findings of previous HFT studies.

The results for market integrity suggest a negative relationship between HFT participation and dislocation of the end-of-day price, which is used as a proxy for closing price manipulations. This evidence implies that while HFT participants may increase their activity towards the end-of-day, they do not do so with enough force or co-ordination to dislocate the closing price. Rather, it seems HFT participants actually reduce the incidence of end-of-day manipulation by *providing* liquidity to potential manipulators, minimising their impact on the market.

The impact of HFT on insider trading is less clear. While it appears that HFT participation is associated with *less* insider trading on Euronext, it seems to be associated with *more* insider trading on the LSE. The ambiguous direction of this relationship may be a function of the regulatory design or enforcement differences between the two markets, or could be due to other market-specific structural changes not controlled for in the current study.

Overall, the results indicate that the increase in the level of HFT activity in the past decade has increased market efficiency without significantly harming the integrity of the market. Indeed, there is evidence that the integrity of the market has actually improved as the level of HFT participation has increased. This additional evidence on market integrity dispels concerns that HFT participants undermine market quality by creating an “uneven” playing field.

Chapter 5

Impact of Dark-Lit Order Interaction

5.1 Introduction

Over the last decade an increasing fraction of equity market trading volume has changed hands without pre-trade transparency. This dark trading occurs on both separate, dedicated venues, such as so-called dark pools, and on public venues that introduce dark order types. The shift of trading to the dark has attracted the attention of regulators and policy-makers worldwide, with particular interest focused on the implications of dark trading for market quality.[38] Proponents of dark trading argue that using dark venues gives larger orders the opportunity to avoid being “front run” by sophisticated computer algorithms that can detect large orders. On the other hand, opponents of dark trading argue that it removes liquidity from visible (or “lit”) markets and harms market participants by hampering the price discovery process.With the impact of dark trading on market quality still uncertain, it has been difficult for regulators to determine what action to take, or even if further regulation is necessary at all.

There are several difficulties with conducting empirical analysis of the impact of dark trading on market quality. One major difficulty is that little data on dark trading

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[38] For instance, Canadian regulators recently decided to take steps to significantly curtail dark trading (starting October 12, 2012), which is the subject of the subsequent chapter.

has been made available. Furthermore, new dark order types have little impact until a sufficient proportion of market participants have access to them, which causes difficulties in performing event type studies. Finally, dark trading may be endogenous to market conditions, as highlighted in Buti et al. (2011b), and so it is challenging to establish a causal relation without sufficiently granular data.

With these challenges in mind, this chapter conducts separate analyses on the effect on market quality of both the introduction, and subsequent intra-day usage, of fully hidden orders on the Toronto Stock Exchange (TSX), using a proprietary order-level data set. Dark orders on the TSX were largely introduced in two-stages. The TSX is the main exchange in Canada with more than 60% market share in trading volume, and all brokers are connected to it. From the first of April 2011, the constituent stocks of the TSX60 (the main index) could be traded using dark orders; starting May 20, 2011, all remaining symbols were enabled for dark trading. These dark on-exchange order types are able to interact with non-dark orders as well as fully hidden orders. Using this staggered introduction of dark trading an event study is performed to examine the impacts of dark trading on market quality. A difference-in-differences design is employed which controls for any market-wide fluctuations in the measures of market quality. The order-level data enables the study of the intra-day relationship between dark trading and market quality.

While the focus of this chapter is the examination of the impact of dark trading on a visible exchange, the results also provide insight into dark trading in general. Specifically, the results of this study also apply to a situation wherein a dark pool venue that matches orders continuously is introduced alongside a visible market, assuming that trades in this new dark pool occur at a price within the visible spread. Obtaining a fill on the dark venue would therefore be cheaper and, ceteris paribus, market-order traders would have incentive to send their order to the dark venue first and then route any unfilled portion to the visible venue. Liquidity providers would then be in a similar situation as found in this study, since they would have to account for the possibility of dark liquidity that would execute before their quotes are hit. Thus, the observations from this analysis also provides insight into the assessment of the impact of such dark pool trading.

Furthermore, studies of markets in Canada are relevant to the world's largest market, the U.S., since many market players (such as high-frequency trading firms) are active in both markets, and key features of market regulation, including so-called best execution and order protection, apply in both markets.

5.2 Institutional Detail

Dark trading in Canada refers to a trading environment characterised by a lack of *pre-trade* transparency. In other words, traders do not publicly reveal their trading intentions. Canadian regulation does, however, mandate immediate post-trade transparency of prices and quantities for all transactions, whether they be dark or lit.

Trading away from visible markets can occur in the form of broker crosses, electronic (buy-side) crossing networks (e.g., Liquidnet), and continuous dark pools (e.g., ITG's MatchNow). Trading in Canada follows rules that, historically, have been designed to foster transparency and trading on marketplaces with pre-trade transparency. For instance, trades in the off-exchange market, colloquially referred to as "upstairs" trades, have to follow a set of rules. Such orders fall under the "order exposure rule" which requires that these orders be exposed to the public market.[39] Once an upstairs cross has been arranged, it must be reported to a public exchange immediately; Canada has no trade reporting facilities as in the U.S. or Europe, and broker crosses are usually posted on the TSX. Unlike the U.S., where a large fraction of retail orders are either internalized by broker-dealers or sold in payment-for-order-flow arrangements, in Canada off exchange internalisation is discouraged, and payment-for-order-flow arrangements are illegal (including those using U.S. based systems).[40]

As mentioned earlier, the focus of this chapter is undisplayed, on-exchange orders, also known as "dark orders". In Canada, the Toronto Stock Exchange (TSX) and Chi-X

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[39] An exception arises if the broker who facilitates an off-exchange trade provides price improvement. If the order is sufficiently large (more than 50 standard trading units (usually 100 shares) or $100,000 in value), price improvement is not required, but order protection regulation still applies so that same-priced orders on visible venues must be cleared; further details are outline in Section 6.4 of the Universal Market Integrity Rules (UMIR). See also Smith, Turnbull and White (2001) for more details on the Canadian upstairs market, or Bessembinder and Venkataraman (2004) for the French upstairs market.

[40] For the TSX Composite stocks there are, on average, less than two dealer crosses per day with an average size in excess of 100,000 shares; see Table 5.1 for details.

Canada offer the submission of priced orders that do not display any volume. These dark orders are part of the limit order book and they interact with incoming marketable orders. Dark orders can be either midpoint orders or priced limit orders. Midpoint orders execute at the midpoint of the national best bid and offer price, provided that the bid-ask spread is not locked or crossed.[41] Submitters of midpoint orders can further specify a limit price such that the order does not execute at prices outside of that limit. Midpoint orders will generally have price priority though at the same price level, visible orders receive priority over dark orders. In the sample, around 65% of all dark order volume is midpoint pegged, and 66% of executions with dark orders involve midpoint-pegged dark orders.

5.3 Data

The analysis uses a proprietary order-level data set, provided by the Toronto Stock Exchange (TSX).[42] This data specifically identifies dealer crosses, and these trades are excluded from the sample as the timing and size of crosses is likely to be determined by a number of unobserved and uncontrollable factors. Most visible market trading in Canada occurs on the TSX, TMX Select, Pure, Alpha, and Chi-X, and to compute their respective market share, their volume data is obtained from SIRCA's ThomsonReuters Tick History.[43] Data on shares outstanding, splits, and index status is obtained from the monthly TSX e-Review publications. Data on the Canadian volatility index VIXC is taken from the Montreal Exchange's website. Trading days that have no or limited U.S. trading (U.S. Thanksgiving and Black Friday, for example) are excluded as there is little trading in Canada on these days. Information on scheduled U.S. market closures is obtained from the NYSE Calendar.

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[41] The NBBO is locked when the best bid on one venue is equal to the best ask on another. The NBBO is crossed when the best bid on one venue is *higher* than the best ask on another.

[42] Legal disclaimer: TSX Inc. holds copyright to its data, all rights reserved. It is not to be reproduced or redistributed. TSX Inc. disclaims all representations and warranties with respect to this information, and shall not be liable to any person for any use of this information.

[43] The only visible market place that the data does not cover is Omega ATS; according to the annual IIROC trading statistics (available on their website, www.iiroc.ca), Omega's market share in 2011 was below 2.2% of all dollar-volume.

The TSX introduced dark orders in three phases, and this structure of introduction informs the design of the analyses in this chapter. On March 15, 2011, three symbols (BBD.B (Bombardier Class B shares), COS (Canadian Oil Sands), and SC (Shopper's Drugmart)) could be traded with dark orders. This was followed with the introduction of the constituents of the TSX60, Canada's blue-chip index, and all Exchange Traded Funds (ETFs) on April 1st, 2011. Then, from May 23, 2011, all symbols were allowed to be traded with dark orders. Figure 5.1 documents the level of dark trading on the three dark venues during the sample period. The way in which these dark order types were introduced allows for two separate natural experiments. The first is an event study designed to understand the impact of the introduction of dark orders, is performed on the April 1st adoption of dark orders for TSX60 symbols. The second is an analysis into the effect of the actual usage of dark orders, and for this the intra-day occurrence of dark trading is examined. For this second analysis to be meaningful a sufficiently large uptake of dark orders is required, and so the second half of 2011 is used as the sample period for this intra-day study, as by then dark trading was available for all securities.[44] To avoid potentially contaminating effects from the market opening and the market-on-close facility (beginning at 3:40 p.m.) only data between 9:45 a.m. and 3:35 p.m. are used for this analysis.

The TSX data encompasses all incoming and outgoing information from the central trading engine, including all messages from the (automated) message protocol between the brokers and the exchange. These messages include all orders, cancellations and modifications, trade reports, and details on dealer (upstairs) crosses. Each message consists of up to 500 sub-entries, such as the date, ticker symbol, time stamp, price, volume, and order visibility. As this chapter focuses solely on dark trading via the limit order book, opening trades, odd-lot trades,[45] dealer crosses, trades in the special terms market, and trades occurring outside normal trading hours are all excluded. The data also specifies the active (liquidity demanding) and passive (liquidity supplying) party, thus identifying each trade as buyer- or seller-initiated. The data provides a

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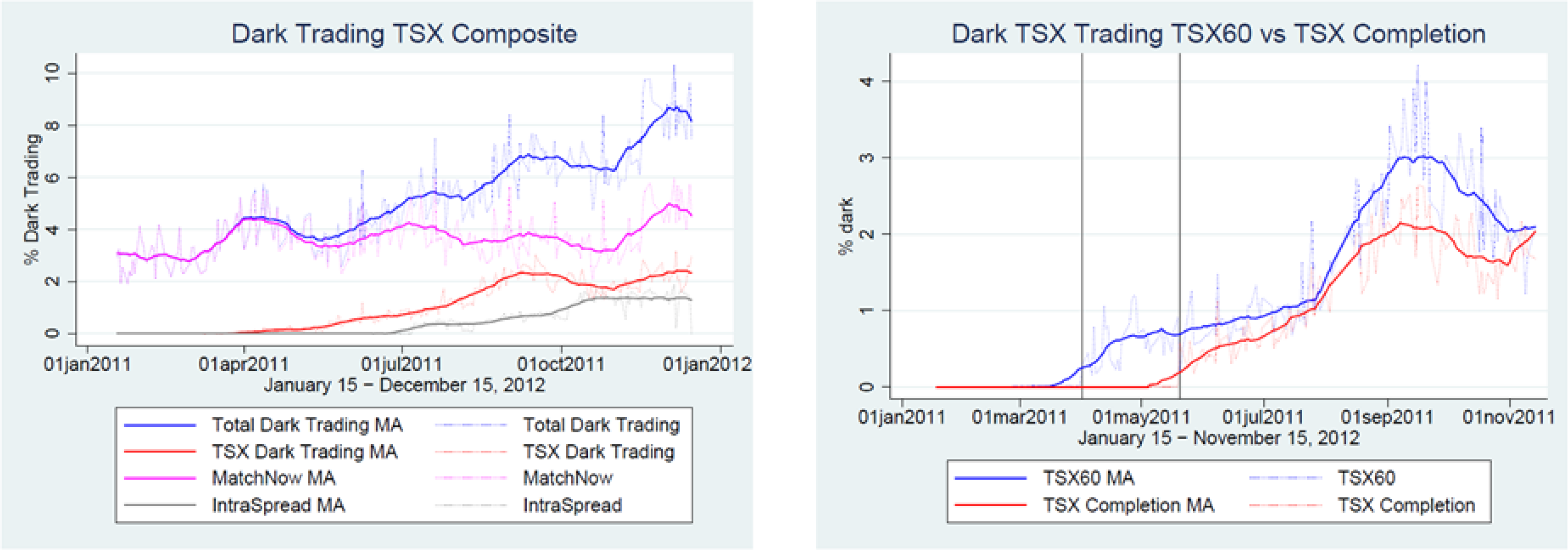
[44] It appears that a number of traders only started using these orders after they were available for all securities.

[45] Odd-lot trades are portions of orders that are not in multiples of 100 shares; these are not cleared via the limit order book, but they are automatically cleared via the so-called registered trader for that symbol.

system message identifying the “prevailing quote”, the best bid and ask quotes, as well as the depth at the best quotes, and is updated each time there is a change in the price or depth of these quotes. Starting with the introduction of dark orders, the data additionally provides the prevailing national best bid and offer prices.

Figure 5.1: Fraction of Canadian Liquidity in the Dark

The left panel plots the percentages of average daily per-company dark volume of all continuous Canadian-trading volume (i.e., excluding dealer crosses) for the sample of TSX Composite securities. The data is also split up by MatchNow, Alpha IntraSpread and TSX dark. The right panel plots the average daily share of TSX volume that involves dark orders, split by the TSX 60 and the TSX Completion constituents. Vertical lines indicate the event dates from the introduction of dark orders for the TSX60 (April 01, 2011) and the TSX Completion (May 20, 2011). All plots contain the levels (thin, light-coloured lines) and 15-day moving averages (thick, bold-colored lines).



5.4 Sample Selection

The TSX Composite index is split into two groups: a treatment group of TSX60 stocks, and a control group which comprises the remaining stocks. This control group, consisting of companies that are in the TSX Composite but not in the TSX60, is also referred to as the “TSX Completion” index. Companies must remain part of the TSX Composite for the entire sample period to be included, and any securities that have stock splits are also excluded (January - May for the introduction, January-December for the intra-day analysis). Furthermore, stock-days with an average midpoint below $1, or stocks with fewer than 10 transactions per day are also excluded. Fairfax Financial Holdings (FFH) is also excluded as it has an average share price above $400 (the second highest priced stock in the sample has an average price of around $120). Finally, because of damaged data files and suspected data errors, all data for January 3rd, October 3rd and November 30th is excluded, and, for symbol ABX only, November 9th is excluded. These exclusions leave 230 securities which are used for both the introduction and intra-day analysis. Of these, 53 are constituents of the TSX60, with the remainder being constituents of the TSX Completion Index. While it is not ideal to consider the TSX60 separately from the rest of the market, this is the natural experiment that has presented itself. In order to overcome the differences that may be inherent between the TSX60 and the remainder of the market, only the TSX Completion index is used in the non-introduction control sample. Additionally, controls are incorporated for differences in the price and level of constraint of the securities, which should control for any structural trading differences between the two samples.

5.5 Regression Methodology for the Introduction of Dark Orders

To understand the impact of the introduction of dark orders, an event study approach is used. A panel of TSX Completion constituents are used as a control group for the TSX60 constituents to account for market-wide fluctuations. There is major limitation to using the composite stocks as a control group, namely, TSX60 constituents are larger and trading in these stocks is more competitive. This manifests in the data in a number of ways: for example, bid-ask spreads are smaller and depth is larger. These issues are controlled for by including firm fixed effects.[46]

Further controls for daily fluctuations in market-wide volatility are introduced by using the Canadian volatility index VIXC. This index is based on the implied volatility of TSX60 index options. To account for the possibility that the TSX60 and the TSX Completion constituents react differently to changes in this index, specifications were estimated in which a differentiated response to the VIXC was allowed by interacting it with a dummy for the TSX60 and the TSX Completion.

Degryse et al. (2011) and O'Hara and Ye (2011) show that market fragmentation plays a major role in understanding trading costs. The method of Degryse et al. (2011) is adopted, with fragmentation measured as one minus the per firm daily Herfindahl-Hirschman Index (HHI) based on the squared shares of total volume that are traded on each venue. The contemporaneous observation of fragmentation is used as a security-level control variable. For the sample of TSX Composite firms in the second half of 2011, market fragmentation was about fifty percent, meaning half of all trading occurred on the TSX, with the other half occurring on other venues; see Table 5.1 for further fragmentation statistics.

To avoid biased standard errors (whether stemming from observations being correlated across time by firm, or across firms by time, or both), an approach suggested in Petersen (2009) is used. This approach compares a variety of specifications to determine which fixed effects need to be included and on which variables the standard errors should be clustered. Based on this approach, standard errors are clustered by both firm and date for all specifications in this paper.[47]

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[46] Alternatively, regression specifications were also run in which controls were introduced for size and a number of other long-term, pre-event liquidity-determining measures; the results from this analysis are similar. A number of securities are also cross-listed with U.S. exchanges. The results for the group of cross-listed securities is similar to the main analysis, though the estimates have lower significance, and the results for the non-cross-listed securities are inconclusive. There are, however, few non-cross-listed securities in the TSX60, while there are few cross-listed securities in the control group of TSX Completion securities, overall causing the tests to have low power. This analysis is thus omitted from the dissertation.

[47] Cameron et al. (2011) and Thompson (2011) developed the double-clustering approach simultaneously. Controlling for autocorrelation of the errors for up to 5 lags had no impact on the results and thus the results presented are without this correction.

5.5.1 Part 1: Event Study.

The first part of this analysis is an event study performed on the effect of the introduction of dark orders. This study is based on daily averages of a number of key measures. For each measure, the following regression is run:

$$\textit{dependent variable}_{it} = \alpha_i + \beta_1 \times \text{event}_t \times \text{tsx60}_i + \beta_2 \times \textit{event}_t + \sum_{j=1}^{n} \beta_{2+j}\, \textit{control}_{ijt} + \epsilon_{it}, \tag{5.1}$$

where: *dependent variable*$_{it}$ is the value of the dependent variable on day t for security i; α_i are firm fixed effects; *event*$_t$ is an indicator variable taking the value 1 after the event date, April 1st, 2011, and 0 before; tsx60$_i$ is an indicator variable taking the value 1 for constituents of the TSX60 (the treatment group) and 0 otherwise; and *control*$_{ijt}$ are daily realisations of security level control variables for the company, and depending on the specifications, the log of the average daily mid-quote, the level of market fragmentation, and the Canadian VIX (possibly interacted with the index constituency indicator). The variable of interest in the regressions is the coefficient on the event-treatment group interaction term, β_1.

To further understand the effect of a change in the level of dark trading on the dependent variables, a specification is constructed in which the daily percentage of dark volume is included. This is defined as the percentage of daily TSX trading volume for which at least one side of a trade is a dark order. Due to the endogeneity between dark trading and measures of market quality (as identified by Buti et al. (2011b)), the specification is estimated using a two-stage approach, whereby an instrument for the percentage of dark trading is used. The interaction of the event with index constituency (event$_t$ × tsx60$_i$) is used to instrument dark trading in the first stage. This instrument provides an exogenous event which activates dark trading for the constituents of the TSX60 without impacting dark trading for the remaining listed securities. The first stage regression is as follows:

$$\begin{aligned} \textit{\% Dark Trading}_{it} = \alpha_i + \beta_1 \times \textit{introduction}_t \times \textit{TSX60}_i + \beta_2 \times \textit{introduction}_t \\ + \beta_3\, \textit{VIXC}_t + \sum_{j=1}^{n} \beta_{3+j}\, \textit{control}_{ijt} + \epsilon_{it}. \end{aligned} \tag{5.2}$$

This estimate of the level of dark trading is then used in the second-stage regression to identify the impact of this dark trading on variables of market quality using Equation 5.3:

$$\begin{aligned} \textit{dependent variable}_{it} &= \alpha_i + \beta_1 \times \%\ \textit{dark trading}_{it} + \beta_2 \times \textit{event}_t \\ &+ \beta_3\, \textit{VIXC}_t + \sum_{j=1}^{n} \beta_{3+j}\, \textit{control}_{ijt} + \epsilon_{it}. \end{aligned} \tag{5.3}$$

The estimated coefficient β_1 can then be interpreted as signifying the linear effect on the dependent variable caused by a 1% increase in dark trading. A number of tests are run to ensure that the regression is not misspecified and the Kleibergen and Paap (2006) Wald statistic of under-identification is computed, which, for this specification, is $\chi^2(1)$ distributed. The Kleibergen and Paap (2006) statistic for weak identification is also computed (critical values as per Andrews and Stock (2005)). Since only a single instrument is used, it is not necessary to test for over-identification.[48]

In principle, the introduction of dark trading for non-TSX60 stocks after May 20, 2011, could allow for the construction of a second event study. In reality, however, a simple event study with a regressor such as second *event 2 × non-TSX60 stock* is difficult to interpret. As the adoption of dark trading took place over time, the extent of dark trading in the TSX60 stocks continued to increase past the second event date - that is, after May 20, dark trading continued to change for both groups. This continuing change in dark trading could instigate learning effects. In addition to this, dark trading for TSX60 stocks may also be affected directly by the second event. One example where this could occur is in a situation where a group of traders are trading in both TSX60 and non-TSX60 stocks, but wait until the second event before starting to use dark trading, perhaps because of technological limitations. With these two caveats in mind, a specification similar to (5.3) is estimated, with the percentage of dark trading instrumented by the interaction of the two events with the affected index constituents - $\text{event}_t^1 \times \text{tsx60}_i$ and $\text{event}_t^2 \times \text{non-tsx60}_i$. For this specification, however, many estimations

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[48] Lindley's paradox identifies that large data sets can result in inflated levels of significance. Robustness tests were conducted clustering the errors so as to account for this phenomenon. The results of these tests are qualitatively similar to those reported in this thesis

led to a rejection of the over-identification test, as based on Hansen's J-stat, indicating that the IV coefficients did not vary significantly when using different subsets of the excluded IV sets. This finding is consistent with the economic intuition that there are spill-over effects following the second event. Any interpretation of the IV coefficient would then be biased with the effect of the second event on the outcomes for non-TSX60 constituents. The results for these estimations are accordingly not presented.

5.5.2 Part 2: Intra-Day Analysis.

To understand what impact dark trading has had on liquidity, continuous dark trading in TSX60 stocks is examined. Of particular interest is whether dark trading has an impact on market liquidity.

Buti et al. (2011b) argue that there may be an endogenous relationship between market quality variables and dark trading activity. As dark trading is found to be concentrated in large, tick constrained stocks, it is difficult to determine whether dark trading has helped constrain the spreads, or these constrained spreads have driven dark trading. To overcome this endogeneity problem, it is necessary to instrument dark trading . The fraction of dark *order* volume at time $t-1$ is used as an instrument for the fraction of dark *trading* volume at time t, where t is measured intra-day, and dark trading volume is defined as the volume of trades for which a dark order was on the passive side. The intuition behind this construction is that lagged dark orders correlate with dark trading because orders precede executions. Since dark orders are invisible until they are part of a trade, they cannot directly affect market quality measures that are based on visible measures. Consequently, dark order volume should only affect market quality variables when dark trades actually occur. Furthermore, dark order volume at time $t-1$ is, arguably, not affected by future bid-ask spreads. One possible limitation of this approach is that liquidity variables such as the bid-ask spread are serially correlated. Therefore, when submitting a dark order at time $t-1$, traders may form expectations about the spreads at t.

As in the first part of the study, firm fixed effects are used and errors are double-clustered by time and firm. Figures 5.2 and 5.3 show that there are intra-day patterns in spreads, depth, volume, and volatility. To control for the possibility that the intra-day patterns of observable variables affect outcomes, time-of-day fixed effects are also included. The impact of dark order introduction is analysed in a number of specifications, that use different controls, including the average log-midpoint in each 10-minute bucket, the level of market fragmentation in each stock, and the daily realisation of the Canadian VIX.[49]

The trading day is split into 35 10-minute intervals between 9:45 a.m. and 3:45 p.m., with average liquidity measures computed and aggregated for each interval. Shorter intervals are undesirable as they result in many empty observations for dark trading, while longer time intervals (eg, daily) would negate the justification for the relationship between dark orders and dark trades, as the dark orders would no longer be contemporaneous with the executions that follow them.

In the first stage regression, the fraction of dark trades is instrumented using the fraction of dark orders submitted in the preceding 10-minute period, as described in Equation 5.4:

$$\%\ \mathit{dark\ trading}_{it} = \beta_1 \%\ \mathit{dark\ orders}_{it-1} + \beta_2 \mathsf{VIXC}_d + \sum_{j=1}^{n} \beta_{3+j}\, \mathit{control}_{ijt} + \epsilon_{it}. \tag{5.4}$$

The following specification is then analysed using in the second-stage regression:

$$\mathit{dependent\ variable}_{it} = \alpha_i + \gamma_{(k)} + \beta_1 \times + \beta_2 \mathsf{VIXC}_d + \sum_{j=1}^{n} \beta_{3+j}\, \mathit{control}_{ijt} + \epsilon_{it} \tag{5.5}$$

where: α_i and $\gamma_{(k)}$ are stock and 34 time-of-day fixed effects respectively;[50] VIXC_d is the daily realisation of the Canadian VIX. Contemporaneous stock-level control variables, suggested by Degryse et al. (2011) are used. These include: volatility (the Hasbrouck and Saar (2013) measure of maximum relative price fluctuation in a 10-minute time

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[49] The Canadian VIX is equivalent to the U.S. VIX and is constructed by the Montreal Exchange. It measures the market's expectation of stock market volatility over the next 30 day period using index options prices.

[50] In untabulated regressions day-dummies were included in addition to the other dummies; the results are similar to the ones presented both in terms of magnitude of the effects and in terms of statistical significance.

interval is used), volume, fill-rate (trade volume relative to order volume), and the average execution size. Finally, the average of volatility, volume, and trade-size over all stocks except for i are used as firm-level controls.

Figure 5.2: Intra-Day Patterns of Volume and Dark Trading

The figure displays a the intra-day trading patterns of TSX volume and the share of dark volume of orders and trades. The horizontal axis marks the 35 10-minute trading intervals between 9:45 a.m. and 3:35 p.m. The left panel plots the patterns of average total and dark log-\$-volume on the TSX over the 230 TSX Composite securities for the second half of 2011. The total TSX volume is measured on the left vertical axis, and the TSX dark volume is measured on the right vertical axis. Both series display a U-shaped pattern. The right panel plots the average share of dark volume of TSX trading and order volume. As the plot illustrates, dark volume as a share of total trading and order volume is, loosely, flat throughout the day.

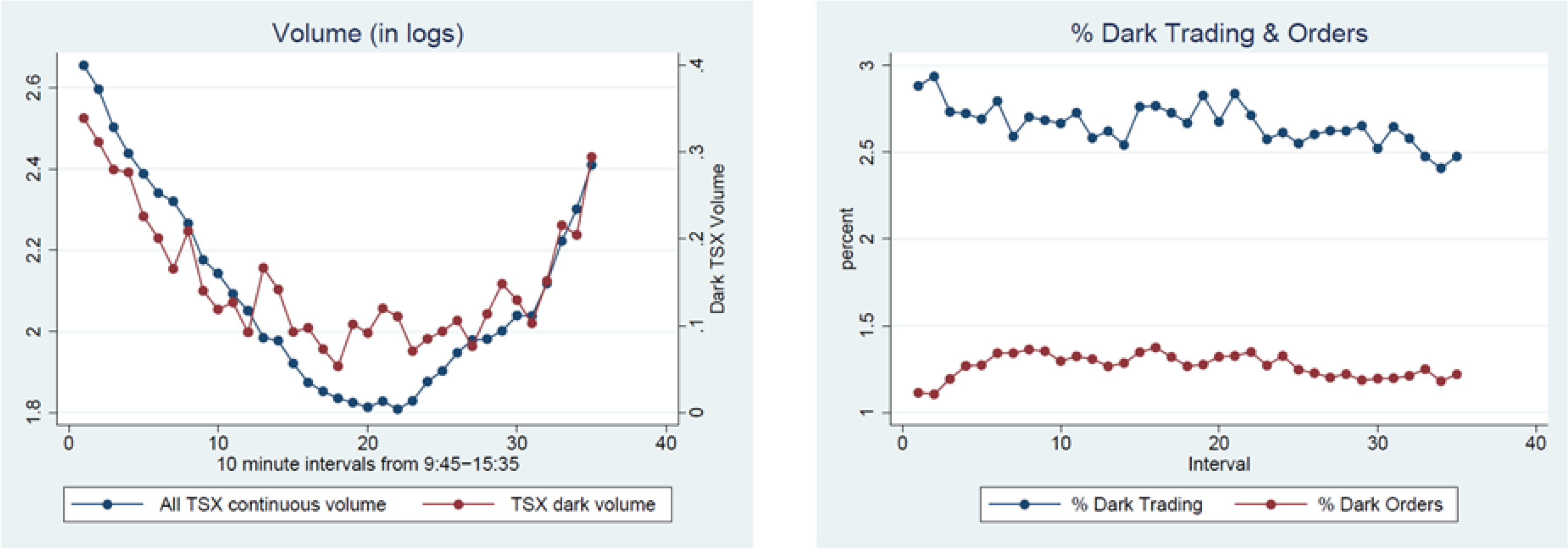
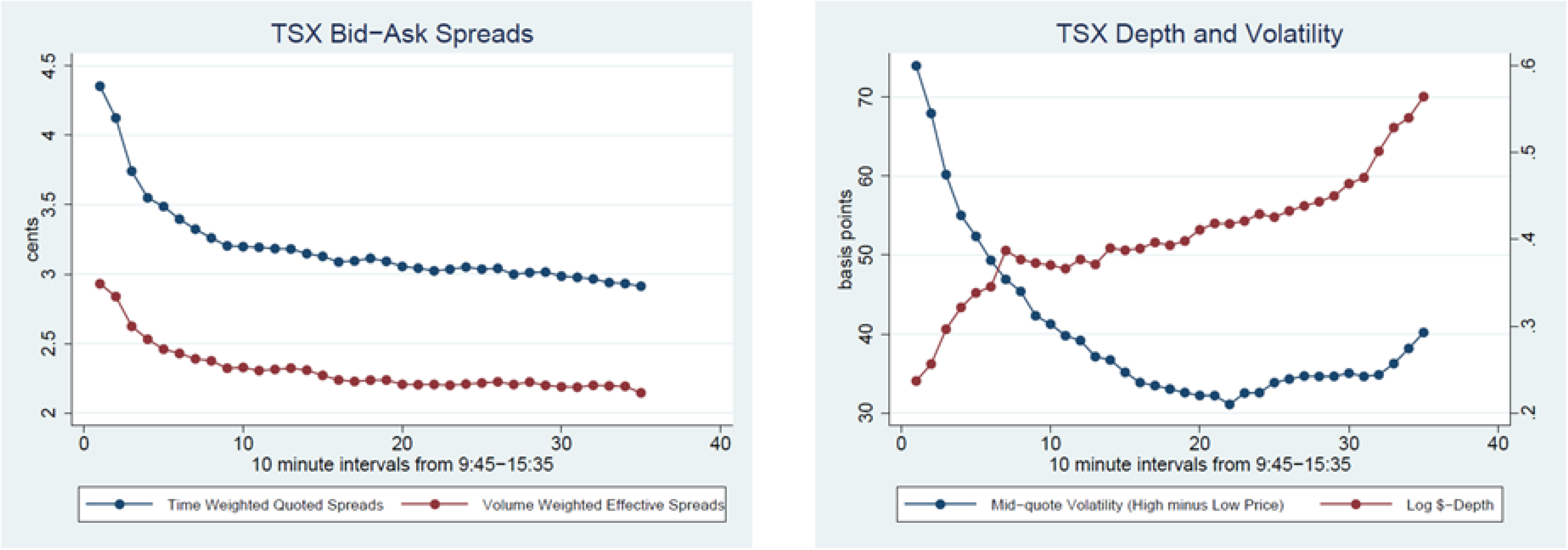


Figure 5.3: Intra-Day Patterns of Liquidity and Volatility

The figure displays the intra-day trading patterns of TSX volume and the share of dark volume of orders and trades. The horizontal axis marks the 35 10-minute trading intervals between 9:45 a.m. and 3:35 p.m. The left panel plots the patterns of average total and dark log-$-volume on the TSX over the 230 TSX Composite securities for the second half of 2011. The total TSX volume is measured on the left vertical axis, and the TSX dark volume is measured on the right vertical axis. Both series display a U-shaped pattern. The right panel plots the average share of dark volume of TSX trading and order volume. As the plot illustrates, dark volume as a share of total trading and order volume is, loosely, flat throughout the day.



The fraction of trading involving dark orders in stock i for time interval t, $\%\ dark\ trading_{it}$, is instrumented by $\%\ dark\ order_{it-1}$, the fraction of dark orders one period lagged, in the first stage of the regression. Since the variable $\%\ dark\ order_{it-1}$ is not defined for the first interval of the day, the first observation for each day is dropped. Both the Kleibergen and Paap (2006) Wald statistic of under-identification and the Kleibergen and Paap (2006) statistic for weak identification are computed to test for misspecification in the first step of the two-stage regression. Since a single instrument is used, a test for over-identification is unnecessary.

5.6 Liquidity Measures

A number of liquidity measures are used to proxy the liquidity that is available in the Canadian market. These include quoted spreads, realised spreads, effective spreads, the $Depth at the best bid and ask, the fill rates, and the volume traded daily. The construction of each of these measures is discussed in detail in the following section.

5.6.1 Quoted Visible Liquidity

Quoted liquidity is measured using time-weighted quoted spreads and depth. The *quoted spread* is the difference between the lowest price a participant is willing to sell, or the best offer price, and the highest price a participant is willing to buy, or the best bid price.[51] *Share depth* is defined as the average of the number of shares that can be traded on the bid and offer side, and *dollar depth* is defined as the value that can be traded at the bid and the offer. The time weighted measures reflect the availability of liquidity throughout the day.

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[51] Spreads can also be expressed in basis points as a proportion of a prevailing quote midpoint. The advantage of the proportional spread is that, in principle, one can compare companies with different price levels. However, in today's markets, most stocks trade at spreads between 1-2 cents. As spreads follow the discrete and fixed increments in cents, it is possible that effects (or non-effects) can be driven entirely by movements in the underlying stock price (i.e., the denominator in proportional spreads). The analysis is performed using cent-spreads, with additional controls for the daily price levels of the underlying stocks (Joel Hasbrouck lead a discussion on this topic during a recent NBER microstructure group meeting).

The event study focuses on the effect of dark order introduction on the TSX spread, and thus uses the best bid-ask spread as quoted on the TSX alone. For the intraday analysis, however, the TSX-only and the Canada-wide spread measures are both computed. Depth is constructed for the TSX only; depth data for the other trading venues is not provided by the TSX, and the integrity of the time-stamps cannot be guaranteed across the multiple sources of data.

5.6.2 Effective Liquidity with and without Maker-Taker Fees

Effective liquidity captures the conditions upon which traders decided to act. The costs of a transaction to the liquidity demander are measured by the *effective spread*, which is the difference between the transaction price and the midpoint of the bid and ask quotes at the time of the transaction. This measure also captures the costs that arise when the volume of an incoming order exceeds the posted volume at the best prices. For the t-th trade in stock i, the effective spread is defined as:

$$espread_{ti} = 2q_{ti}(p_{ti} - m_{ti}), \tag{5.6}$$

where p_{ti} is the transaction price, m_{ti} is the midpoint of the quote prevailing at the time of the trade, and q_{ti} is an indicator variable, which equals 1 if the trade is buyer-initiated and -1 if the trade is seller-initiated. The data includes identifiers for the active and passive side of each transaction, as well as all quote changes, thus allowing the prevailing quote at the time of each transaction to be identified. A large fraction of dark orders in the sample are at the midpoint which results in an effective spread of zero.

To account for the fee that traders of marketable orders pay the exchange (the “taker” fee) an adjusted spread is also computed:

$$taker\ fee\ adjusted\ espread_{ti} = 2q_{ti}(p_{ti} - m_{ti}) + 2 \times taker\ fee_{ti}. \tag{5.7}$$

Colliard and Foucault (2012) refer to this measure as the “cum-fee” spread. In Canada (as in the U.S.), these fees are sub-penny amounts that accrue per share traded. On the TSX, these fees can differ by broker - high-volume brokers pay lower fees. The lowest taker fee on the TSX is \$0.0033 per share, and this is the value used in this study. The highest is \$0.0035.[52] For orders that execute against a dark order, both the active and passive fees are \$0.001 per share.

The change in liquidity provider profits is measured by decomposing the effective spread into its permanent and transitory components, the *price impact* and the *realised spread*:

$$espread_{ti} = priceimpact_{ti} + rspread_{ti}. \tag{5.8}$$

Price impact reflects the proportion of transaction costs that are due to the presence of informed liquidity demanders. Therefore, a decline in price impact costs indicates a decline in the degree of adverse selection. The realised spread reflects the portion of the transaction costs that is attributed to liquidity provider revenues. In this analysis the five-minute realised spread is used, which assumes that liquidity providers are able to close their positions at the midpoint five minutes after the trade. The five-minute realised spread is defined using Equation 5.9:

$$rspread_{ti} = 2q_{ti}(p_{ti} - m_{t+5\ \mathrm{min},i}), \tag{5.9}$$

where: p_{ti} is the transaction price; $m_{t+5\ \mathrm{min},i}$ is the midpoint of the quote 5 minutes after the t-th trade; and q_{ti} is an indicator variable that equals 1 if the trade is buyer-initiated, and -1 if the trade is seller-initiated.

As with effective spreads, the impact of maker rebates can be explicitly accounted for by computing the maker rebate adjusted realised spread, using Equation 5.10 below:

$$maker\ rebate\ adjusted\ rspread_{ti} = 2q_{ti}(p_{ti} - m_{t+5\ \mathrm{min},i}) + 2 \times maker\ rebate_{ti} \tag{5.10}$$

where: $maker\ rebate_{ti}$ is the per share maker fee rebate,[53] and the highest possible rebate is used, which is \$0.0031. Dark orders that clear against incoming marketable orders receive no rebate.

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[52] This information is provided by the TSX and is available at *www.tmx.com/en/trading/feeschedule/*

[53] As with taker fees, maker fees depend on the amount of dollar volume that a broker executes on the exchange.

5.7 Results on the Introduction of Dark Orders

Table 5.1 provides a summary set of statistics for the sample of firms, during the period of July 1st to December 31st, 2011, a period when dark trading was available for all 229 securities. TSX60 firms are larger and trade more frequently than TSX Completion firms. As a fraction of orders and trade volume, dark trading in the groups is similar (3.3% dark trading for TSX60 stocks as compared to 2.7% for TSX completion stocks). Dark orders are between 2.4 and 3 times larger than standard limit orders. Transaction sizes of dark and lit trades are similar, but this size depends on the incoming marketable (not-necessarily dark) order, and so is not directly reflective of the available dark liquidity. During the sample period, around 66% of the total Canadian dollar-volume occurs on the TSX, consistent with the TSX's overall market share of trading, as per the regulator's published statistics.

Quoted depth on the TSX in terms of number of shares is comparable between the TSX60 and TSX Completion constituents, but since share prices for TSX60 constituents are larger, posted dollar-value is also higher for TSX60 constituents. Bid-ask spreads for TSX Completion constituents are larger, and the midpoint more volatile, as compared to TSX60 constituents.

Table 5.1: Summary Statistics

This table represents summary statistics for the main liquidity and volume variables for the sample of TSX Composite stocks, split into the groups of TSX60 and TSX Completion constituents. With the exception of market capitalization, which is based on January 2011, all measures are based on daily per stock averages for the second half of 2011. All volume related numbers exclude odd-lot shares; limit order book (LOB) figures further exclude dealer crosses, market-on-open, market-on-close, after-hours and special terms market trades.

		TSX60	TSX Completion	TSX Composite	Scaling
Number of firms		53	177	230	
av market cap January 2011		21.1	2.6	6.8	(billions)
quoted midpoint (in CAD)		39.4	19.4	24.0	
Limit order book (LOB)	transactions	6.8	1.5	2.7	(thousand)
	volume	1.4	0.4	0.6	(millions)
	$-volume	44.9	5.0	14.2	(millions)
Dealer crosses	transactions	3.3	1.5	1.9	
	volume	0.3	0.1	0.1	(millions)
	$-volume	7.4	1.4	2.8	(millions)
Dark Trades (at least one side)	transactions	166	27	59	
	volume	1.4	0.1	0.4	(millions)
	$-volume	0.0	0.0	0.0	(millions)
Orders LOB	number	147.7	25.1	53.4	(thousand)
	volume	56.9	11.6	22.1	(millions)
	$-volume	1,954	182	590	(millions)
Orders dark	number	452	78	164	
	volume	0.5	0.1	0.2	(millions)
	$-volume	15.5	1.9	5.0	(millions)
Fill-rate LOB orders (volume)		3	4	4	percent
Fill-rate dark orders (volume)		17	14	15	percent
Trade size in shares	LOB	190	239	228	
	dark	214	248	239	
	dealer cross	81,455	64,872	70,094	
Order size in shares	LOB	380	474	452	
	dark	1,138	1,061	1,080	
fragmentation continuous markets		0.53	0.48	0.49	
% dark of all TSX LOB (volume)		3.3	2.7	2.8	percent
% dark of all orders TSX (volume)		1.2	1.2	1.2	percent
Market share TSX $-volume		64.5	66.5	66.0	percent
quoted depth TSX in shares		2.2	2.4	2.4	(thousand)
quoted depth TSX in $		41.9	19.5	24.7	(thousand)
quoted spread		2.6	3.4	3.2	cents
quoted spread		6.6	19.2	16.3	basis points
effective spread		2.0	2.6	2.5	cents
intra-day volatility		36.0	41.9	40.5	basis points

FIGURE 5.4: Quoted Liquidity: Bid-Ask Spreads

The left panel plots the average of daily per-company time-weighted quoted bid ask spreads for TSX60 and TSX Completion securities, where spreads are measured in cents. The right panel plots the difference of the bid-ask-spreads between TSX60 and TSX Completion securities. The plots also contains a line that displays the fraction of TSX continuous-market volume that is traded with dark orders (note that the bold line shows non-zero dark trading before the event date, simply because it is a forward- and backward-looking moving average). Vertical lines represent the two event dates: the first, April 01, marks the date of the introduction of dark orders for TSX60 securities; the second, May 20, marks the introduction date for all remaining securities. As the left panel shows, spreads for TSX60 stocks following the introduction of dark orders. Moreover, as the right panel shows, spreads also increase relative to TSX Completion stocks. All plots contain the levels (thin, light-coloured lines) and 15-day moving averages (thick, bold-colored lines).

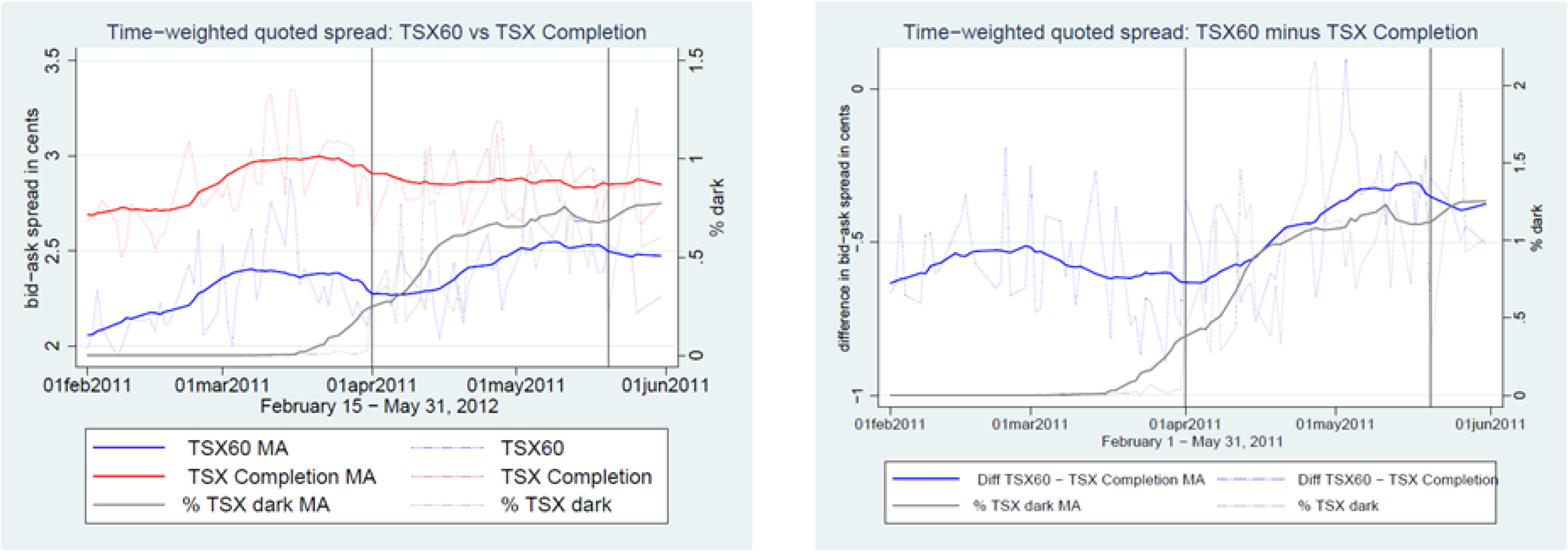


TABLE 5.2: Panel Regressions Results for Time-Weighted Quoted Liquidity

The table presents the results from a regression where the differential impact of the introduction of dark orders is assessed on the treatment group of 53 companies from the TSX60 index relative to a control group of 177 companies in the TSX Composite for daily time-weighted quoted spreads (in cents) and the time weighted logarithms of dollar-depth; both are based on TSX based trading. Panel A describes the result from a least square event study regression and the coefficient of interest is that for the interaction term $Introduction_t \times TSX60_i$. Panel B describes the results from a 2-stage regressions to assess the effect of the extent of dark trading on the dependent variable; here, the fraction of dark trading volume of all trading volume on day t in stock i is instrumented in the first stage by the interaction variable $Introduction_t \times TSX60_i$. Control variables are the contemporaneous logarithm of the average daily mid-quote, the daily realization of the Canadian volatility index VIXC, and market fragmentation (measure by one minus the Herfindahl Index of market fragmentation in Canada). A specification is also considered in which the volatility index VIXC is interacted with index constituency to allow for differential reactions of the treatment and control group to market-wide volatility. The analysis is based on daily measures and covers the time span from January 01, 2011 to May 20, 2011; dark orders were introduced on April 1st for TSX60 symbols and on May 22 for TSX Completion symbols. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Panel A: OLS Regressions Dependent variable	Time weighted quoted spread				Time-weighted Log $-Depth			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\text{Introduction}_t \times \text{TSX60}_i$	0.2475*+	0.2668**	0.2973**	0.3208**	-0.0732**+	-0.0796**+	-0.0882***	-0.0959***
	(0.1270)	(0.1271)	(0.1386)	(0.1380)	(0.0303)	(0.0312)	(0.0307)	(0.0317)
Introduction_t	0.0645	-0.0177	0.0531	-0.0304	-0.1590***	-0.1320***	-0.1555***	-0.1281***
	(0.0556)	(0.0580)	(0.0550)	(0.0576)	(0.0172)	(0.0169)	(0.0171)	(0.0168)
Log-Midpoint_{it}	1.4836***	1.5436***	1.4715***	1.5307***	0.2532***	0.2336***	0.2569***	0.2375***
	(0.2586)	(0.2628)	(0.2589)	(0.2629)	(0.0754)	(0.0766)	(0.0755)	(0.0767)
VIXC_t	0.0631***	0.0639***			-0.0326***	-0.0329***		
	(0.0163)	(0.0157)			(0.0050)	(0.0046)		
$\text{Fragmentation}_{it}$		1.9512***		1.9588***		-0.6400***		-0.6424***
		(0.3285)		(0.3281)		(0.0550)		(0.0549)
$\text{VIXC}_t \times \text{TSX60}_i$			0.1119***	0.1168***			-0.0473***	-0.0489***
			(0.0248)	(0.0244)			(0.0081)	(0.0080)
$\text{VIXC}_t \times \text{TSX Completion}_i$			0.0484***	0.0480***			-0.0282***	-0.0281***
			(0.0171)	(0.0165)			(0.0045)	(0.0042)
Observations	21,607	21,607	21,607	21,607	21,607	21,607	21,607	21,607
adjusted R-squared	0.862	0.865	0.862	0.865	0.799	0.806	0.8	0.806

Panel B: 2-stage IV Estimation Dependent variable	Time weighted quoted spread				Time-weighted Log $-Depth			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
% dark TSX_{it}	0.2511**	0.2704**	0.2949**	0.3179**+	-0.0743**	-0.0806**+	-0.0875***	-0.0951***
	(0.1257)	(0.1265)	(0.1359)	(0.1363)	(0.0332)	(0.0346)	(0.0337)	(0.0353)
Introduction	0.0633	-0.0179	0.0532	-0.029	-0.1586***	-0.1319***	-0.1555***	-0.1286***
	(0.0558)	(0.0580)	(0.0550)	(0.0574)	(0.0173)	(0.0169)	(0.0171)	(0.0167)
Log-Midpoint_{it}	1.4723***	1.5306***	1.4599***	1.5172***	0.2566***	0.2374***	0.2603***	0.2415***
	(0.2585)	(0.2620)	(0.2596)	(0.2629)	(0.0765)	(0.0776)	(0.0768)	(0.0779)
VIXC_t	0.0614***	0.0621***			-0.0321***	-0.0323***		
	(0.0163)	(0.0157)			(0.0050)	(0.0047)		
$\text{Fragmentation}_{it}$		1.9259***		1.9281***		-0.6325***		-0.6332***
		(0.3271)		(0.3269)		(0.0557)		(0.0557)
$\text{VIXC}_t \times \text{TSX60}_i$			0.1034***	0.1076***			-0.0448***	-0.0462***
			(0.0249)	(0.0251)			(0.0084)	(0.0084)
$\text{VIXC}_t \times \text{TSX Completion}_i$			0.0483***	0.0479***			-0.0282***	-0.0280***
			(0.0171)	(0.0165)			(0.0045)	(0.0042)

5.7.1 Quoted Liquidity

Figure 5.4 shows that the quoted spread increases after the introduction of dark orders. The average quoted spreads before and after the introduction are 2.18 cents and 2.44 cents, respectively, for the TSX60 symbols, and 2.82 cents and 2.85 cents, respectively, for the TSX Completion firms.

The panel regression results for the change in the quoted spreads are in Panel A of Table 5.2. These results confirm that spreads for TSX60 stocks increased after the introduction of dark orders. The increase is estimated to be between 0.24 to 0.32 cents, depending on the specification, and are significant at the 5% level. The average time-weighted quoted spread before April 1st, 2011 for TSX60 constituents was 2.18 cents, and thus marks an increase in spreads of between 11-15%. This result implies that liquidity suppliers may be more reticent to quote at the best bid and ask during the introduction of dark orders. This is consistent with the theoretical predictions of Zhu (2013) who contends the existence of midpoint dark orders will attract uninformed traders but not informed traders, leaving a higher level of adverse selection in the lit market. This result is found to be robust to the inclusion of a variety of controls for volatility, fragmentation and the price of the security.

Table 5.3 displays the first-stage results from the instrumental variable regression; the instrument is significant at the 1% level and all tests of over and under identification are rejected.

Panel B of Table 5.2 displays the results from the second-stage instrumental variable regression. Depending on the specification, a 1% increase in the usage of dark orders leads to a widening of the spread of between 0.25 and 0.32 cents. This observation is consistent with the finding from the first regression - the fraction of dark trading was about 1% by the end of May. These results of the spreads analysis are also consistent with Buti et al. (2011b), who show that the introduction of fully hidden orders widens quoted bid-ask spreads.

Figure 5.5 indicates that depth decreased between January and June 2011; however, the decline was before the introduction of dark orders, and depth was constant afterwards.

Table 5.3: First Stage of the IV Regression on the Introduction of Dark Orders

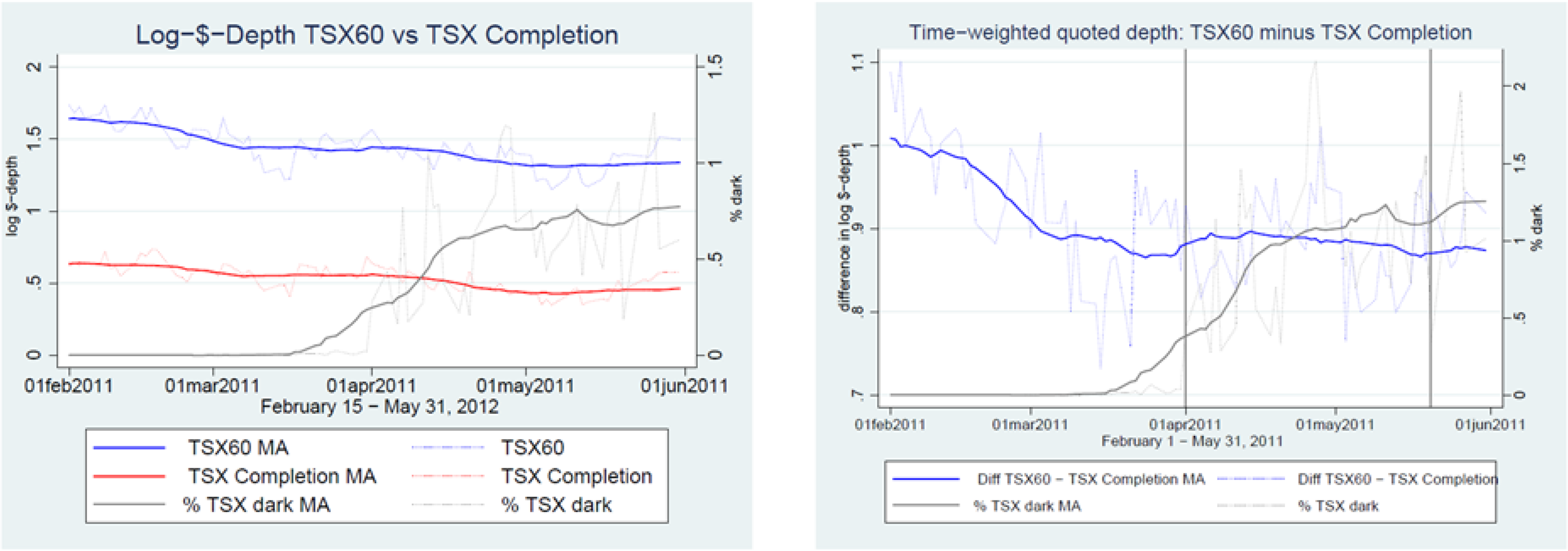
The table presents the results from the first-stage regressions where the fraction of dark trading on day t in stock i is instrumented by the interaction variable $Introduction_t \times TSX60_i$. Control variables are the contemporaneous logarithm of the average daily mid-quote, the daily realisation of the Canadian volatility index VIXC, and market fragmentation (measured by one minus the Herfindahl Index of market fragmentation in Canada). A specification is also considered in which the volatility index VIXC is interacted with index constituency to allow for differential reactions of the treatment and control group to market-wide volatility. The analysis is based on daily measures and covers the time span from January 01, 2011 to May 20, 2011; dark orders were introduced on April 1st for TSX60 symbols and on May 22 for TSX Completion symbols. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level. This table represents the results from the first stage of the IV regressions where the fraction of dark trading on the TSX is instrumented with the introduction-TSX60 dummy. The Kleibergen and Paap (2006) Wald statistic of underidentification is included, which, in this specification is $\chi^2(1)$ distributed, and the Kleibergen and Paap (2006) statistic for weak identification (following the Andrews and Stock (2005) critical values; for this specification, the 10% maximal IV size critical value is 16.38). All regressions include firm fixed effects, and standard errors are double-clustered by firm and date.

instrumented variable: % dark TSX trading	(1)	(2)	(3)	(4)
Introduction$_t$ × TSX60$_i$	0.9858***	0.9868***	1.0082***	1.0094***
	(0.1473)	(0.1472)	(0.1403)	(0.1403)
Introduction$_t$	0.0049	0.0009	-0.0003	-0.0044
	(0.0060)	(0.0063)	(0.0008)	(0.0032)
Log-Midpoint$_{it}$	0.045	0.0479	0.0395	0.0425
	(0.1056)	(0.1059)	(0.1051)	(0.1053)
VIXC$_t$	0.0069	0.0069		
	(0.0069)	(0.0069)		
Fragmentation$_{it}$		0.0936		0.0968
		(0.0706)		(0.0713)
VIXC$_t$ × TSX60$_i$			0.0288	0.029
			(0.0292)	(0.0292)
VIXC$_t$ × TSX Completion$_i$			0.0002	0.0002
			(0.0007)	(0.0007)
Observations	21,607	21,607	21,607	21,607
F(4,93)	15.02	12.06	12.06	10.10
Kleibergen and Paap (2006) under-identification	21.00	21.01	21.08	21.09
Kleibergen and Paap (2006) weak identification	44.80	44.93	51.62	51.79

That is, even though the panel regression results for the change in the quoted depth (from Table 5.2) indicate a decrease, the graph indicates that the drop happened before the introduction of dark orders. This effect is accordingly not attributed to the introduction of dark orders; when the regression is run for a shorter event window (e.g., starting mid-February), there is no effect for depth.

FIGURE 5.5: Quoted Liquidity: Log-$-Depth at the Best Bid and Ask Prices

The left panel plots the average of daily per-company time-weighted quoted log-$-depth for TSX60 and TSX Completion securities. The right panel plots the difference of the log-depths between TSX60 and TSX Completion securities. The plots also contains a line that displays the fraction of TSX continuous-market volume that is traded with dark orders (note that the bold line shows non-zero dark trading before the event date, simply because it is a forward- and backward-looking moving average). Vertical lines represent the two event dates: the first, April 01, marks the date of the introduction of dark orders for TSX60 securities; the second, May 20, marks the introduction date for all remaining securities. As the left panel shows, depth declines for both TSX60 and TSX Completion constituents. The right panel displays that the average difference in depths before the event was larger than after the event, suggesting a decline in depth following the introduction of dark orders. However, it is clearly visible that the decline happened before mid-March and that afterwards, depth-differences were stable. This leads to the conclusion that the introduction of dark orders had no effect on depth. All plots contain the levels (thin, light-coloured lines) and 15-day moving averages (thick, bold-colored lines).



5.7.2 Effective Liquidity

As orders are allowed to execute at the midpoint in the dark, an increase in quoted spreads is not necessarily correlated with an increase in effective spreads. Nevertheless, Panel A of Table 5.4 shows that after the introduction of dark trading, effective spreads increased significantly. The increase in quoted spreads dominates any reduction in effective spreads resulting from midpoint executions.

Similarly, since taker fees for executions against dark orders are lower, an increase in effective spreads without taker fees need not be accompanied by an increase in effective spreads with taker fees. Once again, however, Panel A of Table 5.4 shows after the introduction of dark orders, effective spreads with taker fees also increased.

5.7.3 Other Measures of Market Quality

Tables 5.5 and 5.6 show that the introduction of dark orders had no impact on realised spreads (including maker fees), price impact, or volume. The fill rate (i.e., the fraction of order volume that is executed) is also unaffected. A measure of midpoint volatility is also computed, following Hasbrouck and Saar (2013), whereby the day is split into 36 10-minute intervals. For each of these, the difference between the highest and the lowest midpoint is computed and scaled by the average midpoint. The average over these 36 periods is the daily midpoint volatility. No change is found after the introduction of dark orders for this volatility measure.

Table 5.4: Panel Regression Results for Volume-Weighted Effective Spreads

The table presents the results from a regression where the differential impact of the introduction of dark orders is assessed on the treatment group of 53 companies from the TSX60 index relative to a control group of 177 companies in the TSX Composite for daily volume-weighted effective spreads without and with taker fees; both are measured in cents and are based on TSX based trading. Panel A describes the result from a least square event study regression and the coefficient of interest is that for the interaction term $Introduction_t \times TSX60_i$. This table does not contain a 2-stage regression to assess the effect of the extent of dark trading on the dependent variable, because such a regression would be misleading. However, since dark trades execute at the midpoint, any increase in the extent of dark trading, ceteris paribus, would mechanically lower effective spreads. Thus, there are two opposing forces, the second of which, however, cannot be represented adequately in the IV regression. Control variables are the contemporaneous logarithm of the average daily mid-quote, the daily realization of the Canadian volatility index VIXC, and market fragmentation (measure by one minus the Herfindahl Index of market fragmentation in Canada).A specification is also considered in which the volatility index VIXC is interacted with index constituency to allow for differential reactions of the treatment and control group to market-wide volatility. The analysis is based on daily measures and covers the time span from January 01, 2011 to May 20, 2011; dark orders were introduced on April 1st for TSX60 symbols and on May 22 for TSX Completion symbols. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Panel A: OLS Regressions **Dependent variable**	**Effective spread**				**Effective spread plus taker fee**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Introduction$_t$ × TSX60$_i$	0.1594*	0.1711**	0.1904**	0.2046**	0.1547*	0.1664*+	0.1856**	0.1998**
	(0.0859)	(0.0868)	(0.0919)	(0.0922)	(0.0859)	(0.0867)	(0.0918)	(0.0921)
Introduction$_t$	-0.0714	-0.1210**+	-0.0785	-0.1289**+	-0.0714	-0.1210**+	-0.0785	-0.1289**+
	(0.0498)	(0.0507)	(0.0495)	(0.0503)	(0.0497)	(0.0507)	(0.0495)	(0.0503)
Log-Midpoint$_{it}$	1.1067***	1.1429***	1.0992***	1.1349***	1.1065***	1.1427***	1.0990***	1.1347***
	(0.1989)	(0.2038)	(0.1994)	(0.2042)	(0.1989)	(0.2038)	(0.1994)	(0.2042)
Canadian VIXC$_t$	0.0411***	0.0416***			0.0411***	0.0416***		
	(0.0122)	(0.0120)			(0.0122)	(0.0120)		
Fragmentation$_{it}$		1.1770***		1.1818***		1.1766***		1.1813***
		(0.2569)		(0.2564)		(0.2569)		(0.2564)
VIXC$_t$ × TSX60$_i$			0.0715***	0.0745***			0.0714***	0.0744***
			(0.0165)	(0.0163)			(0.0165)	(0.0164)
VIXC$_t$ × TSX Completion$_i$			0.0320**+	0.0317**+			0.0320**+	0.0317**+
			(0.0136)	(0.0134)			(0.0136)	(0.0134)
Observations	21,607	21,607	21,607	21,607	21,607	21,607	21,607	21,607
adjusted R-squared	0.789	0.791	0.789	0.791	0.788	0.79	0.789	0.791

Table 5.5: Panel Regression Results for Volume-Weighted Realised Spreads and Price Impacts

The table presents the results from a regression where the differential impact of the introduction of dark orders is assessed on the treatment group of 53 companies from the TSX60 index relative to a control group of 177 companies in the TSX Composite for daily volume-weighted 5-minute realized spreads with maker rebate and volume-weighted 5-minute price impacts; both are measured in cents and are based on TSX only trading. Panel A describes the result from a least square event study regression and the coefficient of interest is that for the interaction term $Introduction_t \times TSX60_i$. Panel B describes the results from a 2-stage regressions to assess the effect of the extent of dark trading on the dependent variable; here, the fraction of dark trading volume of all trading volume on day t in stock i is instrumented in the first stage by the interaction variable $Introduction_t \times TSX60_i$. Control variables are the contemporaneous logarithm of the average daily mid-quote, the daily realization of the Canadian volatility index VIXC, and market fragmentation (measured using one minus the Herfindahl Index of market fragmentation in Canada). A specification is also considered in which the volatility index VIXC is interacted with index constituency to allow for differential reactions of the treatment and control group to market-wide volatility. The analysis is based on daily measures and covers the time span from January 01, 2011 to May 20, 2011; dark orders were introduced on April 1st for TSX60 symbols and on May 22 for TSX Completion symbols. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Panel A: OLS Regressions

Dependent variable	realized spread plus maker rebate				5-minute price impact			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Introduction_t \times TSX60_i$	0.0150	0.0146	0.0197	0.0193	0.0691	0.0751	0.0821	0.0894
	(0.1001)	(0.1000)	(0.1051)	(0.1050)	(0.0598)	(0.0592)	(0.0650)	(0.0643)
$Introduction_t$	-0.0675	-0.0659	-0.0686	-0.067	-0.002	-0.0276	-0.005	-0.0309
	(0.0557)	(0.0558)	(0.0559)	(0.0560)	(0.0303)	(0.0301)	(0.0300)	(0.0300)
$Log\text{-}Midpoint_{it}$	-0.7744***	-0.7755***	-0.7755***	-0.7766***	0.9404***	0.9591***	0.9372***	0.9556***
	(0.2344)	(0.2335)	(0.2346)	(0.2337)	(0.1527)	(0.1520)	(0.1526)	(0.1519)
$VIXC_t$	-0.0250*	-0.0250*			0.0330***	0.0333***		
	(0.0144)	(0.0144)			(0.0100)	(0.0099)		
$Fragmentation_{it}$		-0.0376		-0.0369		0.6070***		0.6091***
		(0.1605)		(0.1607)		(0.1269)		(0.1270)
$VIXC_t \times TSX60_i$			-0.0203	-0.0204			0.0458***	0.0474***
			(0.0166)	(0.0167)			(0.0128)	(0.0127)
$VIXC_t \times TSX\ Completion_i$			-0.0264	-0.0264			0.0292***	0.0291***
			(0.0172)	(0.0172)			(0.0112)	(0.0110)
Observations	21,607	21,607	21,607	21,607	21,607	21,607	21,607	21,607
adjusted R-squared	0.0831	0.0831	0.0831	0.083	0.507	0.508	0.507	0.508

Panel B: 2-stage IV Estimation

Dependent variable	realized spread plus maker rebate				5-minute price impact			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	0.0152	0.0148	0.0196	0.0191	0.07	0.0761	0.0814	0.0886
% dark TSX_{it}	(0.1023)	(0.1021)	(0.1051)	(0.1049)	(0.0579)	(0.0571)	(0.0620)	(0.0612)
	-0.0675	-0.0659	-0.0686	-0.0669	-0.0023	-0.0276	-0.005	-0.0305
$Introduction_t$	(0.0560)	(0.0559)	(0.0559)	(0.0558)	(0.0304)	(0.0301)	(0.0300)	(0.0298)
	-0.7751***	-0.7762***	-0.7763***	-0.7775***	0.9373***	0.9554***	0.9340***	0.9519***
$Log\text{-}Midpoint_{it}$	(0.2343)	(0.2334)	(0.2343)	(0.2334)	(0.1540)	(0.1534)	(0.1543)	(0.1537)
	-0.0251*	-0.0251*			0.0325***	0.0328***		
$VIXC_t$	(0.0143)	(0.0143)			(0.0101)	(0.0099)		
		-0.039		-0.0388		0.5999***		0.6005***
$Fragmentation_{it}$		(0.1611)		(0.1612)		(0.1270)		(0.1270)
			-0.0209	-0.021			0.0435***	0.0448***
$VIXC_t \times TSX60_i$			(0.0154)	(0.0155)			(0.0128)	(0.0129)
			-0.0264	-0.0264			0.0291***	0.0290***
$VIXC_t \times TSX\ Completion_i$			(0.0172)	(0.0172)			(0.0112)	(0.0110)

TABLE 5.6: Panel Regression Results for Volatility, Volume and Fill-Rates

The table presents the results from a regression where the differential impact of the introduction of dark orders is assessed on the treatment group of 53 companies from the TSX60 index relative to a control group of 177 companies in the TSX Composite for the daily 10-minute midpoint volatility, the logarithms of dollar volume, and the fill-rate. Panel A describes the result from a least square event study regression and the coefficient of interest is that for the interaction term $Introduction_t \times TSX60_i$. Panel B describes the results from a 2-stage regressions to assess the effect of the extent of dark trading on the dependent variable; here, the fraction of dark trading volume of all trading volume on day t in stock i is instrumented in the first stage by the interaction variable $Introduction_t \times TSX60_i$. Control variables are the contemporaneous logarithm of the average daily mid-quote, the daily realization of the Canadian volatility index VIXC, and market fragmentation (measured using one minus the Herfindahl Index of market fragmentation in Canada). The analysis is based on daily measures and covers the time span from January 01, 2011 to May 20, 2011. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Panel A: OLS Regressions

Dependent variable	midpoint volatility				Log $-Volume				Fill rate			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$Introduction_t \times TSX60_i$	0.4901	0.4927	0.5721	0.5754	0.0438	0.0278	0.0549	0.0355	-0.0053	-0.0734	-0.0899	-0.1728
	(0.6719)	(0.6732)	(0.7157)	(0.7175)	(0.0393)	(0.0376)	(0.0390)	(0.0372)	(0.2204)	(0.2124)	(0.2245)	(0.2128)
$Introduction_t$	1.6050**	1.5932**	1.5859**	1.5735*+	-0.1812***	-0.1131***	-0.1837***	-0.1149***	-0.0697	0.2205	-0.0503	0.2438
	(0.7989)	(0.8096)	(0.7996)	(0.8107)	(0.0316)	(0.0298)	(0.0314)	(0.0297)	(0.2087)	(0.1927)	(0.2096)	(0.1931)
$Log\text{-}Midpoint_{it}$	2.4092	2.4217	2.3889	2.4017	1.3515***	1.3018***	1.3488***	1.3000***	-0.4743	-0.6859	-0.4537	-0.6623
	(4.0781)	(4.0854)	(4.0764)	(4.0836)	(0.1559)	(0.1636)	(0.1559)	(0.1637)	(0.6924)	(0.7648)	(0.6934)	(0.7653)
$VIXC_t$	1.8565***	1.8567***			0.0210**	0.0203**+			0.0879**+	0.0849**+		
	(0.3072)	(0.3071)			(0.0091)	(0.0086)			(0.0364)	(0.0364)		
$Fragmentation_{it}$		0.2874		0.2985		-1.6161***		-1.6151***		-6.8906***		-6.9046***
		(1.4807)		(1.4812)		(0.0854)		(0.0854)		(1.0248)		(1.0238)
$VIXC_t \times TSX60_i$			1.9366***	1.9373***			0.0319***	0.0278**+			0.005	-0.0124
			(0.3084)	(0.3086)			(0.0119)	(0.0114)			(0.0307)	(0.0299)
$VIXC_t \times TSX\ Completion_i$			1.8320***	1.8320***			0.0178*+	0.0180**			0.1129***	0.1142***
			(0.3265)	(0.3264)			(0.0093)	(0.0088)			(0.0428)	(0.0427)
Observations	21,306	21,306	21,306	21,306	21,607	21,607	21,607	21,607	21,607	21,607	21,607	21,607
adjusted R-squared	0.544	0.544	0.544	0.544	0.867	0.879	0.867	0.879	0.509	0.537	0.509	0.537

Panel B: 2-stage IV Estimation

Dependent variable	midpoint volatility				Log $-Volume				Fill rate			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	0.4972	0.4994	0.5675	0.5701	0.0444	0.0282	0.0544	0.0351	-0.0054	-0.0744	-0.0891	-0.1712
% dark TSX_{it}	(0.6845)	(0.6852)	(0.7144)	(0.7154)	(0.0412)	(0.0387)	(0.0407)	(0.0378)	(0.2235)	(0.2148)	(0.2218)	(0.2107)
	1.6025**	1.5926**	1.5860**	1.5759*+	-0.1814***	-0.1132***	-0.1837***	-0.1148***	-0.0697	0.2205	-0.0503	0.2431
$Introduction_t$	(0.8004)	(0.8100)	(0.7996)	(0.8094)	(0.0316)	(0.0298)	(0.0314)	(0.0297)	(0.2096)	(0.1928)	(0.2095)	(0.1923)
	2.3865	2.3968	2.3661	2.3763	1.3495***	1.3005***	1.3466***	1.2985***	-0.4741	-0.6824	-0.4502	-0.655
$Log\text{-}Midpoint_{it}$	(4.0871)	(4.0948)	(4.0850)	(4.0926)	(0.1564)	(0.1642)	(0.1565)	(0.1643)	(0.6942)	(0.7662)	(0.6954)	(0.7666)
	1.8531***	1.8532***			0.0207**	0.0201**+			0.0880**+	0.0854**		
$VIXC_t$	(0.3072)	(0.3072)			(0.0092)	(0.0086)			(0.0367)	(0.0367)		
		0.2394		0.242		-1.6188***		-1.6185***		-6.8836***		-6.8881***
$Fragmentation_{it}$		(1.4814)		(1.4815)		(0.0859)		(0.0860)		(1.0314)		(1.0306)
			1.9202***	1.9208***			0.0303**+	0.0268**+			0.0075	-0.0075
$VIXC_t \times TSX60_i$			(0.3063)	(0.3064)			(0.0120)	(0.0115)			(0.0309)	(0.0312)
			1.8318***	1.8318***			0.0177*+	0.0180**			0.1129***	0.1142***
$VIXC_t \times TSX\ Completion_i$			(0.3265)	(0.3264)			(0.0093)	(0.0087)			(0.0428)	(0.0428)

Spreads can also be expressed as a proportion of the prevailing quoted midpoint (i.e., in basis points). The introduction of dark orders is found to have no significant effect on basis point spreads. The advantage of the proportional spread is that stocks with different price levels may be more comparable, though these effects (or non-effects) can be driven entirely by movements in the underlying stock price (i.e., the denominator in proportional spreads). For the period July to December 2011, volume-weighted effective spreads are just under 2.0 cents for TSX60 stocks, and 2.6 cents for TSX Completion stocks, and so while they are different, this difference is not major. When scaled by the midpoint, however, effective spreads are 5.4 basis points for TSX60 stocks, and 16.8 for the TSX Completion stocks, a difference arising from the lower prices (on average) at which TSX completion stocks trade; as TSX Completion stocks trade at lower dollar prices, their proportional spreads are systematically more sensitive to price changes. Due to this systematic difference, the regressions for the spreads in basis points are not unbiased, and so have not been reported.

5.8 Results for the Intra-Day Usage of Dark Orders

Table 5.7 presents results from a two-stage instrumental variable regression analysis of equation (5.5). As described earlier, in this regression the percentage of dark orders submitted at $t-1$ is used as an instrument for the percentage of dark executions at time t. Table 5.7 indicates that this instrument is highly significant and that all tests for over-, under- and weak specification are rejected for all of the estimated specifications.

Table 5.8 illustrates that transactions involving dark orders occur at wider spreads than transactions that involve only lit orders. One reason this can occur is that, when spreads are large, traders may submit orders to tighten the spread. If these new quotes cross the midpoint, an execution against a dark midpoint order will occur, if such an order exists. Such an execution differs fundamentally from a dark pool trade - these specifically require that both sides of a trade deliberately access the dark pool at the same time.

TABLE 5.7: First Stage of the IV Regression on the Intra-Day Impact of Trading in Dark Orders

This table represents the results from the first stage of the IV regressions where the fraction of dark trading on the TSX, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it?1}$. The Kleibergen and Paap (2006) Wald statistic of under-identification is computed, which, in this specification is $\chi^2(1)$ distributed, and the Kleibergen and Paap (2006) statistic for weak identification (following the Andrews and Stock (2005) critical values; for this specification, the 10% maximal IV size critical value is 16.38). Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), market fragmentation (measured using one minus the Herfindahl Index of market fragmentation in Canada), the logarithm of dollar-volume, the fill-rate (the fraction of executed volume of all order volume), the 10-minute price volatility (highest quoted midpoint minus lowest quoted midpoint, scaled by the average quoted midpoint, measured in basis points), and the contemporaneous average over all other symbols for log-\$-volume, trade size and volatility. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. All regressions include stock fixed effects and fixed effects for the 10-minute interval. Standard errors are double-clustered by firm and time. * indicates significance of non-zero correlation at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

instrumented variable: Main instrument:	% dark TSX trading % dark dark orders$_{it-1}$	(1)	(2)	(3)	(4)	(5)
% dark orders$_{it-1}$		0.5635***	0.5642***	0.5633***	0.5606***	0.5633***
		(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
VIXC$_d$		0.0573***	0.0643***	0.0646***	0.0626***	0.0638***
		(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
log mid-quote$_{it}$			1.0042***	0.9954***	0.8591**	0.9798***
			(0.350)	(0.349)	(0.377)	(0.349)
Fragmentation$_{it}$		1.9284***		1.9269***	2.1267***	1.9271***
		(0.145)		(0.146)	(0.160)	(0.146)
log \$-volume$_{it}$					0.0113	
					(0.038)	
Average order size one week ago$_i$					0.0007*+	
					(0.000)	
Fillrate$_{it}$					0.0011	
					(0.003)	
Volatility$_{it}$					-0.0113***	
					(0.001)	
Average *log*-\$-volume in all other symbols$_{it}$						0.0000
						(0.000)
Average trade size in all other symbols$_{it}$						-17.0212
						(12.410)
Average volatility in all other symbols$_{it}$						-0.0000***
						(0.000)
Observations		715,212	715,212	715,212	715,159	715,212
adjusted R-squared		0.1	0.099	0.1	0.102	0.1
F		32.18	25.42	32.04	30.56	30.21
Kleibergen and Paap (2006) under-identification		106.4	106.6	106.5	106.8	106.5
Kleibergen and Paap (2006) weak identification		707.2	704.5	704.5	703.4	704.5

Table 5.8: Summary Statistics Dark vs. Lit Trading

This table represents summary statistics for several key liquidity and market quality variables split up by dark vs. visible trade for our sample of TSX Composite stocks. All measures are based on daily per stock averages for the second half of 2011. Dark vs. lit is to be understood as follows: we compute the daily average of, for instance, quoted spreads, separately for all executions that involve only lit orders and those that involve dark order on the passive side of the transaction. We then compute the equal weighted average for all daily, per company, averages. Wilcoxon tests of matched pairs (by firm and date) for equality of means and medians for the daily lit vs. dark realizations are all rejected at the 1% level except for the equality of means test for trade size for the TSX Composite, which is rejected at the 5% level of significance.

		TSX60			TSX Completion			TSX Composite		
		Visible	Dark	Diff.	Visible	Dark	Diff.	Visible	Dark	Diff.
Quoted Spread at transaction	Average	1.9	2.5	-0.6	2.5	3.4	-0.9	2.4	3.1	-0.7
	StDev	1.6	2.4		2.7	4.2		2.5	3.8	
	Median	1.2	1.7		1.6	2.0		1.4	2.0	
Depth at transaction (in thousands of shares)		42	48	-6	19	22	-3	24	29	-5
		33	43		69	107		63	94	
		31	34		13	12		15	16	
Effective Spreads		2.0	0.3	1.7	2.7	0.6	2.1	2.5	0.5	2.0
		1.6	1.5		2.9	3.2		2.7	2.8	
		1.3	0.0		1.7	0.0		1.6	0.0	
Effective Spreads plus taker fee		2.6	0.5	2.2	3.4	0.8	2.6	3.2	0.7	2.5
		1.6	1.5		2.9	3.2		2.7	2.8	
		2.0	0.2		2.4	0.2		2.3	0.2	
Realized spread		-0.8	0.5	-1.3	-0.7	0.3	-1.0	-0.7	0.3	-1.1
		1.5	9.1		2.4	8.1		2.2	8.4	
		-0.6	0.3		-0.6	0.0		-0.6	0.1	
Price Impact		1.4	-0.1	1.5	1.7	0.2	1.6	1.6	0.1	1.6
		1.2	4.7		1.8	4.2		1.7	4.3	
		1.0	-0.1		1.2	0.0		1.1	0.0	
Fill rate		2.7	17.1	-14.3	4.2	14.3	-10.2	3.8	15.0	-11.2
		2.4	38.1		3.4	53.6		3.3	50.3	
		2.1	10.0		3.4	7.3		3.0	7.9	

5.8.1 Quoted Liquidity

Table 5.9 presents the results from the estimations of the intra-day impact of dark trading on quoted liquidity. These results show that a 1% increase in dark trading decreases TSX spreads by between 0.019 to 0.027 cents, depending on the model specification. Increases in dark trading also lead to an increase in quoted depth, and this result is statistically significant at the 1% level

Taken together, these findings indicate improvements in quoted liquidity that are associated with contemporaneous increases in dark trading. This finding is notable for two reasons: firstly, the results from the introduction of dark trading indicate that quoted spreads *increased* following the introduction of dark trading; secondly, that one fact unique to dark trading is that the prevailing quoted spreads for trades that involve a dark order are greater than when the trade only involves lit orders (see Table 5.8). Trades against dark orders can be identified from the published trades, and are primarily identified as being within-spread executions.[54] An explanation for this surprising finding is that traders may post wider spreads when they suspect that a dark midpoint order may be present. When an execution against a dark order is observed, traders learn that: (a) there was a dark order; and (b) dark liquidity has now been reduced. These traders may then be posting quotes more aggressively in order to capture the dark liquidity that they know was recently in existence.

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[54] TMX offers a number of data feeds. The cheapest of these rounds prices and thus midpoint executions at one cent spreads are not identifiable; data from Thomson Reuters Tick History is based on this feed. Professional traders and major brokerages, however, usually subscribe to the Level 2 feed which provides more detailed information.

TABLE 5.9: IV Regression on the Intra-Day Impact of Trading in Dark Orders on Quoted Liquidity

The table presents the regression results from the second stage of an instrumental variable regressions of time-weighted quoted spreads (in cents) and log-\$-depth (both on the TSX) on the fraction of volume that is traded with dark orders and a number of control variables. In the first stage, the variable of interest, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it-1}$. Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), market fragmentation (measure by one minus the Herfindahl Index of market fragmentation in Canada), the logarithm of dollar-volume, the fill-rate (the fraction of executed volume of all order volume), the 10-minute price volatility (highest quoted midpoint minus lowest quoted midpoint, scaled by the average quoted midpoint, measured in basis points), and the contemporaneous average over all other symbols for log-\$-volume, trade size and volatility. All regressions include stock fixed effects and fixed effects for the 10-minute interval. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Second stage of the intra-day IV estimation
Main instrument: % dark orders$_{it-1}$

Dependent variable	time-weighted quoted spread					time-weighted log-\$-depth				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
% dark trading$_{it}$	-0.0267***	-0.0255***	-0.0270***	-0.0198***	-0.0269***	0.0072***	0.0066***	0.0070***	0.0048**+	0.0070***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VIXC$_d$	0.0350***	0.0410***	0.0413***	0.0463***	0.0430***	-0.0102***	-0.0065***	-0.0066***	-0.0078***	-0.0065***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
log mid-quote$_{it}$		0.8793***	0.8724***	1.2101***	0.9070***		0.4887***	0.4904***	0.4623***	0.4922***
		(0.177)	(0.187)	(0.186)	(0.187)		(0.159)	(0.158)	(0.166)	(0.159)
Fragmentation$_{it}$	1.8278***		1.8270***	1.1567***	1.8266***	-0.4662***		-0.4666***	-0.2421***	-0.4666***
	(0.191)		(0.191)	(0.139)	(0.191)	(0.018)		(0.018)	(0.013)	(0.018)
log \$-volume$_{it}$				-0.2412***					0.1036***	
				(0.027)					(0.005)	
Average order size one week ago$_i$				0					0.0003***	
				(0.000)					(0.000)	
Fillrate$_{it}$				-0.0186***					0.0063***	
				(0.004)					(0.001)	
Volatility$_{it}$				0.0129***					-0.0027***	
				(0.002)					(0.000)	
Average *log*-\$-volume in all other symbols$_{it}$					0.0000					0.0000
					(0.000)					(0.000)
Average trade size in all other symbols$_{it}$					37.7414***					1.8790*
					(6.141)					(1.132)
Average volatility in all other symbols$_{it}$					0.0000***					-0.0000***
					(0.000)					(0.000)
Observations	715,212	715,212	715,212	715,159	715,212	715,212	715,212	715,212	715,159	715,212
adjusted R-squared	0.024	0.01	0.025	0.082	0.026	0.03	0.019	0.038	0.126	0.038

Table 5.10: IV Regression on the Intra-Day Impact of Trading in Dark Orders on Effective Trading Costs

The table presents the regression results from the second stage of an instrumental variable regression of volume weighted effective spreads (in cents) and volume weighted effective spreads plus taker fees (in cents) (both on the TSX) on the fraction of volume that is traded with dark orders and a number of control variables. In the first stage, the variable of interest, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it-1}$. Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), market fragmentation (measure by one minus the Herfindahl Index of market fragmentation in Canada), the logarithm of dollar-volume, the fill-rate (the fraction of executed volume of all order volume), the 10-minute price volatility (highest quoted midpoint minus lowest quoted midpoint, scaled by the average quoted midpoint, measured in basis points), and the contemporaneous average over all other symbols for log-\$-volume, trade size and volatility. All regressions include stock fixed effects and fixed effects for the 10-minute interval. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Second stage of the intra-day IV estimation Main instrument: % dark orders$_{it-1}$										
Dependent variable	Effective spread					Effective spread plus taker fee				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
% dark trading$_{it}$	-0.0455***	-0.0446***	-0.0456***	-0.0417***	-0.0456***	-0.0460***	-0.0450***	-0.0461***	-0.0422***	-0.0461***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
VIXC$_d$	0.0178***	0.0211***	0.0214***	0.0233***	0.0230***	0.0178***	0.0211***	0.0213***	0.0233***	0.0229***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
log mid-quote$_{it}$		0.4943***	0.4891***	0.6810***	0.5212***		0.4930***	0.4879***	0.6800***	0.5200***
		(0.123)	(0.130)	(0.131)	(0.130)		(0.123)	(0.130)	(0.131)	(0.130)
Fragmentation$_{it}$	1.3689***		1.3685***	1.0412***	1.3681***	1.3684***		1.3680***	1.0404***	1.3676***
	(0.135)		(0.135)	(0.109)	(0.135)	(0.135)		(0.135)	(0.109)	(0.135)
log \$-volume$_{it}$				-0.0683***					-0.0685***	
				(0.014)					(0.014)	
Average order size one week ago$_i$				0					0	
				(0.000)					(0.000)	
Fillrate$_{it}$				-0.0110***					-0.0110***	
				(0.002)					(0.002)	
Volatility$_{it}$				0.0083***					0.0083***	
				(0.001)					(0.001)	
Average *log*-\$-volume in all other symbols$_{it}$					0.0000					0.0000
					(0.000)					(0.000)
Average trade size in all other symbols$_{it}$					35.0160***					35.0663***
					(4.945)					(4.945)
Average volatility in all other symbols$_{it}$					0.0000***					0.0000***
					(0.000)					(0.000)
Observations	715,212	715,212	715,212	715,159	715,212	715,212	715,212	715,212	715,159	715,212
adjusted R-squared	0.039	0.029	0.04	0.064	0.041	0.04	0.03	0.04	0.065	0.041

5.8.2 Effective Liquidity

Table 5.10 examines the impact of changes in effective spreads associated with increases in dark trading. These measures are estimated both in terms of the raw effective spread and the effective spread plus the maker-taker fee. The table documents that a 1% increase in dark trading is associated with a 0.45 cent decline in effective spreads. The point estimate of 0.45 cents is remarkably consistent across the both constructions of the effective spread. The decrease in trading costs associated with dark trading is also robust to the inclusion of controls for a variety of market conditions, including market wide volatility, price, level of fragmentation, traded volume, the average order size in the preceding week, the average fill rate, unsystematic (stock-specific) volatility as well as controls for the traded value, size and volatility in all other symbols. This finding of reduced transaction costs in the presence of dark trading is consistent with the findings for previous measures of liquidity, such as reduced quoted and realised spreads.

Table 5.11 illustrates that this effect applies not only when the effective spread is computed based on the local TSX best bid and offer prices, but also when the effective spread is based on the national mid-quote. Effective spreads for orders that involve visible trades on the passive side are also computed. Here, reductions in the spread are also found, with similar magnitudes to the reduction in the quoted spread. In other words, the reduction in effective spreads is not solely caused by the zero-spreads that dark midpoint executions generate, but also by more aggressive quoting by liquidity providers leading to reduced quoted spreads.

5.8.3 Volume

For TSX data, it is generally observed that quoted spreads at transactions are lower than time-weighted quoted spreads, indicating that executions occur when spreads are small. As dark trading reduces spreads, one can expect an increase in volume, and the results shown in Table 5.12 indicate that this is what has occurred. Additionally, the ratio of executed to submitted volume, which can be interpreted as the fill-rate, is also examined to determine if it is affected by dark trading. As Table 5.12 shows, fill-rates increase with higher levels of dark trading, including for orders executed solely on lit markets.

TABLE 5.11: IV Regression on the Intra-Day Impact of Dark Orders on NBBO and Lit-Only Effective Spreads

The table presents the regression results from the second stage of an instrumental variable regression of volume weighted effective spreads (in cents, on theTSX) and the volume weighted effective spreads (in cents) based on the national mid-quote on the fraction of volume that is traded with dark orders and a number of control variables. In the first stage, the variable of interest, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it-1}$. Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), market fragmentation (measured by one minus the Herfindahl Index of market fragmentation in Canada), the logarithm of dollar-volume, the fill-rate (the fraction of executed volume of all order volume), the 10-minute price volatility (highest quoted midpoint minus lowest quoted midpoint, scaled by the average quoted midpoint, measured in basis points), and the contemporaneous average over all other symbols for log-\$-volume, trade size and volatility. All regressions include stock fixed effects and fixed effects for the 10-minute interval. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Second stage of the intra-day IV estimation
Main instrument: % dark orders$_{it-1}$

Dependent variable	volume-weighted effective spread – only lit trading					volume-weighted effective spread based on the NBBO				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
% dark trading$_{it}$	-0.0215***	-0.0204***	-0.0217***	-0.0173***	-0.0217***	-0.0434***	-0.0427***	-0.0435***	-0.0402***	-0.0435***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
VIXC$_d$	0.0185***	0.0217***	0.0220***	0.0237***	0.0236***	0.0194***	0.0225***	0.0227***	0.0241***	0.0241***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
log mid-quote$_{it}$		0.4824***	0.4774***	0.6625***	0.5096***		0.4583***	0.4543***	0.6050***	0.4819***
		(0.123)	(0.131)	(0.131)	(0.131)		(0.112)	(0.118)	(0.119)	(0.118)
Fragmentation$_{it}$	1.4052***		1.4048***	1.0758***	1.4044***	1.0645***		1.0641***	0.7894***	1.0638***
	(0.139)		(0.139)	(0.112)	(0.138)	(0.109)		(0.109)	(0.090)	(0.109)
log \$-volume$_{it}$				-0.0625***					-0.0492***	
				(0.014)					(0.011)	
Average order size one week ago$_i$				0					0	
				(0.000)					(0.000)	
Fillrate$_{it}$				-0.0113***					-0.0099***	
				(0.002)					(0.002)	
Volatility$_{it}$				0.0084***					0.0070***	
				(0.001)					(0.001)	
Average *log*-\$-volume in all other symbols$_{it}$					0.0000					0.0000
					(0.000)					(0.000)
Average trade size in all other symbols$_{it}$					35.1427***					30.1122***
					(4.940)					(4.157)
Average volatility in all other symbols$_{it}$					0.0000***					0.0000***
					(0.000)					(0.000)
Observations	713,413	713,413	713,413	713,363	713,413	715,212	715,212	715,212	715,159	715,212
adjusted R-squared	0.016	0.005	0.016	0.042	0.017	0.041	0.034	0.042	0.065	0.043

TABLE 5.12: IV Regression on the Intra-day Impact of Dark Orders on Volatility, Volume and Fill Rates

The table presents the regression results from the second stage of an instrumental variable regression of 10-minute mid-quote volatility, log-dollar-volume, the fill-rate for all orders (the fraction of executed volume of all order volume), and the fill-rate for lit orders on the fraction of volume that is traded with dark orders and a number of control variables. In the first stage, the variable of interest, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it-1}$. Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, and the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), and market fragmentation (measured by one minus the Herfindahl Index of market fragmentation in Canada). All regressions include stock fixed effects and fixed effects for the 10-minute interval. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Second stage of the intra-day IV estimation
Main instrument: % dark orders$_{it-1}$

Dependent variable	mid-quote volatility			*log*-$- volume			Fill rate all orders			Fill rate lit orders		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
% dark trading$_{it}$	-0.3585***	-0.3389***	-0.3513***	0.0076***	0.0067***	0.0075***	0.0481***	0.0403***	0.0488***	0.0892***	0.0811***	0.0899***
	(0.025)	(0.024)	(0.024)	(0.001)	(0.001)	(0.001)	(0.008)	(0.008)	(0.008)	(0.011)	(0.010)	(0.011)
VIXC$_d$	-0.0643	-0.2367***	-0.2341***	0.0133***	0.0162***	0.0160***	-0.0825***	-0.0970***	-0.0989***	-0.0865***	-0.1015***	-0.1034***
	(0.047)	(0.054)	(0.054)	(0.002)	(0.002)	(0.002)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
log mid-quote$_{it}$		-23.2330***	-23.2929***		0.3653***	0.3693***		-2.2788***	-2.2375***		-2.3596***	-2.3181***
		(3.057)	(3.085)		(0.120)	(0.123)		(0.594)	(0.611)		(0.613)	(0.630)
Fragmentation$_{it}$	15.9162***		15.9363***	-1.0724***		-1.0727***	-10.9687***		-10.9668***	-11.1266***		-11.1246***
	(1.064)		(1.066)	(0.055)		(0.055)	(0.511)		(0.511)	(0.526)		(0.526)
Observations	715,212	715,212	715,212	715,212	715,212	715,212	715,159	715,159	715,159	715,150	715,150	715,150
adjusted R-squared	0.006	0.005	0.009	0.076	0.051	0.077	0.039	0.003	0.039	0.025	-0.009	0.025

TABLE 5.13: IV Regression on the Intra-day Impact of Dark Orders on Price Impact, Realised Spreads + Maker Fees

The table presents the regression results from the second stage of an instrumental variable regression of volume weighted 5-minute realized spreads plus maker rebate (in cents) and the volume weighted 5-minute price impact (in cents) (both on the TSX) on the fraction of volume that is traded with dark orders and a number of control variables. In the first stage, the variable of interest, $\%darktrading_{it}$, is instrumented by the fraction of dark orders in the preceding time period, $\%darkorders_{it-1}$. Control variables are the daily realization of the Canadian volatility index VIXC, the average order size in the stock in the preceding week, the contemporaneous realizations of the logarithm of the time-weighted average mid-quote (over the 10-minute interval), market fragmentation (measured by one minus the Herfindahl Index of market fragmentation in Canada), the logarithm of dollar-volume, the fill-rate (the fraction of executed volume of all order volume), the 10-minute price volatility (highest quoted midpoint minus lowest quoted midpoint, scaled by the average quoted midpoint, measured in basis points), and the contemporaneous average over all other symbols for log-\$-volume, trade size and volatility. All regressions include stock fixed effects and fixed effects for the 10-minute interval. The sample consists of 229 companies that are in the TSX Composite Index and it covers the time span from July 01, 2011 to December 30, 2011. Standard errors are double-clustered by firm and time. * indicates significance at the 10% level, *+ at the 6% level, ** at the 5% level, **+ at the 2% level, and *** at the 1% level.

Second stage of the intra-day IV estimation
Main instrument: % dark orders$_{it-1}$

Dependent variable	5-minute price impact					5-minute realized plus maker rebate				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
% dark trading$_{it}$	-0.0246***	-0.0242***	-0.0247***	-0.0175***	-0.0246***	0.0030	0.0031	0.0030	-0.0074	0.0030
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
VIXC$_d$	0.0125***	0.0142***	0.0143***	0.0184***	0.0158***	-0.0073***	-0.0074***	-0.0074***	-0.0136***	-0.0086***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
log mid-quote$_{it}$		0.2532***	0.2508***	0.6685***	0.2795***		-0.0138	-0.0142	-0.6574***	-0.0394
		(0.082)	(0.084)	(0.087)	(0.084)		(0.110)	(0.110)	(0.126)	(0.109)
Fragmentation$_{it}$	0.6336***		0.6334***	0.1847***	0.6331***	0.101		0.101	0.6708***	0.1012
	(0.077)		(0.077)	(0.055)	(0.077)	(0.077)		(0.077)	(0.083)	(0.077)
log \$-volume$_{it}$				-0.0505***					0.0323	
				(0.015)					(0.022)	
Average order size one week ago$_i$				0					0	
				(0.000)					(0.000)	
Fillrate$_{it}$				-0.0096***					0.0083***	
				(0.002)					(0.002)	
Volatility$_{it}$				0.0181***					-0.0279***	
				(0.002)					(0.002)	
Average *log*-\$-volume in all other symbols$_{it}$					0.0000					0.0000
					(0.000)					(0.000)
Average trade size in all other symbols$_{it}$					31.3064***					-27.5291***
					(4.767)					(7.196)
Average volatility in all other symbols$_{it}$					-0.0000***					0.0000***
					(0.000)					(0.000)
Observations	715,212	715,212	715,212	715,159	715,212	715,212	715,212	715,212	715,159	715,212
adjusted R-squared	0.012	0.01	0.012	0.077	0.012	0.001	0.001	0.001	0.04	0.001

5.8.4 Price Impact and Volatility

Tables 5.12 and 5.13 outline that there is a reduction in price impact and volatility following increases in dark trading. One possible explanation for this effect is that although informed traders will trade regardless of the spread, there are some price-sensitive, uninformed traders that act only once spreads are sufficiently small and who are thus attracted by the reduction in spreads that occurs following dark executions. This finding is consistent with those of Comerton-Forde and Putnins (2012) - that uninformed traders are more likely to move to the dark.

The decline in the price impact is then consistent with the arguments made for the result on quoted liquidity: upon observing dark executions (which, by themselves, reduce the price impact), traders submit limit orders attempting to pick off the dark orders. Assuming the purpose of these trades is to execute cheaply against the dark order, the information content of such trades is small, and thus the price impact is low. Table 5.13 further outlines a decline in volatility, in line with the reduced average price impact over the time interval.

The effects of dark orders on effective spreads presented are not only statistically significant, but also economically significant. For each 1% increase in dark order executions, effective spreads (an active order execution cost) reduce by 0.045 cents. This is more than double the net exchange fee (i.e. the taker fee minus the maker rebate) that the TSX charges per transaction (being 0.02 cents).

5.9 Conclusion

The impact of dark trading is studied from two angles. Firstly, the impact of the introduction of dark orders is analysed using a difference-in-differences approach. Consistent with Buti, et al. (2011a)'s theoretical predictions, the introduction of dark orders is found to increase both quoted and effective spreads, suggesting that dark trading causes an increase in trading costs. No changes are found in volume or volatility as a result of this introduction.

Secondly, the usage of dark orders at the intra-day level is examined to understand how dark trading is treated by market participants. Dark trading is found to lead to lower spreads, higher volume, and lower volatility. The findings of these two separate studies present two sides of the same coin: upon observing dark executions, traders may infer that existing dark liquidity is diminished, and may thus post quotes more aggressively, either to access this dark liquidity or to determine if it still exists.

Overall, however, these results may understate the potential benefits of having the option to trade with dark orders, as standard liquidity measures do not capture several of their potential advantages. For example, traders may benefit by switching from submitting marketable orders to posting dark midpoint orders. Dark orders have high fill rates, and execute at a price that is superior to the visible quotes. Furthermore, limit orders of market participants who don't have the ability to monitor the market at high frequencies may become stale, and allowing midpoint-pegged dark orders gives these traders an option to avoid this pitfall. Finally, marketable orders that execute against dark orders always obtain a superior price. While the effective spread does account for these savings, the uptake of dark orders immediately after their introduction may have been too low to reflect this benefit — the uptake continued to increase well past the time frame that can be used for the difference-in-difference analysis.

Chapter 6

The Impact of Continuous External Dark Pools

6.1 Introduction

Dark trading refers to trades that are executed without pre-trade transparency. While it has long been a feature of equity markets in the form of upstairs block trades, it is only in recent years, with the introduction of continuous dark pools for smaller sized non-transparent orders, that dark trading has attracted the attention of regulators and policy makers worldwide. Dark pools have been very successful in attracting order flow, and are estimated to account for approximately 15% of US consolidated volume, 14% in Australia, and 10% in Canada.[55] Proponents of dark trading attribute this success to certain attributes, such as the ability to avoid large orders being front run, reduced information leakage, and lower market impact costs.

The rapid increase of dark market share has caused considerable concern among market regulators. For example, the US Securities Exchange Commission (SEC) proposed rules in 2009 for the "Regulation of non-public trading interest", the Committee of European

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[55] The US estimate is from Rosenblatt Securities for April 2013. The Australian estimate is from the Australian Securities and Investments Commission Report 331 for the September quarter 2012 and includes some internalization. The Canadian estimate combines statistics from the Investment Industry Regulatory Organization of Canada and proprietary data obtained for this study and corresponds to the period Aug-Dec 2012.

Securities Regulators (CESR) has undertaken a review of dark trading with recommendations to limit the activities of broker crossing systems; and the Australian Securities Investment Commission (ASIC) released a report in 2013 identifying their intention to restrict the kinds of trades that can be undertaken in the dark.[56] Although these regulatory bodies have all conducted public consultations for proposed limits on dark trading, they have hesitated to introduce any new regulations for dark trading. Such hesitance reflects the scarcity of evidence on the costs and benefits of dark pools, the distribution of costs and benefits among the different market participants. This chapter aims to address this problem by providing empirical evidence on the impact of continuous dark trading on market quality.

The investigation in this chapter focuses on the dark trading minimum price improvement rules introduced in Canada in October 2012 - the first such regulation in the world. These rules require that dark orders of 5,000 shares or less provide one full tick of price improvement (or half a tick if the spread is constrained at one tick). These rules reduced the amount of dark trading in Canada by over one third on the day of their introduction. This unique natural experiment, together with proprietary trade-level data from dark trading venues, allows the study of the causal impact of dark trading on liquidity and informational efficiency, both in dark pools and dark trades in lit venues. By using a two-stage instrumental variables analysis with the rule change as an exogenous instrument, the endogeneity issues that have hindered the empirical analysis of dark trading and market quality are avoided.

One of the main concerns raised by market participants and market operators during the consultation process for the minimum price improvement regulation was that dark trading would migrate to the US to circumvent the new rules. Given that a large number of Canadian stocks are cross-listed in the US, such a shift could harm the overall quality of the Canadian market. In order to test the possibility of such “regulatory flight”, a difference-in-differences model is constructed to compare dark trading volume in cross-listed stocks with dark trading volume in matched samples of stocks listed only in Canada and the US.

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[56] ASIC Report 331 “Dark liquidity and high-frequency trading”.

6.2 Continuous Dark Trading

6.2.1 Trading Venues and Order Types

Canada has experienced rapid fragmentation of its trading landscape over the last decade. In addition to the main listing exchange, the Toronto Stock Exchange (TSX), there are currently five Alternative Trading Systems, on which trading occurs with pre-trade transparency (referred to as "lit" venues): Alpha, Chi-X, Pure Trading, TMX-Select, and Omega. TSX is still the dominant market, executing approximately 61% of Canadian dollar volume during the sample period, followed by Alpha (15%) and Chi-X (13%). Additionally, there are four continuous auction venues in which orders can be submitted without pre-trade transparency: ITG's MatchNow, Alpha Intraspread, Chi-X and TSX.[57] MatchNow and Alpha Intraspread fall into the category of markets often referred to as "dark pools" because only dark orders can be submitted to these venues and therefore dark orders execute exclusively against other dark orders. They account for approximately 3.0% and 2.5% of Canadian dollar volume, respectively, during the sample period. In contrast, Chi-X and TSX allow dark orders in addition to lit orders and the two types of orders interact and can execute against one another. Following the introduction of the minimum price improvement rules in 2012, Alpha Intraspread (which had been a stand-alone continuous dark pool) was merged with the Alpha lit exchange. Subsequently, Intraspread orders are able to interact with both lit and dark liquidity, similar to the situation in both the TSX and Chi-X. Table 6.1 provides a summary of the market shares, order types and other characteristics of each of the Canadian trading venues.

Prior to 15 October 2012, all dark orders were required to provide some price improvement, resulting in dark executions within the national best bid and offer (NBBO) spread. The required amount of price improvement, however, was not specified in legislation. MatchNow and Intraspread both offered two types of price improvement: midpoint (i.e., 50% improvement over the NBBO) and 20% (on MatchNow) or 10% (on Instraspread) improvement over the NBBO. Price improvement of 10%, for example, means that if

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[57] MatchNow was launched in July 2007. Intraspread was launched in May 2011. Chi-X introduced dark midpoint orders in February 2008. TSX introduced dark orders between April and May 2011, as analysed in the previous chapter.

Table 6.1: Summary of all trading venues in Canada

This table provides an overview of all of the lit and dark trading venues in Canada. The types of orders allowed include lit-only, dark-only or both lit and dark. The execution priority rules for each trading venue are reported in the table. They include: price priority (highest price receives priority, including most price improvement for dark orders), visibility (meaning lit orders receive priority over dark orders), broker (passive orders that are from the same broker as incoming active orders receive priority), size (passive orders are prioritized by their ability to entirely fill incoming active orders) and time (older orders are given priority over newer orders). The approximate market share of total traded dollar volume (including dark and lit trades on all listed venues) is reported for the period 15 August 2012 – 15 December 2012. The market share of Liquidnet / Instinet is obtained from IIROC statistics, whereas the other market shares are calculated from our data.

Venue	Lit / Dark	Market share	Priority rules
TSX	Both	61.3%	Price, visibility, broker, time
Chi-X	Both	12.9%	Price, visibility, broker, time
Alpha (Lit)	Both (post 15 Oct 2012)	15.0%	Price, visibility, broker, time
MatchNow	Dark	3.0%	Price, size (proportional)
Alpha Intraspread	Dark	2.5%	Price, broker, size, time
Pure	Lit	2.4%	Price, broker, time
TMX Select	Lit	1.4%	Price, time
Omega	Lit	1.2%	Price, broker, time
Liquidnet / Instinet	Dark (block)	0.2%	Negotiated trades

a stock has a national best bid of \$10.00 and a national best offer of \$10.01, a passive dark buy order could be placed at a price of \$10.001 (an improvement of 10% of the NBBO spread) and a passive dark sell order could be placed at a price of \$10.009 (also an improvement of 10% of the NBBO spread).

Both MatchNow and Intraspread previously supported price priority, meaning a passive midpoint order would execute before a passive 20% or 10% price improvement order. When an active order is submitted to a dark pool, the matching engine first checks if there are any passive orders available to execute against. If there are, the order is executed and immediately reported to the Canadian marketplace.[58] If the active order cannot be matched it is either cancelled (akin to a fill or kill order) or it is forwarded to a lit venue based on the user's routing table preferences. TSX and Chi-X previously only offered floating midpoint orders, which could execute against both incoming active lit orders as well as other dark orders.

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[58] The reporting is facilitated by TMX Datalinx and is required according to Universal Market Integrity Rules. While this forms a consolidated feed of quotes and trades, it does not provide the NBBO for Canada; rather, participants must reconstruct it from the order flow. For more information see www.tmxdatalinx.com.

The order execution priority rules in Canada differ significantly from those in other countries, primarily in the existence of broker preferencing, which allows passive orders resting in the limit order book to break time priority if an incoming active order is from the same broker. Many of the dark trading venues have employed unique priority systems in order to differentiate themselves from other venues. Of these, the most complex are found on Alpha Intraspread. Intraspread provides priority based on the amount of price improvement first, with orders offering 50% of the spread receiving priority over those that offer 10% of the spread. Given equal price improvement, broker preferencing provides priority for orders from the same broker. Assuming equality on these two rules, priority will be given to passive orders that are able to fulfil the entire active order. If all four of these priorities are equivalent, time priority will be given to the oldest order.

In addition to the continuous dark pools, systems to negotiate block trades without pre-trade transparency have existed for decades. Two that currently operate in Canada are Liquidnet and Instinet. These venues provide "trade blotter" services that facilitate the execution of "upstairs" trades. Typically, clients enter their desire to trade large blocks into the system. The system then identifies whether any potential counterparties exist, and if so, allows the counterparties to negotiate the trade anonymously. While these systems also have limited or no pre-trade transparency, they differ from dark pools that have captured significant market share in recent years in that they are generally only used by large institutional traders, are non-continuous, and only offer services for block trades. Although block trading facilities have existed for many years, the combined market share of Liquidnet and Instinet in Canadian equities during the third quarter of 2012 was only 0.2%.[59] Brokers are also able to internalize orders off-market. The order exposure rule requires however, that internalised trades are provided one full tick of price improvement, in conjunction with the fair access regulations that prohibit venues from providing exclusive access to certain types of clients.[60] This has hampered the development of automated "internalizers" such as those that exist in the US, Australia and elsewhere.

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[59] This statistic is taken from the IIROC "Marketplace Statistics Report" available at www.iiroc.ca.

[60] See the Universal Market Integrity Rules (UMIR) section 6.3.

6.3 Minimum Price Improvement Regulation

The Investment Industry Regulatory Organization of Canada (IIROC) sets and enforces the Universal Market Integrity Rules (UMIR), which govern trading on debt and equity marketplaces in Canada. On 13 April 2012 IIROC notice 12-0130 announced changes to the UMIR, which became effective on 15 October 2012. These changes imposed a minimum threshold for price improvement by dark orders of one full tick relative to the prevailing NBBO, except where the spread is already constrained to one tick, in which case dark orders are allowed at the midpoint of the NBBO (half a tick price improvement). An exemption to this requirement was allowed for dark orders larger than either 50 standard trading units (STU) - usually 5,000 shares or \$100,000.[61] Such large dark orders are able to execute at the NBBO, without providing *any* price improvement, as long as they give priority to lit orders at the same price on the same trading venue. Prior to the change in regulation, dark orders were required to provide a “better price” than the prevailing NBBO but with no minimum increment of price improvement to constitute a “better price”.[62]

The minimum price improvement requirements caused a significant decline in dark volume, and a change in the prices at which dark trades execute. Figure 6.1 documents the significant decrease in dark volume as a result of the change in regulation. The level of dark trading fell from approximately 7.5% of dollar volume during the two months preceding the regulatory change to approximately 4.6% in the two months after the change - a decrease of over one third. The reduction in dark trading occurred very quickly and distinctly around the change in regulation.

Figure 6.2 shows that prior to the introduction of the minimum price improvement requirements approximately 70% of orders were executed at fractional price increments (10% and 20% of the NBBO spread), which are not allowed under the new rules, and the remaining 30% executed at the midpoint. Under the new regulation, fractional price improvement orders disappeared and almost all dark trading now takes place at

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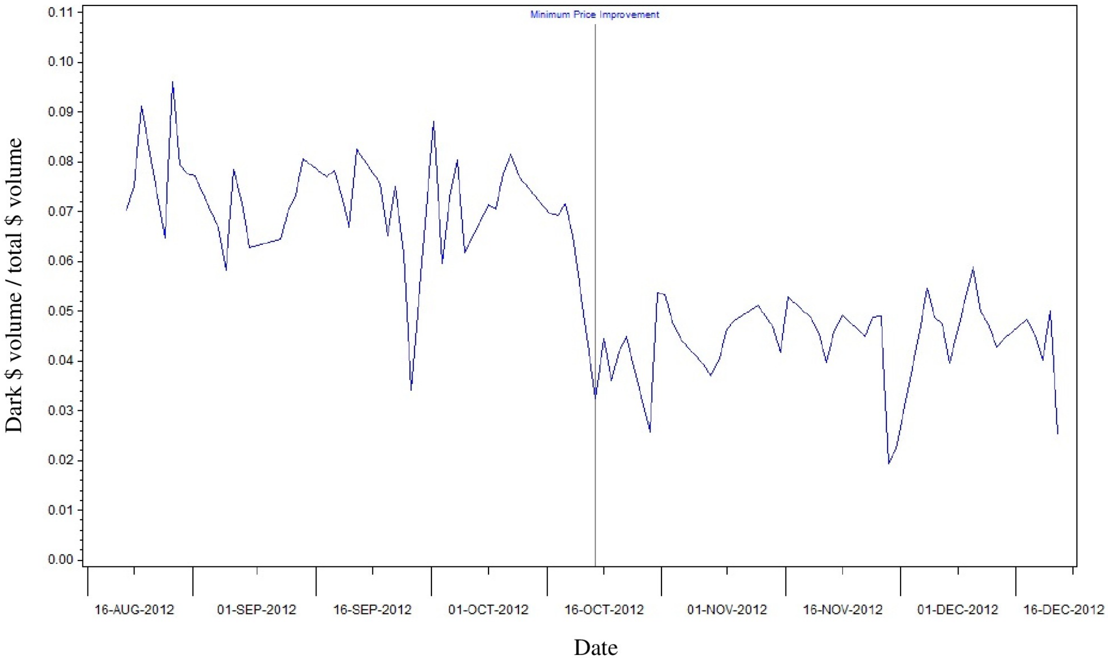
[61] A standard trading unit is 100 shares for stocks priced above \$1.00, 1,000 shares for stocks priced between \$0.10 and \$1.00, and 10,000 shares for stocks priced below \$0.10.

[62] The UMIR defined “better price” simply as a lower price than the best ask price in the case of a purchase and higher price than the best bid price in the case of a sale.

Figure 6.1: Dark Trading in Canada as a Percentage of Consolidated Dollar Volume

This figure shows daily dark trading in Canada as a fraction of total consolidated dollar volume, for constituents of the TSX Composite Index, from 15 August 2012 to 15 December 2012. The dark trading fraction is constructed by aggregating the dollar volume of dark trades executed on MatchNow, Intraspread, Chi-X, and Alpha, and dividing it by the total dollar volume of trading on all of the main venues (TSX, Chi-X, Alpha, MatchNow, Intraspread, TMX Select, Pure Trading, and Omega). The aggregation of trading volume uses proprietary data from MatchNow, Intraspread, Chi-X, and Alpha. The aggregation of dark trading volume does not include dark trades executed on TSX or dark block trades executed on Liquidnet/Instinet. The vertical bar indicates the introduction of minimum price improvement requirements on 15 October 2012.

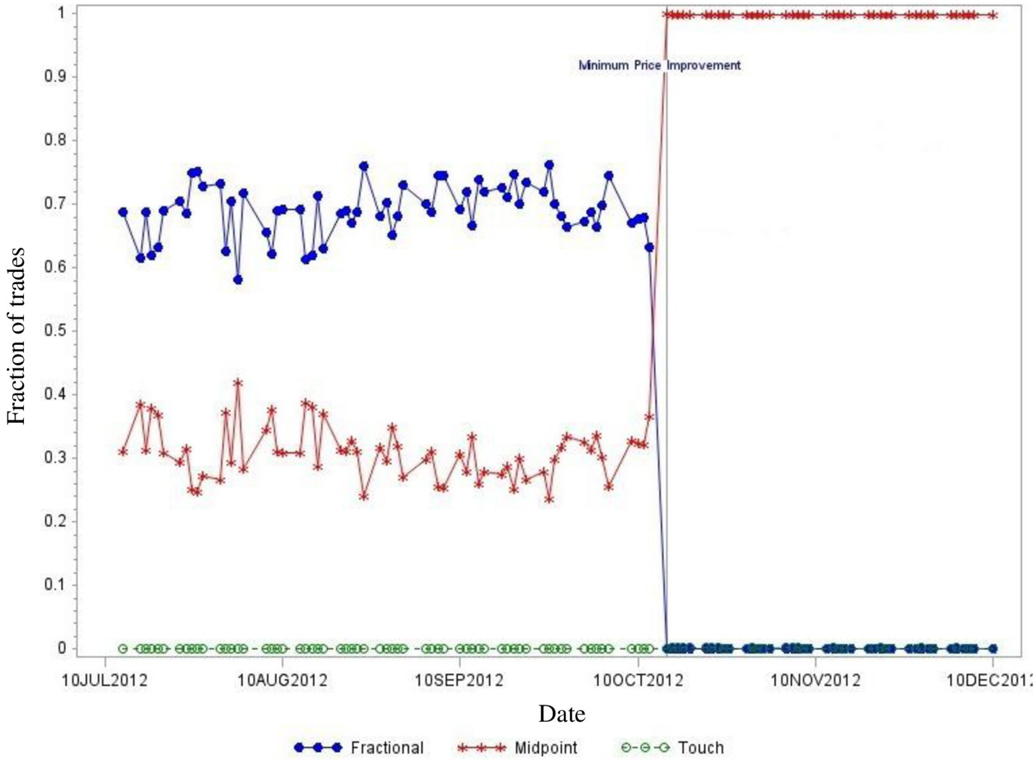


the midpoint of the NBBO (99.8% of all dark trades). Although the rule change still allowed large dark orders to execute at the NBBO after giving priority to lit orders, such dark orders are rare and account for a negligible fraction of dark trades.

To comply with the new regulations all venues providing dark orders were required to adjust the types of dark orders provided. Table 6.2 documents these changes for each venue. For the continuous dark pools Intraspread and MatchNow, orders offering 10% or 20% price improvement were removed on 15 October 2012. Intraspread retained dark midpoint orders and added the potential for large orders to execute at the NBBO. MatchNow removed their 20% order type but chose not to introduce orders at the NBBO, offering only midpoint orders after the rule change. Chi-X and TSX did not need to remove any dark order types to comply with the new rules because they did not provide dark orders at increments finer than the midpoint. Both exchanges enabled large orders to execute at the NBBO, although as shown in Figure 6.2 these orders never account

FIGURE 6.2: Price Improvement Provided by Dark Trades

This figure shows the fraction of dark trades providing different levels of price improvement around the introduction of the minimum price improvement regulation (indicated by the vertical bar). Fractional price improvement consists of 10% and 20% price improvement orders executed on MatchNow and Alpha Intraspread, respectively. Midpoint consists of orders executed at the midpoint of the NBBO, and could be executed on any of the dark venues. Touch refers to orders larger than 50 Standard Trading Units or $100,000 executed at the NBBO. This order type only became valid after the introduction of the minimum price improvement rules.



for more than %0.3 of daily volume.

6.4 Data

The constituents of the TSX Composite Index (which comprises approximately 250 of the most actively traded Canadian listed securities), are analysed over a period of two months either side of the introduction of the minimum price improvement rules (15 August 2012 - 15 December 2012).[63] Tick-by-tick data is combined for lit and dark trades from a number of sources. Proprietary data on all dark trades executed on MatchNow,

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[63] Two trading days in which the US markets were closed (during US Thanksgiving and Hurricane Sandy) are removed, so that the sample is consistent across all analyses including those that use US data.

TABLE 6.2: Effect of price improvement regulation by venue

This table shows the price improvement (as a percentage of the prevailing national best bid and offer (NBBO) spread) provided by dark order types on each of the Canadian venues that accept dark orders, before and after the introduction of minimum price improvement requirements on 15 October 2012. Before the change in regulation dark venues offered only midpoint (50% price improvement) and fractional price improvement (10% or 20% of the NBBO spread). After the regulation change, large dark orders (those greater than 50 Standard Trading Units or greater than $100,000) are able to trade at the NBBO (0% price improvement) or at the midquote in all venues apart from MatchNow, while small dark orders can only trade at the midquote.

Venue	Order Size	Before 15 Oct 2012	After 15 Oct 2012
Intraspread	Large	10% + 50%	0% + 50%
	Small	10% + 50%	50%
MatchNow	Large	20% + 50%	50%
	Small	20% + 50%	50%
Chi-X	Large	50%	0% + 50%
	Small	50%	50%
TSX	Large	50%	0% + 50%
	Small	50%	50%

Intraspread, Chi-X, and Alpha is obtained directly from the trading venues.[64] The data on dark trades includes the stock ticker, date, time, price and volume. As it has not been possible to obtain data on dark trades executed on the TSX or dark block trades negotiated on Liquidnet/Instinet, the measures of dark trading presented as a fraction of the total dollar volume are therefore lower bounds.

Estimates from other sources provide an indication of the coverage of the dark trading data. The previous chapter reports that TSX dark trades at the beginning of 2012 account for approximately 2.3% of total Canadian dollar volume, and IIROC Marketplace Statistics indicate that in the third quarter of 2012 Liquidnet and Instinet together accounted for only 0.2% of total Canadian dollar volume, including traded block volume. The dark trades for which data is available account for 7.2% of total Canadian dollar volume before the rule change, which when combined with the dark trades for which data is unavailable (approximately 2.3% + 0.2% = 2.5% of total dollar volume) suggests that before the rule change dark trading on all Canadian marketplaces accounted for 7.2% + 2.5% = 9.7% of total dollar volume. Therefore, the sample contains approximately three quarters (7.2% / 9.7%) of the dark trades on all Canadian marketplaces.

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[64] This proprietary data consists only of information that was publically reported to the consolidated tape.

The lack of dark trading data from the TSX is unlikely to significantly alter our results, as although it is the largest venue in Canada, it did not experience any change in the type of dark trades that could be offered as a result of the minimum price improvement regulations. Both TSX and Chi-X already only offered 50% (ie. midpoint) dark trades. Very little shift was observed in Chi-X dark volumes as a result of the minimum price improvement, and it is likely for this reason that there would have been a similarly small change in the dark volumes observed on the TSX.

Data for all lit trades and quotes for all Canadian lit marketplaces (Alpha, Omega, TSX, TMX Select, Pure and Chi-X) is obtained from the *Thomson Reuters Tick History* database.[65] Lit trades contain information on the stock ticker, date, time, price and volume, and the quotes comprise the best bid and ask quotes at every point in time for every venue, with timestamps on trades and quotes recorded to the millisecond. The best bid and ask quotes are consolidated across all lit Canadian venues at every point in time to obtain the NBBO.

To examine the impact of the minimum price improvement rule on the migration of lit and dark trading volume, similar trade-level data for the US markets is obtained from the *Thomson Reuters Tick History* database. Lit trades and quotes are consolidated across all lit US trading venues. A proxy for US dark trading is arrived at by using transactions reported to Trade Reporting Facilities (TRF). TRFs are used to report dark trades and block trades negotiated away from lit marketplaces. The US dark trading proxy is only used in an alternative test of possible dark trading migration and is not used in the main analysis of Canadian dark trading and market quality.

Data on shares outstanding, stock splits, index constituents and cross-listed securities is obtained from the monthly TSX e-Review publications. The sample is restricted to stocks that are included in the TSX Composite Index at both the start and end of the sample period to avoid effects arising from index inclusion and deletion. This results in 246 Canadian stocks. To avoid problems associated with differing STU's and tick sizes, stocks with a price less than $1 are omitted. This criterion removes five stocks, leaving a final sample of 241 stocks.

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[65] The data for Omega only became available from July 2012, hence its inclusion in this chapter despite exclusion in the previous chapter.

For the purpose of calculating market quality metrics, the regular market hours of 9:30am - 4:00pm are used, less the first and last 15 minutes to exclude the impacts of the opening auction and market on close facility, though these periods as well as the opening and closing auctions, are included in the summations of daily volume.

6.5 Method

6.5.1 Instrumental Variables Regressions

One of the main challenges in empirically studying the impact of dark trading on market quality is the endogeneity of dark trading with respect to market conditions. For example, dark trading tends to increase when spreads are structurally constrained to the minimum tick size because dark trades are allowed to occur within the spread at sub-penny price increments (Kwan et al., 2013). Buti et al. (2011b) find that dark pool activity is higher when limit order depth is high, spreads are narrow and tick sizes are large. They argue that the conditional nature of the decision to execute in the dark results in an endogeneity issue between market quality variables and dark trading activity. To overcome the endogeneity issue, the introduction of the minimum price improvement rule is used as an instrumental variable (IV) for dark trading in a two-stage regression framework. This allows for the creation of a series of dark trades which is highly correlated with actual dark trading and which varies exogenously due to the change in the regulations. This allows the potentially endogenous nature of dark trading to be eliminated in the instrument. In the first stage, the level of dark trading in stock i is regressed on a dummy variable that takes the value 1 after the minimum price improvement rule and 0 otherwise, and a time trend to remove any general trends in the level of dark trading that are unrelated to the price improvement rule, as shown in Equation 6.1:

$$Dark_{it} = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 Time_t + \epsilon_{it}, \tag{6.1}$$

where: $Dark_{it}$ is the fraction of dollar volume in stock i on day t that is dark, $D_t^{PostPeriod} = 1$ after the rule change and 0 before, and $Time_t$ is a time trend variable that takes the value 0 on the first day in the sample and increments by 1 for every subsequent day. In the main results, the first stage documented in Equation 6.1 is estimated on the pooled sample of stock-days. Robustness tests indicate that estimating the first stage separately for each stock produces similar results in the second-stage, as does inclusion of stock fixed effects in the first stage.

Using the parameter estimates from Equation 6.1 allows fitted values of the level of dark trading in stock i on day t, $\widehat{Dark_{it}}$ to be obtained. The second-stage regressions estimate the impact of dark trading on a number of market quality metrics that measure liquidity and informational efficiency, as documented in Equation 6.2:

$$y_{it} = \alpha_i + \beta_1 \widehat{Dark_{it}} + \beta_2 Time_t + \sum_{j=1}^{5} \gamma_j Control_{j,it} + \epsilon_{it}, \tag{6.2}$$

where: y_{it} is a market quality metric for stock i on day t, α_i is a set of stock fixed effects, $\widehat{Dark_{it}}$ is the fitted level of dark trading, $Time_t$ is the trend variable. $Control_{j,it}$ is a set of control variables: $\$Volume_{it}$ is the natural logarithm of traded dollar volume; $MarketCap_{it}$ is the natural logarithm of the stock's market capitalization; $Volatility_{it}$ is the stock-day's high-low price range divided by the time-weighted midpoint; $Price_{it}$ is the time-weighted midpoint; and $Constrained_{it}$ is the percentage of the trading day for which the stock's NBBO is constrained at the minimum tick size, which is omitted when the dependent variable is a spread measure.

Time fixed effects are not included in Equation 6.2 because the exogenous variation in dark trading (from the introduction of the minimum price improvement rules) occurs around one point in time. Instead, the variable $Time_t$ acts as a control for general trends in the market quality metrics through time, and the other control variables account for possible effects of changing market conditions on the market quality metrics. For robustness, an alternative approach is tested to control for pre/post changes in the market quality metrics that may be unrelated to dark trading. This alternative approach utilizes a difference-in-differences design to remove pre/post changes in the market quality metrics that are not attributable to changes in dark trading. As the control group (the "untreated" group), stocks that do not experience a decrease in dark trading after the minimum price improvement rules are used. The difference-in-differences results are consistent with those from the two-stage IV regressions. Therefore, the focus of this chapter is on interpreting the two-stage IV results first, with the difference-in-difference design and results described in the robustness tests section.

6.5.2 Liquidity Measures

A variety of measures are used to analyse the impact of dark pools on market liquidity. These include: quoted spreads which measure the conditions posted throughout the day; effective spreads which measure the conditions prevailing when trades occur; realised spreads which measure the returns to liquidity suppliers; and Amihud's (2002) illiquidity metric, which measures the ability of the limit order book to absorb large trades without significant price movement.

The first measure of liquidity is the time-weighted quoted bid-ask spread. The quoted spread is the difference between the lowest ask price available on any lit market in Canada and the highest available bid price, i.e., the NBBO spread. The quoted spread is measured in basis points by dividing the spread in cents by the prevailing midpoint, $m = \frac{Ask+Bid}{2}$:

$$QuotedSpread = \left[\frac{Ask - Bid}{m}\right] 10^4. \tag{6.3}$$

The time-weighted quoted spread for each stock-day, $QuotedSpread_{it}$, is calculated by taking the time-weighted average of quoted spreads between 9:45am and 3:45pm.

Effective and realised spreads are also examined, which take into consideration the actual prices at which trades execute. Effective spreads reflect the cost of a transaction for the liquidity demander. Realised spreads reflect the proportion of the transaction cost that is earned by the liquidity provider. For a trade that occurs at time τ its effective spread and five-minute realised spread (both in basis points relative to the prevailing midpoint) are measured using Equations 6.4 and 6.5 below:

$$EffectiveSpread = 2q\left[\frac{p_{\mathcal{T}} - m_{\mathcal{T}}}{m_{\mathcal{T}}}\right]10^4, \tag{6.4}$$

$$RealisedSpread = 2q\left[\frac{p_{\mathcal{T}} - m_{\mathcal{T}+5}}{m_{\mathcal{T}}}\right]10^4, \tag{6.5}$$

where: $p_{\mathcal{T}}$ is the transaction price, $m_{\mathcal{T}}$ is the midpoint of the NBBO prevailing at the time of the trade, $m_{\mathcal{T}+5}$ is the midpoint of the NBBO five minutes after the trade, and q indicates the direction of the trade (+1 for buyer-initiated trades and -1 for seller initiated trades). Buyer and seller initiated trades are identified by comparing the prevailing NBBO to the transaction price using the Lee and Ready (1991) algorithm. While Ellis et al. (2000) and Chakrabarty et al. (2007) document that the Lee and Ready (1991) algorithm may misclassify trades at the midpoint, we are able to identify the direction of the dark transactions using our proprietary dataset. This will limit the impact of misclassifying within-spread executions, as inferred transactions (ie. lit trades) will occur either at the bid or ask. To obtain estimates of the effective and realised spreads at the stock-day level, $EffectiveSpread_{it}$ and $RealisedSpread_{it}$, the volume-weighted average of effective and realised spreads are taken across all lit trades during the stock-day.

Amihud's (2002) illiquidity metric is also computed, which is a measure of price impact scaled by traded dollar volume. Amihud's illiquidity measure is a stock-day average of hourly absolute midpoint returns divided by the dollar volume traded in the hour, as described by Equation 6.6:

$$ILLIQ_{it} = log\left[1 + \frac{10^5}{H}\sum_{h=1}^{H}\frac{|r_{it,h}|}{\$Volume_{it,h}}\right], \tag{6.6}$$

where: $r_{it,h}$ and $\$Volume_{it,h}$ are the midpoint return and traded dollar volume, respectively, for stock i during hour h of day t. As indicated in Equation 6.6 the $ILLIQ_{it}$ metric is log transformed to reduce the impact of outliers, consistent with Karolyi et al. (2012). If there is no volume traded in a given hour, the denominator in the $ILLIQ_{it}$ metric would be zero. Rather than generating a missing observation, such instances are replaced with the stock's 99th percentile value of valid $\frac{|r_{it,h}|}{\$Volume_{it,h}}$ observations. To further reduce the influence of outliers, all liquidity metrics are winsorized at the 1% level for each stock and each date.

6.5.3 Informational Efficiency Measures

Four measures of the informational efficiency of prices are used: autocorrelations, variance ratios, high-frequency standard deviations, and measures of short-term return predictability using lagged market returns.

Both positive and negative midpoint return autocorrelation indicates that quotes deviate from a stochastic random walk process and exhibit short-term return predictability. Such predictability is inconsistent with an informationally efficient market. The absolute value of first-order midpoint return autocorrelations are calculated for each stock-day at three intraday frequencies, $k \in$ (10sec., 30sec., 60sec.), similar to Hendershott and Jones (2005):

$$Autocorrelation_k = |Corr(r_{k,\tau}, r_{k,\tau-1}|, \tag{6.7}$$

where: $r_{k,\tau}$ is the τ^{th} midpoint return of length k in a given stock-day. Taking the absolute value of the autocorrelation yields a measure of informational efficiency that measures both the under- and over-reaction of returns to information, with larger values indicating greater inefficiency. For each stock-day, the absolute autocorrelations of the three frequencies are combined by calculating their first principle component. The combined measure, $Autocorrelation_{it}$, is scaled so that it ranges from 0 (highly efficient) to 100 (highly inefficient).

The second measure of informational efficiency is the variance ratio. For stock prices that follow a random walk, the variance of returns is a linear function of the return measurement frequency - $\theta^2_{k-PeriodReturn}$ is k times larger than $\theta^2_{1-PeriodReturn}$. The variance ratio makes use of this property to measure inefficiency as the deviation of a price series from the characteristics that would be expected under a random walk (e.g., Lo and MacKinlay (1988)). Three variance ratios are constructed for each stock-day, utilizing different intra-day frequencies:

$$VarianceRatio_kl = |\frac{\theta^2_{kl}}{k\theta^2_l} - 1|, \tag{6.8}$$

where: θ^2_l and θ^2_{kl} are the variances of $l - second$ and $kl - second$ midpoint returns for a given stock-day. The three (l, kl) combinations used are: (1sec., 10sec.), (10sec., 60sec.), and (1min., 5min.). For each stock-day, the three variance ratios are combined by calculating their first principle component. The combined variance ratio, $VarianceRatio_{it}$, is scaled so that it ranges from 0 (indicating high levels of efficiency) to 100 (indicating low levels of efficiency).

For each stock-day the intra-day midpoint standard deviations calculated at 10, 30 and 60 second frequencies are also combined by taking their first principal component. This produces a single measure of high-frequency volatility, $HFVolatility_{it}$, which is a proxy for noise and temporary deviations of prices from their equilibrium values due to trading frictions. In the regressions, volatility in the fundamental value is controlled using a lower frequency measure of realised variance.

The final measure of informational efficiency is an intraday adaptation of the Hou and Moskowitz (2005) *Delay* metric. This metric measures short-term return predictability by the extent to which lagged market returns predict a stock's midpoint returns. For each stock-day it a regression of intraday 1-minute midpoint returns for the stock, $r_{it,\tau}$, is estimated on the TSX60 market index return, $r_{mt,\tau}$, and ten lags:

$$r_{it,\tau} = \alpha_{it} + \beta_{it} r_{mt,\tau} + \sum_{k=1}^{1} 0\delta_{it,k} r_{mt,\tau-k} + \epsilon_{it,\tau}. \tag{6.9}$$

The R^2 from this unconstrained regression is saved as $R^2_{Unconstrained,it}$ with the regression then re-estimated constraining the coefficients on all lagged market returns to zero (i.e., $\delta_{it,k} = 0, \forall k$), with the R^2 from the constrained regression saved as $R^2_{Constrained,it}$. *Delay* is calculated from the ratio of the constrained and unconstrained regression R^2s as documented in equation 6.10:

$$Delay_{it} = 100 \left(1 - \frac{R^2_{Constrained,it}}{R^2_{Unconstrained,it}} \right), \tag{6.10}$$

where: $Delay_{it}$ takes values between 0 and 100 and describes the amount of variation in a stock's intraday returns that is explained by lagged market returns. An increase in $R^2_{Unconstrained,it}$ indicates an increase in the explanatory power of the lagged returns, and thus $Delay_{it}$ approaches 100, implying a delayed incorporation of market-wide information into the stock's price, and lower overall informational efficiency.

6.5.4 Regulatory Flight

One main concern raised during the consultation process for the minimum price improvement legislation was that these restrictions could result in dark trading in cross-listed stocks migrating to the US where such price improvement regulations do not apply. Under this "regulatory flight" scenario the Canadian minimum price improvement rules would be expected to result in: (i) a larger decrease in Canadian dark trading for Canadian stocks that are cross-listed in the US than for stocks listed in Canada only, and (ii) an increase in US dark trading of US-Canada cross-listed stocks compared to stocks listed only in the US.

To test for this migration of dark trading, two difference-in-differences models are applied to the 200 Canadian listed securities that are cross listed in the US: one that compares cross-listed stocks to stocks listed in Canada only and a second that compares cross-listed stocks to stocks listed in the US only. For this purpose, each US-Canada cross-listed stock is matched to both a stock listed only in Canada and a stock listed only in the US. The matching procedure requires that matched stocks are traded on the same venue as their cross-listed counterpart to limit the influence that the trading venue may have on dark trading. Matched stocks are chosen in a manner similar to Huang and Stoll (1996) using price and traded dollar volume as the matching characteristics. Price has been found to be an important determinant of dark trading volume, especially around tick-size price thresholds (Kwan et al., 2013), while larger stocks (and thus those with higher trading volume) tend to have more dark trading than smaller stocks (Buti et al., 2011b). Matched stocks are chosen as those that minimize the sum of squared relative differences in price and trading volume, X_j, measured as the average daily values during the two months prior to the price improvement rules (15 August - 15 October 2012):

$$MatchingScore_{CO} = \sum_{j=1}^{2} \left(\frac{X_j^C - X_j^O}{X_j^C + X_j^O)/2} \right)^2 . \tag{6.11}$$

The superscript C indexes US-Canada cross-listed stocks, and the superscript O indexes stocks listed only in Canada (when constructing the Canadian matched sample) or stocks listed only in the US (when constructing the second matched sample).[66]

The following difference-in-differences model is then constructed separately for the cross-listed stocks with the matched sample of stocks listed only in Canada, and the cross-listed stocks with the matched sample of stocks listed only in the US:

$$Dark_i t = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 D_i^{CrossListed} + \beta_3 (D_t^{PostPeriod} D_i^{CrossListed}) + \epsilon_{it}, \tag{6.12}$$

where: $D_t^{PostPeriod} = 1$ after the rule change and 0 before, $D_i^{CrossListed} = 1$ for US-Canada cross-listed stocks and 0 otherwise. When comparing cross-listed stocks with stocks listed only in Canada $Dark_{it}$ is the dollar volume of dark trading in Canada as a fraction of total dollar volume traded in Canada in stock i on day t, and when comparing cross-listed stocks with stocks listed only in the US, $Dark_{it}$ is the dollar volume of dark trading in the US as a fraction of total dollar volume traded in the US in stock i on day t. The coefficient of interest is β_3, which captures the effects of regulatory flight. For robustness a modified specification is also estimated in which the pre/post dummy variable and the cross-listing dummy variable are replaced with stock and time fixed effects, as documented in Equation 6.13:

$$Dark_{it} = \alpha_i + \alpha_t + \beta (D_t^{PostPeriod} D_i^{CrossListed}) + \epsilon_{it}. \tag{6.13}$$

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[66] The median differences between the cross-listed and matched stocks' prices, average traded dollar volume and dark volume as a percentage of total volume are all less than 15%, suggesting the matching is relatively precise.

Table 6.3: Descriptive statistics on trading activity

This table reports descriptive statistics on market-wide dark and lit trading activity during the two months preceding the minimum price improvement rules (15 August 2012 – 14 October 2012) and two months after (15 October 2012 – 15 December 2012). The trading activity variables are calculated on each trading day, pooling across all stocks in our sample (TSX Composite Index constituents). The mean, median and standard deviation are calculated from the daily observations.

	Pre-regulation			Post-regulation		
	Mean	Median	Standard deviation	Mean	Median	Standard deviation
Dark \$ volume / total \$ volume (%)	7.49	7.52	1.11	4.63	4.93	0.90
Dark trade size (\$1,000)	6.25	3.24	26.75	6.49	3.28	31.15
Lit trade size (\$1,000)	6.48	3.08	177.32	6.40	3.04	322.74
Dark daily \$ volume (\$100m)	3.25	3.30	1.42	2.65	2.93	0.92
Lit daily \$ volume (\$100m)	58.48	55.47	18.73	58.96	59.66	14.05
Total daily \$ volume (\$100m)	63.09	60.41	19.15	61.82	62.84	14.56

6.6 Results

6.6.1 Descriptive Statistics

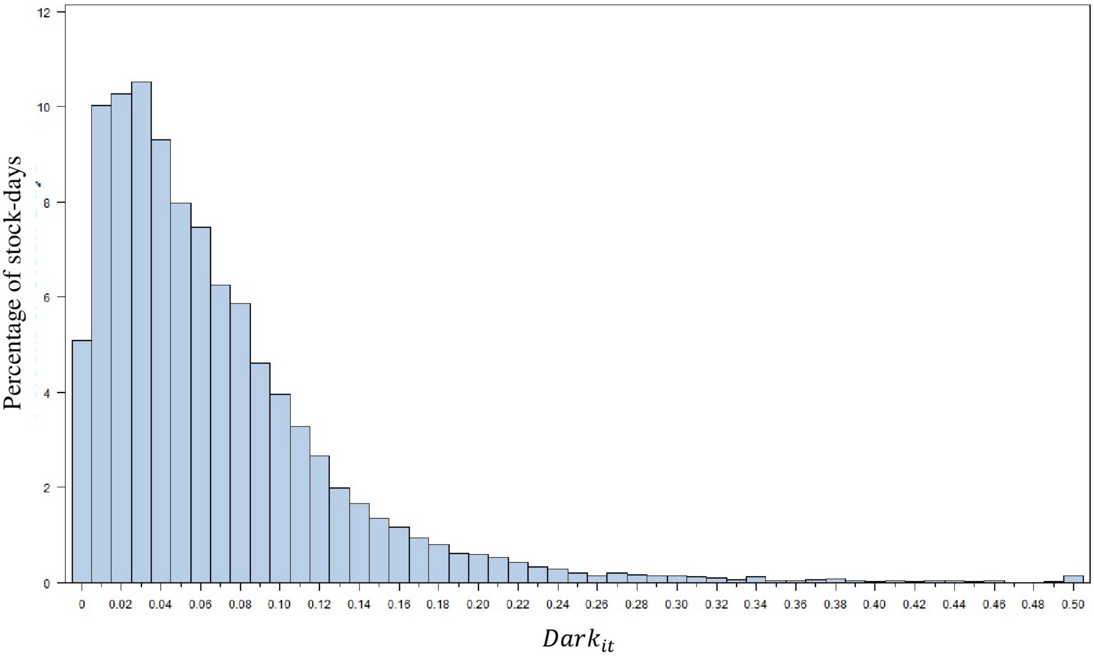
Table 6.3 reports market-wide descriptive statistics on trading activity. The trading activity variables are calculated daily, pooling across all stocks, and then the mean, median and standard deviation are computed from the daily observations. Consistent with Figure 6.1 and the previous discussion, the level of dark trading is considerably lower after the minimum price improvement rules come into effect. The mean (median) percentage of daily dollar volume executed in the dark falls from 7.49% (7.52%) to 4.63% (4.93%) after the new regulation. Lit and dark trades tend to have a similar size (mean of approximately \$6,400 and median of approximately \$3,100) and their size does not change noticeably after the minimum price improvement rules. While the total amount of dark trading is reduced from an average of \$325 million per day to \$265 million per day, this is somewhat offset by an increase in lit trading. Average total daily traded dollar volume remains unchanged at approximately \$6.3 billion per day.

To get a sense of the variation in dark trading, Figure 6.3 presents the pooled sample histogram of stock-day level dark trading as a fraction of total stock-day dollar volume, $Dark_{it}$. Approximately 5% of stock-days have no dark trading at all. Around 50% of stock-days have between 1% and 5% of their dollar volume executed in the dark. There are very few stock days with greater than 20% dark trading, and only six stock-days have dark trading in excess of 50% of total dollar volume. The pooled sample mean and standard deviation of $Dark_{it}$ are 6.6% and 6.3%, respectively. The pooled standard deviation of 6.3% is larger than the time-series standard deviation of approximately 1% in Table 6.3 because it includes cross-sectional variation, and the (equal-weighted) mean of $Dark_{it}$ is lower than the mean of daily aggregated dark trading in Table 6.3 due to the tendency for large stocks to have higher levels of dark trading.

Table 6.4 reports descriptive statistics on the stock-day market quality metrics and control variables. Quoted spreads have a mean and median of 12.56 bps and 9.89 bps respectively; effective spreads have a slightly lower mean of 10.5 bps due to some trades being executed within the spread; and realised spreads are even smaller with a mean of 2.75 bps due to the fact that trades tend to have a positive price impact on average. The variable $Constrained_{it}$ indicates that quoted spreads tend to be constrained to the minimum of one tick approximately 52% of the time for an average stock. The means and medians of the informational efficiency metrics do not have a natural interpretation due to their arbitrary scale but are useful in interpreting the magnitude of effects in the regressions.

FIGURE 6.3: Distribution of Dark Trading Across Stock-Days

This histogram shows the distribution of the share of dark trading (fraction of total dollar volume), $Dark_{it}$, across stock-days. Values of $Dark_{it}$ greater than 0.5 have been aggregated into the 0.5 bucket.



6.6.2 Instrumental Variables Regressions

The results from the first stage of the instrumental variables regressions, in which the level of dark trading is regressed on an indicator variable for the introduction of the minimum price improvement rules and a time trend, are reported in Table 6.5. The estimates indicate that the effect of the minimum price improvement regulation is a decline in the average level of dark trading by approximately 2.9 percentage points, which is of high statistical significance. In contrast to the earlier descriptive statistics, the results in Table 6.5 control for the possibility of general trends in the level of dark trading (with the control variable $Time_t$), though these turn out to be statistically indistinguishable from zero. The estimated effect of the minimum price improvement regulation is similar when stock fixed effects are included to account for differences in the levels of dark trading across stocks.

Problems associated with "weak" instruments arise when first-stage F-statistics for the instruments are close to one (Bound et al. (1995), p. 446). The F-statistics in the first

Table 6.4: Descriptive Statistics on Liquidity, Informational Efficiency and Control Variables

This table reports means, standard deviations and quartile values of liquidity, informational efficiency and control variables. The variables are calculated across all Canadian lit venues for the period 15 August 2012 – 15 December 2012. Quoted spreads are time-weighted based on the lit national best bid and offer (NBBO). Realized and effective spreads are volume-weighted averages for the trades in each stock-day. Realized spreads are calculated using the NBBO midquote five minutes after the trade. Quoted, effective and realized spreads are measured relative to the midquote, in basis points. $ILLIQ_{it}$ is Amihud's price impact metric calculated for each stock-day using hourly return and volume observations. $Autocorrelation_{it}$, $VarianceRatio_{it}$, and $HFVolatility_{it}$ are the first principle components of midquote return absolute autocorrelations, variance ratios, and standard deviations at different intraday frequencies. $Delay_{it}$ measures intraday midquote return predictability using lagged market returns. $\$Volume_{it}$ is the natural logarithm of traded dollar volume. $MarketCap_{it}$ is the natural logarithm of the stock's market capitalization. $Volatility_{it}$ is the stock-day's high-low price range divided by the time-weighted midquote. $Price_{it}$ is the time-weighted midquote. $Constrained_{it}$ is the percentage of the trading day for which the stock's NBBO spread is constrained at one tick.

	Mean	Standard deviation	Q1	Median	Q3
Panel A. Liquidity variables					
$QuotedSpread_{it}$	12.56	9.67	5.78	9.89	15.71
$EffectiveSpread_{it}$	10.50	9.24	4.61	7.86	12.98
$RealizedSpread_{it}$	2.75	12.09	-1.11	1.84	5.99
$ILLIQ_{it}$	1.48	1.07	0.62	1.29	2.12
Panel B. Informational efficiency variables					
$Autocorrelation_{it}$	20.61	16.74	9.01	14.99	26.53
$VarianceRatio_{it}$	26.29	20.15	11.91	19.13	34.17
$HFVolatility_{it}$	2.95	6.62	0.87	1.34	2.12
$Delay_{it}$	87.29	14.80	81.14	93.07	98.45
Panel C. Control variables					
$\$Volume_{it}$	15.84	1.43	14.84	15.73	16.82
$MarketCap_{it}$	21.78	1.23	20.85	21.55	22.62
$Volatility_{it}$	297.94	318.96	114.2	184.76	327.87
$Price_{it}$ (\$)	27.59	29.63	10.60	22.3	37.12
$Constrained_{it}$ (%)	51.81	36.19	15.64	52.68	89.02

stage regression, both with and without stock fixed effects, are well above this level (17 to 566), suggesting the instrument is strong.

TABLE 6.5: First-Stage IV Regressions of the Impact of Minimum Price Improvement Rules on Dark Trading

This table reports coefficient estimates from the first stage of the instrumental variables regressions in which the introduction of the minimum price improvement rule is used as an instrument for the level of dark trading (measured as a fraction of total dollar volume), $Dark_{it}$:

$$Dark_{it} = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 Time_t + \varepsilon_{it} \, .$$

$D_t^{PostPeriod}$ is a dummy variable that takes the value 1 after the minimum price improvement rules come into effect and 0 before. $Time_t$ is a trend variable that starts at 0 at the beginning of the sample period and increments by 1 every trading day. The first regression model is estimated without fixed effects, and the second model is estimated with stock fixed effects. Standard errors are clustered both by stock and date, and t-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively. The F-statistic tests the null hypothesis that the instruments do not affect the level of dark trading, i.e., that the coefficient of $D_t^{PostPeriod}$ is 0.

	$Dark_{it}$	$Dark_{it}$
Intercept	0.0811	0.0664
	(82.2)***	(24.0)***
$D_t^{PostPeriod}$	-0.0293	-0.0295
	(-16.6)***	(-17.5)***
$Time_t$	-0.0000	-0.0000
	(-0.21)	(-0.17)
Observations	19,639	19,639
Adjusted R^2	0.06	0.15
F-statistic	566.4	17.4
Fixed effects	None	Stock

Table 6.6 reports second-stage estimates of the impact of dark trading on liquidity. The results indicate that dark trading has a negative and statistically significant effect on all of the spread measures, as well as Amihud's illiquidity proxy, which suggests that dark trading at the levels experienced in Canada actually *benefits* liquidity. A small increase in dark trading by 1% of total dollar volume is expected to decrease average quoted spreads by approximately 1.5 bps (0.01×(-149.9)), decrease effective spreads by 1.3 bps, and decrease realised spreads by 0.23 bps. These decreases for just a small change in dark trading are economically meaningful compared to the means of quoted, effective and realised spreads: 12.56 bps, 10.50 bps, and 2.75 bps, respectively. These reductions in quoted and effective spreads represent a reduction in transactions costs of between 2.5% to 10%, being a significant component of overall costs. An alternative way to interpret the magnitude of the effects is in terms of pooled standard deviations. A one standard deviation increase in dark trading (6.3% of total dollar volume) is expected to decrease quoted spreads by 0.98 standard deviations (0.063×(-149.9)/9.67),

TABLE 6.6: Second-Stage IV Regressions of the Impact of Dark Trading on Liquidity

This table reports regression estimates from second stage instrumental variables regressions:

$$y_{it} = \alpha_i + \beta_1 \widehat{Dark}_{it} + \beta_2 Time_t + \sum_{j=1}^{5} \gamma_j \, Control_{j,it} + \varepsilon_{it}.$$

The dependent variables, y_{it}, are estimates of liquidity and transaction costs each stock-day. Quoted spreads are time-weighted based on the lit national best bid and offer (NBBO). Realized and effective spreads are volume-weighted averages for the trades in each stock-day. Realized spreads are calculated using the NBBO midquote five minutes after the trade. Quoted, effective and realized spreads are measured relative to the midquote, in basis points. $ILLIQ_{it}$ is Amihud's price impact metric calculated for each stock-day using hourly return and volume observations. The key independent variable, $\widehat{Dark}_{it}$, is the fitted value of a stock-day's dark dollar volume as a fraction of the stock-day's total dollar volume, and is obtained from the first stage. $Time_t$ is a trend variable that starts at 0 at the beginning of the sample period and increments by 1 every trading day. $\$Volume_{it}$ is the natural logarithm of traded dollar volume. $MarketCap_{it}$ is the natural logarithm of the stock's market capitalization. $Volatility_{it}$ is the stock-day's high-low price range divided by the time-weighted midquote. $Price_{it}$ is the time-weighted midquote. $Constrained_{it}$ is the percentage of the trading day for which the stock's NBBO spread is constrained at one tick. The second-stage regression model is estimated separately for each dependent variable with stock fixed effects. Adjusted R^2s do not include the variance explained by the fixed effects. Standard errors are clustered both by stock and date, and t-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	$QuotedSpread_{it}$	$EffectiveSpread_{it}$	$RealizedSpread_{it}$	$ILLIQ_{it}$
Intercept	263.2	269.5	261.2	16.60
	(3.24)***	(2.76)***	(6.36)***	(8.91)***
$\widehat{Dark}_{it}$	-149.9	-133.3	-23.70	-0.806
	(-4.33)***	(-3.37)***	(-2.10)**	(-1.79)*
$Time_t$	0.002	-0.015	0.001	-0.000
	(0.09)	(-0.68)	(0.14)	(-0.45)
$\$Volume_{it}$	-3.70	-2.52	1.11	-0.39
	(-7.78)***	(-5.31)***	(4.73)***	(-50.5)***
$MarketCap_{it}$	-8.35	-9.67	-11.94	-0.36
	(-2.36)**	(-2.28)**	(-6.59)***	(-4.40)***
$Volatility_{it}$	0.037	0.038	-0.019	0.001
	(10.86)***	(8.81)***	(-15.06)***	(16.04)***
$Price_{it}$	0.231	0.324	0.224	-0.005
	(1.95)*	(2.26)**	(5.05)***	(-2.04)**
$Constrained_{it}$				-0.809
				(-23.9)***
Observations	19,639	19,639	19,639	19,639
Adjusted R^2	0.03	0.02	0.03	0.27
Fixed effects	Stock	Stock	Stock	Stock

decrease effective spreads by 0.91 standard deviations, decrease realised spreads by 0.20 standard deviations, and decrease price impacts (Amihud's $ILLIQ_{it}$) by 0.05 standard deviations. Therefore, while there is variation in the magnitudes across the different liquidity measures, the results suggest that dark trading at the levels experienced in Canada has economically meaningful benefits to liquidity. This result is consistent with the notion that the ability to trade easily in the dark increases competition among informed traders in providing liquidity (as predicted by Boulatov and George (2013)) and that the increased competition for dark liquidity provision has a positive spillover effect on the liquidity of lit markets.

Coefficients on the time trend are not statistically distinguishable from zero and vary in sign across the liquidity metrics suggesting the absence of a meaningful trend in liquidity during the sample period, after controlling for other market characteristics. Most coefficients on the control variables are consistent with expectations - liquidity tends to be higher for days with greater volume, higher market capitalization, and lower volatility. The adjusted R^2 of the regressions, which do not include the variation explained by the stock fixed effects range between 0.02 and 0.27, suggesting that there are many factors beyond the variables included in the model that influence liquidity.

Turning to the informational efficiency proxies, Table 6.7 reports second-stage regression estimates of the impact of dark trading. The results suggest that dark trading has a negative and statistically significant effect on absolute autocorrelations, variance ratios and delay in reflecting market-wide information, suggesting that dark trading at the levels experienced in Canada *benefits* informational efficiency.

Because the units of the informational efficiency proxies do not have a natural interpretation, the magnitude of the effects are examined in terms of standard deviations. A one standard deviation increase in dark trading (6.3% of total dollar volume) is expected to decrease absolute midpoint return autocorrelations by 0.29 standard deviations (0.063×(-77.93)/16.74), decrease variance ratios by 0.29 standard deviations, decrease high-frequency midpoint volatility by 0.05 standard deviations, and decrease delay in impounding market-wide information by 0.16 standard deviations, after controlling for other market characteristics and stock fixed effects. Therefore, while there is variation

TABLE 6.7: Second-Stage IV Regressions of the Impact of Dark Trading on Informational Efficiency

This table reports regression estimates from second stage instrumental variables regressions:

$$y_{it} = \alpha_i + \beta_1 \widehat{Dark}_{it} + \beta_2 Time_t + \textstyle\sum_{j=1}^{5} \gamma_j \, Control_{j,it} + \varepsilon_{it}.$$

The dependent variables, y_{it}, are estimates of informational efficiency each stock-day. $Autocorrelation_{it}$, $VarianceRatio_{it}$, and $HFVolatility_{it}$ are the first principle components of midquote return absolute autocorrelations, variance ratios, and standard deviations at different intraday frequencies. $Delay_{it}$ measures intraday midquote return predictability using lagged market returns. The key independent variable, $\widehat{Dark}_{it}$, is the fitted value of a stock-day's dark dollar volume as a fraction of the stock-day's total dollar volume, and is obtained from the first stage. $Time_t$ is a trend variable that starts at 0 at the beginning of the sample period and increments by 1 every trading day. $\$Volume_{it}$ is the natural logarithm of traded dollar volume. $MarketCap_{it}$ is the natural logarithm of the stock's market capitalization. $Volatility_{it}$ is the stock-day's high-low price range divided by the time-weighted midquote. $Price_{it}$ is the time-weighted midquote. $Constrained_{it}$ is the percentage of the trading day for which the stock's NBBO spread is constrained at one tick. The second-stage regression model is estimated separately for each dependent variable with stock fixed effects. Adjusted R^2s do not include the variance explained by the fixed effects. Standard errors are clustered both by stock and date, and t-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Variable	$Autocorrelation_{it}$	$VarianceRatio_{it}$	$HFVolatility_{it}$	$Delay_{it}$
Intercept	82.86	87.44	63.46	79.08
	(2.16)**	(2.54)**	(2.48)**	(1.54)
$\widehat{Dark}_{it}$	-77.93	-91.97	-5.20	-38.18
	(-7.32)***	(-9.46)***	(-1.16)	(-2.67)***
$Time_t$	0.011	-0.001	0.006	-0.004
	(1.78)*	(-0.13)	(2.30)**	(-0.48)
$\$Volume_{it}$	0.260	0.193	0.094	0.364
	(1.77)*	(1.41)	(1.58)	(2.04)**
$MarketCap_{it}$	-2.857	-2.820	-2.765	0.134
	(-1.69)*	(-1.86)*	(-2.47)**	(0.06)
$Volatility_{it}$	0.003	0.004	0.006	-0.002
	(4.05)***	(5.54)***	(16.78)***	(-3.54)***
$Price_{it}$	0.000	-0.003	0.048	0.056
	(0.00)	(-0.04)	(1.38)	(0.61)
$Constrained_{it}$	-5.472	-6.715	-1.314	-0.906
	(-7.86)***	(-10.21)***	(-4.86)***	(-0.98)
Observations	19,612	19,627	19,639	19,461
Adjusted R^2	0.03	0.03	0.06	0.02
Fixed effects	Stock	Stock	Stock	Stock

in the magnitudes across the different informational efficiency measures, the results suggest dark trading at the levels observed in Canada has economically meaningful benefits for informational efficiency. These benefits include reduced uncertainty around the true price of the security, reflected by the reduced midquote autocorrelation and reduced midpoint volatility. The decrease in delay also implies that market wide information is impounded more rapidly in the presence of dark trading. These results are robust to the inclusion of controls for a time trend, the traded value of the security, the market capitalization of the firm, the price of the firm, the frequency with which it is constrained as well as firm-specific volatility.

This result is consistent with the beneficial impact of low levels of dark trading on liquidity, due to the close relationship between liquidity and informational efficiency (Chordia et al. (2008)). It is also consistent with the prediction of Boulatov and George (2013) that the ability to hide orders encourages not only more liquidity provision by informed traders, but also increases the aggressiveness with which informed traders trade, which in turn promotes informational efficiency. Furthermore, the improvement of informational efficiency at low levels of dark trading complements the findings of Comerton-Forde and Putnins (2012) in the Australian market, who conclude that dark trading below 10% of dollar volume does not harm price discovery and may be beneficial.

6.6.3 Robustness Tests

The robustness of the results are tested to a variety of alternative specifications of the IV regressions and different sub-samples. To concisely summarize the results of these tests, Table 6.8 reports the t-statistics for the coefficient on the key independent variable, $\widehat{Dark_{it}}$, in the second-stage regressions. The rows of Table 6.8 correspond to different dependent variables and the columns correspond to different specifications and sub-samples. Specification (1) is the base case specification reported in Tables 6.6 and 6.7, corresponding to Equation 6.2, which includes all of the control variables and stock fixed effects. Specification (2) is identical to specification (1), but without stock fixed effects. Specification (3) contains no control variables except for stock fixed effects. Specification (4) is identical to specification (1) except that the first stage IV regression

Table 6.8: Robustness Tests

This table reports t-statistics for the coefficients on the key independent variable in the second-stage instrumental variables regressions, for seven different specifications. The independent variable to which the t-statistics correspond is the fitted value of a stock-day's dark dollar volume as a fraction of the stock-day's total dollar volume, which is obtained from the first-stage instrumental variables regression. The rows correspond to different dependent variables and the columns correspond to different specifications and samples and are used to assess the robustness of the results. Specification (1) is the base case specification (the specification reported in Tables 6 and 7), which includes control variables for a time trend, natural log of traded dollar volume, natural log of the company's market capitalization, volatility, the time-weighted midquote, the percentage of the day the quoted spread is constrained to one tick (omitted when the dependent variable is a spread) and stock fixed effects. Specification (2) is identical to specification (1), but without stock fixed effects. Specification (3) contains no control variables except for stock fixed effects. Specification (4) is identical to specification (1) except that the first stage IV regression is estimated on each stock separately. Specification (5) is identical to specification (1) omitting two weeks either side of the introduction of the minimum price improvement rules. Specification (6) and (7) are estimated on the largest 121 stocks and smallest 120 stocks, respectively, using the same variables as in specification (1). Standard errors are clustered both by stock and date in all specifications. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$QuotedSpread_{it}$	(-4.33)***	(-3.41)***	(-9.83)***	(-5.43)***	(-5.30)***	(-3.28)***	(-4.04)***
$EffectiveSpread_{it}$	(-3.37)***	(-2.86)***	(-6.03)***	(-4.97)***	(-4.44)***	(-2.69)***	(-2.77)***
$RealizedSpread_{it}$	(-2.10)**	(-1.87)*	(-5.62)***	(-3.25)***	(-2.61)***	(-1.19)	(-2.22)**
$ILLIQ_{it}$	(-1.79)*	(-0.94)	(-3.64)***	(-2.38)**	(-1.01)	(-0.15)	(-4.52)***
$Autocorrelation_{it}$	(-7.32)***	(-6.21)***	(-17.93)***	(-11.62)***	(-8.42)***	(-5.08)***	(-5.21)***
$VarianceRatio_{it}$	(-9.46)***	(-6.39)***	(-18.48)***	(-10.76)***	(-10.42)***	(-6.34)***	(-7.07)***
$HFVolatility_{it}$	(-1.16)	(-1.25)	(-6.73)***	(-7.85)***	(-1.43)	(-2.29)**	(1.05)
$Delay_{it}$	(-2.67)***	(-2.31)**	(-4.53)***	(-3.04)***	(-2.19)**	(-1.46)	(-2.40)**
Observations	19,639	19,639	19,639	19,639	15,060	9,917	9,722
Fixed effects	Stock	None	Stock	Stock	Stock	Stock	Stock
Control variables	All	All	None	All	All	All	All
First stage IV	Pooled	Pooled	Pooled	By stock	Pooled	Pooled	Pooled

is estimated on each stock separately, allowing for heterogeneity in the way in which the dark trading of individual stocks is affected by the minimum price improvement rules. Specification (5) is identical to specification (1) except that it omits two weeks either side of the introduction of the minimum price improvement rules to allow for transitory effects and adjustment in trading behaviour. Specifications (6) and (7) are estimated on the largest 121 stocks and smallest 120 stocks, respectively, using the same variables as in specification (1).[67]

The results from the different specifications and sub-samples are consistent with the base specification. Dark trading is associated with improved liquidity and informational efficiency (or decreased illiquidity and informational inefficiency) across all proxies and specifications with few exceptions. The results are robust to heterogeneity in the impact of the instrumental variable, allowing for transitory effects around the rule change, and

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[67] Lindley's paradox identifies that large data sets can result in inflated levels of significance. Robustness tests were conducted clustering the errors so as to account for this phenomenon. The results of these tests are qualitatively similar to those reported in this thesis

are similar for the largest and the smallest stocks in the sample. The latter result is consistent with Comerton-Forde and Putnins (2012) who find that the effects of dark trading on price discovery are similar for both large and small stocks. This implies that it is not sample-specific nor regression specific factors which are driving the results.

The IV regressions control for changes in the market quality metrics that are unrelated to dark trading in two ways: (i) any general time trends in market quality are removed by the control variable $Time_t$; and (ii) a series of control variables (including volatility, total traded dollar volume and others) account for possible effects of changing market conditions on the market quality metrics. For robustness, a difference-in-differences design is used as an alternative approach for controlling for changes in the market quality metrics that may be unrelated to dark trading. This design exploits the fact that although the minimum price improvement rules decreased the level of dark trading in most stocks, some stocks did not experience a decrease on average after the rules became effective. Such stocks are utilised as the control group (the "untreated" group) and other stocks are designated as the "treated" group (stocks that were impacted by the minimum price discovery rules). The difference-in-differences design measures changes in the market quality metrics for the treated group, relative to changes for the untreated stocks and thus removes the presence of changes in market quality through time that are unrelated to the rule change. This following difference-in-differences model is constructed in Equation 6.14:

$$\begin{gathered} y_{it} = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 D_i^{DarkReduction} + \\ \beta_3 (D_t^{PostPeriod} D_i^{DarkReduction}) + \sum_{j=1}^{5} \gamma_j (Control_{j,it} + \epsilon_{it}, \end{gathered} \tag{6.14}$$

where: y_{it} is a market quality metric, $D_t^{PostPeriod} = 1$ after the rule change and 0 before, $D_i^{DarkReduction} = 1$ for stocks that experience a decline in the mean level of dark trading after the rule change and 0 otherwise, and the set of control variables, $Control_{j,it}$, is the same as in previous models ($\$Volume_{it}, MarketCap_{it}, Volatility_{it}, Price_{it}$, and $Constrained_{it}$).

Table 6.9: Difference-in-Differences Estimates of the Impact of Dark Trading on Market Quality

This table reports estimates from a difference-in-differences regression in which 'untreated' control group consists of stocks for which the level of dark trading did not decrease on average after the introduction of minimum price improvement rules:

$$y_{it} = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 D_i^{DarkReduction} + \beta_3 \left(D_t^{PostPeriod} D_i^{DarkReduction}\right) + \sum_{j=1}^{5} \gamma_j \, Control_{j,it} + \varepsilon_{it}$$

$D_t^{PostPeriod} = 1$ after the rule change and 0 before. $D_i^{DarkReduction} = 1$ for stocks that experienced a decline in the mean level of dark trading after the rule change and 0 otherwise. The dependent variables, y_{it}, are market quality metrics estimated each stock-day. Quoted spreads are time-weighted based on the lit national best bid and offer (NBBO). Realized and effective spreads are volume-weighted averages for the trades in each stock-day. Realized spreads are calculated using the NBBO midquote five minutes after the trade. Quoted, effective and realized spreads are measured relative to the midquote, in basis points. $ILLIQ_{it}$ is Amihud's price impact metric calculated for each stock-day using hourly return and volume observations. $Autocorrelation_{it}$, $VarianceRatio_{it}$, and $HFVolatility_{it}$ are the first principle components of midquote return absolute autocorrelations, variance ratios, and standard deviations at different intraday frequencies. $Delay_{it}$ measures intraday midquote return predictability using lagged market returns. The set of control variables is as follows. $\$Volume_{it}$ is the natural logarithm of traded dollar volume. $MarketCap_{it}$ is the natural logarithm of the stock's market capitalization. $Volatility_{it}$ is the stock-day's high-low price range divided by the time-weighted midquote. $Price_{it}$ is the time-weighted midquote. $Constrained_{it}$ is the percentage of the trading day for which the stock's NBBO spread is constrained at one tick. Standard errors are clustered both by stock and date, and t-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Variable	$Quoted\ Spread_{it}$	$Effective\ Spread_{it}$	$Realized\ Spread_{it}$	$ILLIQ_{it}$	$Autocorr-elation_{it}$	$Variance\ Ratio_{it}$	$HFVolat-ility_{it}$	$Delay_{it}$
Intercept	131.4	100.8	88.10	11.09	-2.35	0.65	4.80	96.9
	(21.9)***	(16.4)***	(69.8)***	(122.2)***	(-0.93)	(0.64)	(1.69)*	(40.5)***
$D_t^{PostPeriod}$	2.737	0.074	0.037	-0.026	2.062	-0.859	2.148	0.520
	(1.52)	(0.03)	(0.21)	(-1.36)	(3.79)***	(-2.68)***	(3.59)***	(1.09)
$D_i^{DarkReduction}$	-3.98	-5.953	1.488	-0.02	-2.55	-2.432	-2.337	-1.159
	(-2.90)***	(-3.33)***	(9.61)***	(-1.27)	(-5.93)***	(-8.66)***	(-4.99)***	(-2.88)***
$(D_t^{PostPeriod}$	2.114	3.946	0.501	0.050	1.215	1.535	1.087	0.542
$\times D_i^{DarkReduction})$	(1.10)	(1.64)	(2.36)**	(2.37)**	(2.07)**	(4.69)***	(1.68)*	(1.01)
$\$Volume_{it}$	-6.102	-5.068	-1.682	-0.513	1.318	0.109	1.696	0.026
	(-14.1)***	(-13.7)***	(-21.4)***	(-85.9)***	(9.70)***	(1.77)*	(11.1)***	(0.20)
$MarketCap_{it}$	-1.691	-0.964	-2.585	-0.077	0.251	0.038	-0.029	-0.336
	(-3.61)***	(-2.23)**	(-27.8)***	(-12.3)***	(1.45)	(0.44)	(-0.15)	(-2.05)**
$Volatility_{it}$	0.083	0.074	0.016	0.001	0.020	0.009	0.027	-0.001
	(27.1)***	(22.9)***	(29.8)***	(30.4)***	(27.5)***	(28.6)***	(35.9)***	(-2.62)***
$Price_{it}$	0.136	0.109	0.024	-0.001	-0.062	-0.011	-0.082	0.001
	(12.43)***	(11.30)***	(9.38)***	(-6.96)***	(-11.1)***	(-9.20)***	(-12.0)***	(0.32)
$Constrained_{it}$				-0.053	-14.194	-1.700	-20.60	-3.945
				(-3.62)***	(-37.7)***	(-12.0)***	(-47.5)***	(-10.7)***
Observations	19,639	19,639	19,639	19,639	19,612	19,627	19,639	19,461
Adjusted R^2	0.03	0.02	0.05	0.28	0.03	0.06	0.03	0.02

Table 6.9 reports estimates from the difference-in-differences model. The key variable, $(D_t^{PostPeriod} D_i^{DarkReduction})$, arises from the interaction of the two dummy variables. This interaction term measures the effect of a *reduction* in dark trading, after controlling for pre-post changes in market quality that are unrelated to dark trading (via the post rule change dummy variable, $D_t^{PostPeriod}$). Therefore, these coefficients are expected to take the opposite sign to those on the variable $\widehat{Dark_{it}}$ in the IV regression (which is *increasing* in the level of dark trading). The results are largely consistent with this expectation - the point estimates of the coefficient on $(D_t^{PostPeriod} D_i^{DarkReduction})$ are

positive for all market quality metrics, with statistical significance for five of the eight metrics at the 10% level. The reduced level of statistical significance compared to the two-stage IV results is likely due to lower statistical power in the difference-in-differences design.

Similar to the IV regressions, these results suggest that dark trading improves liquidity and informational efficiency (reductions in dark trading are associated with increased illiquidity and increased informational inefficiency), and the estimated magnitudes are similar to the IV results. For example, for stocks that experienced a decline in dark trading after the minimum price improvement rules came into effect, quoted, effective, and realised spreads are respectively estimated to be 2.1 bps, 3.9 bps, and 0.50 bps larger after the rule change as compared to stocks that did not experience a decline in dark trading. Importantly, these results mitigate the potential concern that the findings of the main analysis could be driven by unrelated changes in market conditions that occur between the pre and post rule change periods and therefore allow for greater confidence to be placed in the estimated effects of dark trading.

6.6.4 Regulatory Flight

One of the major concerns raised by market participants and marketplace operators during the consultation process for the minimum price improvement legislation was the potential for dark trading in the large number of cross-listed stocks to migrate to the US. Such a “regulatory flight” could damage the quality of capital markets in Canada, and potentially lead to a “race to the bottom” in terms of security market regulation. This possibility is assessed using a difference-in-differences design that seeks to identify decreases in Canadian dark trading for cross-listed stocks compared to dark trading for stocks listed in Canada only, or increases in US dark trading of cross-listed stocks compared to US stocks. Each cross-listed stock is matched to one stock listed only in Canada and one stock listed only in the US, with the models comparing the cross-listed stocks to Canadian stocks and the models comparing cross-listed stocks to US stocks estimated separately.

TABLE 6.10: Difference-in-Differences Tests for Migration of Dark Trading

This table reports estimates from difference-in-differences models testing for migration of dark trading from Canada to the US:

$$Dark_{it} = \alpha + \beta_1 D_t^{PostPeriod} + \beta_2 D_i^{CrossListed} + \beta_3\left(D_t^{PostPeriod} D_i^{CrossListed}\right) + \varepsilon_{it}$$

$D_t^{PostPeriod} = 1$ after the rule change and 0 before. $D_i^{CrossListed} = 1$ for US-Canada cross-listed stocks and 0 otherwise. In columns (1) and (2) the model is estimated on cross-listed stocks and a set of matched stocks that are listed only in Canada and $Dark_{it}$ is the stock day's dollar volume of dark trading in Canada as a fraction of its total dollar volume traded in Canada. In columns (3) and (4) the model is estimated on cross-listed stocks and a set of matched stocks that are listed only in the US and $Dark_{it}$ is the stock day's dollar volume of dark trading in the US as a fraction of its total dollar volume traded in the US. In columns (2) and (4) the dummy variables $D_t^{PostPeriod}$ and $D_i^{CrossListed}$ are replaced with stock and date fixed effects. Adjusted R^2s do not include the variance explained by the fixed effects. Standard errors are clustered both by stock and date, and t-statistics are reported in parentheses. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

	Cross-listed stocks and matched Canadian stocks		Cross-listed stocks and matched US stocks	
	(1)	(2)	(3)	(4)
Intercept	0.041	0.076	0.312	0.355
	(68.2)***	(31.6)***	(215.2)***	(34.4)***
$D_t^{PostPeriod}$	-0.030		0.014	
	(-29.8)***		(5.91)	
$D_i^{CrossListed}$	-0.002		-0.023	
	(-2.56)***		(11.1)	
$\left(D_t^{PostPeriod} D_i^{CrossListed}\right)$	0.006	0.006	-0.001	-0.135
	(4.03)***	(1.224)	(-0.406)	(-53.9)***
Observations	50,390	50,390	49,588	49,588
Adjusted R^2	0.23	0.20	0.18	0.17
Fixed effects	No	Stock and date	No	Stock and date

Table 6.10 reports the results of the difference-in-differences models testing for regulatory flight. The first two specifications compare Canadian dark trading of cross-listed stocks to Canadian dark trading of matched stocks that are listed in Canada only (specification (1) controls for "treatment" and time effects with dummy variables, whereas specification (2) uses stock and time fixed effects). If some dark trading in cross-listed stocks were to migrate to the US following the introduction of the minimum price improvement rules, a larger decline would be expected in Canadian dark trading of cross-listed stocks than for stocks listed in Canada only, and therefore a negative coefficient would be expected on the interaction term $(D_t^{PostPeriod} D_i^{CrossListed})$. The results, however, do not support the hypothesis of regulatory flight; in fact, the coefficient of $(D_t^{PostPeriod} D_i^{CrossListed})$ is positive in specifications (1) and (2).

The second two specifications provide an alternative way of examining the regulatory flight hypothesis by comparing US dark trading of cross-listed stocks to US dark trading of matched US stocks (similarly, specification (3) controls for "treatment" and time effects with dummy variables, whereas specification (4) uses stock and time fixed effects). If some dark trading in cross-listed stocks were to migrate to the US following the introduction of the minimum price improvement rules, an increase would be expected in US dark trading of cross-listed stocks relative to US dark trading of stocks listed in the US only, and therefore a positive coefficient would be expected on the interaction term $(D_t^{PostPeriod} D_i^{CrossListed})$. Again, the results do not support the hypothesis of regulatory flight, as the coefficient of $(D_t^{PostPeriod} D_i^{CrossListed})$ is found to be negative in specifications (3) and (4). Therefore, both sets of tests provide consistent evidence against the hypothesis that some dark trading in Canada-US cross-listed stocks would migrate to the US in order to circumvent the Canadian minimum price improvement rules.

6.7 Conclusions

The results of this chapter suggest that dark trading has benefits for both price efficiency and liquidity, at least at the levels seen in Canada. Using Canada's introduction of minimum price improvement rules as an exogenous instrument for dark trading, dark trading is found to lower quoted, effective and realised spreads, reduce price impact measures of illiquidity, make prices closer to the random walk process that would be expected under informational efficiency, and reduce the delay with which stock prices reflect market-wide information. These findings are robust to controlling for changes in other market characteristics such as volume and volatility, controlling for time trends in dark trading and in market quality, and to difference-in-differences estimation, which provides an alternative way of controlling for changes in market quality that are unrelated to dark trading. The magnitude of the impact of dark trading is economically and statistically meaningful.

These findings are consistent with the theoretical predictions of Boulatov and George (2013) that hidden limit orders (dark trading) will encourage informed traders to increasingly act as liquidity suppliers and to trade more aggressively on their information, thereby increasing both liquidity and informational efficiency. Informed traders face a trade-off between: (i) earning profits from providing liquidity but at the same time giving away some of their private information to traders that observe the liquidity-proving orders; and (ii) paying to consume liquidity and thereby preventing disclosing their information before they trade. When trading occurs in the dark informed traders prefer supplying liquidity because they can capture the rents from liquidity provision without giving away their private information because their liquidity supplying orders are not visible. It is this aggressive competition between informed traders for liquidity provision when they can trade in the dark that benefits market quality. While Boulatov and George (2013) do not model a setting in which a lit and a dark venue exist side by side, the results suggest that strong competition among informed traders in providing dark liquidity has positive spillover effects on the lit market. For example, if there is strong competition among dark liquidity providers, liquidity demanding traders that have a choice of trading in lit or dark venues would be attracted to the dark unless the lit market liquidity providers can offer equally competitive liquidity. This causes increasingly competitive lit market liquidity (i.e., narrower spreads) at the expense of lit liquidity provider profits. This mechanism is made possible due to the lack of restrictions on participation in Canadian dark pools due to the fair access provisions in Canadian legislation.

Comerton-Forde and Putnins (2012) conclude that dark trading becomes harmful to price discovery once it exceeds 10% of dollar volume in the Australian market. The results of this chapter complement this finding by suggesting that dark trading levels below this 10% threshold does not harm price discovery, but in fact appears to be beneficial. Taken together these two studies provide support for the notion of a “tipping” point - an optimal level of dark trading beyond which dark trading harms market quality. The notion of a tipping point may prove to unify the apparent contradictions in the extant empirical literature, especially if this point is unique to each marketplace.

This chapter also provides evidence on a potential form of regulatory arbitrage that could undermine the effectiveness of dark trading restrictions. Prior to the introduction of the minimum price improvement rules in Canada, a number of market participants and marketplace operators raised the concern that dark trading in the large number of Canadian stocks that are cross-listed in the US would migrate to the US in order to circumvent the Canadian rules. No evidence is found for such migration of dark trading.

The combination of regulatory decisions in Canada has achieved a balance between dark and lit trading and provides lessons for other regulators and market operators. The regulatory prohibition of restricted-access venues, the existence of broker preferencing, and price improvement requirements for broker internalization have impeded the development of dealer-sponsored dark pools and systematic internalizers, which have substantially contributed to the growth in dark volumes in the US, Europe, and Australia. The immediate post-trade transparency mandated for both lit and dark markets provides a useful mechanism for dark trades to contribute to price discovery, unlike the 30 second delay in dark trade reporting in the US. Finally, the recently introduced minimum price improvement rules mandate a meaningful price improvement for dark trades and thereby prevent the increasing use of fractional price levels, as often encountered in the US. In arresting the increase in dark volumes, the minimum price improvement legislation may help ensure that dark trading in Canada does not exceed the point beyond which market quality is harmed.

Chapter 7

Conclusion

A number of new types of trading have been introduced over the last decade. These new trade types have been driven by rapidly fragmenting market structures, resulting in the establishment of dark pools and the wide-spread use of high-frequency trading. This dissertation considers the effects of the microstructure of financial equity markets on elements of market integrity and efficiency, specifically focusing on the behaviour of interconnected, yet fragmented markets and their associated impact on key market outcomes such as the degree of liquidity, the size of trading costs, the level of market efficiency and the extent to which traders engage in prohibited conduct.

An efficient market comprises of of informed and uninformed (liquidity) traders. Informed traders are necessary for gathering costly information, and ensuring that prices fundamentally reflect all publicly available information. Liquidity traders are necessary to ensure that frequent trading occurs and to avoid the "market failure" that would occur if only informed participants exist. To ensure that both types of traders participate in the market, it falls upon regulators to keep markets both "fair" and "efficient". These two goals are necessary to ensure that participants have confidence in the integrity of the markets in which they trade. If markets are perceived to lack this "level playing field", there is a risk that investors in a globally connected market may move their trading to other venues, or simply cease trading all together.

One way that the perception of a level playing field can be damaged is when not all traders have access to the same advantages. The development and growth of high-frequency trading and dark pools risks creating a “two-tiered” market, where those with access to these technologies benefit at the expense of those for whom such technologies are too complex, expensive, or impractical. The removal of this level playing field, whether it be due to integrity breaches such as insider trading and market manipulation, or due to the lack of access to new technologies, risks alienating the liquidity traders that are necessary for efficient markets to operate.

The recent emergence of these new forms of trading has left regulators, participants and academics uncertain of the benefits of these trading innovations. The literature survey (as presented in Chapter 2 of this dissertation) identifies a significant amount of literature devoted to examining issues of market microstructure and their implications for market efficiency and integrity. The findings of these studies have often produced conflicting results, and are not able to be generalised due to differing market structures, time periods and approaches to the measurement of variables such as the level of high-frequency and dark trading. This dissertation builds on the existing literature in a number of areas. Specifically it examines the role of insider trading during the takeover announcement period, the impact of high-frequency trading on market quality, and the degree to which dark pools have changed and affected the market landscape. These issues are examined in the four core essays that constitute this thesis.

Chapter 3 of this dissertation contributes to a greater understanding of the pre-announcement price run-up observed around takeover events. A number of studies over the last few decades have attributed such run-up to the role of insiders profiting from their knowledge illegally. This result has been supported by studies of confirmed illegal insider traders as well as by more general studies into the causes of the run-up. Chapter 3 examines the determinants of the price run-up ahead of takeover announcements and focuses on the role of toeholds established prior to this date. The finding that toeholds have significant explanatory power provides new evidence about the extent to which insiders’ may be trading prior to takeover events. Whilst insider trading cannot be discounted as an explanation for the price run-up, this finding implies that existing studies may exaggerate the extent of insider trading.

The second essay in this dissertation, found in Chapter 4, examines the rise of high-frequency trading in the LSE and Euronext Paris markets. The rise of high-frequency trading and market fragmentation has resulted in a vast array of new, electronically-executed, strategies. The increasing prevalence of high-frequency trading in the global market has led many regulators, including those in Australia, Canada and Italy, to introduce order-based “Tobin Taxes” to try to discourage the practice that has resulted in increased message traffic. Proponents of high-frequency trading argue that the strategies employed are simply faster versions of strategies that have existed for years. Detractors, however, argue that high-frequency trading creates a multi-tiered market, where high-frequency traders are able to prey on orders placed by slower participants.

Whereas existing studies of high-frequency trading have focused on the impact of high-frequency trading on efficiency, Chapter 4 examines the issues of efficiency *and* integrity jointly. Assessing integrity and efficiency together is important as improvements in efficiency may come at the expense of integrity. For example, a market with a significant amount of insider trading may be “strong-form efficient”, but this efficiency comes at the expense of the integrity of the market. As the conduct of HFT traders is largely undocumented in the academic literature, their impact on integrity has not, as yet, been analysed in any real depth.

The results presented in Chapter 4 show that high-frequency trading leads to increased competition between liquidity suppliers for order-flow. This has decreased the transaction costs paid by market participants, as electronic liquidity suppliers narrow their inventory holding and order processing costs. This improvement in efficiency is not found to have had any adverse impacts on the level on integrity, with the level of insider trading remaining unaffected. Indeed, high-frequency trading is found to *improve* the integrity of the market by reducing the frequency of end-of-day manipulations. These findings confirm the consensus in the literature that high-frequency trading does, in fact, improve the liquidity supplied to markets. Additionally, the existence of high-frequency trading is found to improve the integrity of the market as a whole.

Despite mounting evidence of the positive impacts that high-frequency trading has for market quality, many regulators around the world have been implementing taxes and cost-recovery mechanisms designed specifically to limit the practice. The results of this dissertation suggest that more research needs to be conducted, especially where these taxes have been introduced, to identify what impact deterring high-frequency trading has on market quality. An additional conclusion that can be drawn from these findings is that, when assessing market quality, regulators should not focus solely on efficiency. This dissertation has developed a framework to examine both integrity *and* efficiency concurrently. Such a framework should assist regulators in meeting their mandate of ensuring that future changes to market design improve both the fairness and efficiency of the market.

Chapters 5 and 6 of this dissertation focus on the impact of dark trading on market quality. While private block trading (which lacks pre-trade transparency) has existed for many years, the development of venues that aggregate small orders in a continuous, separate pool is a recent phenomenon. The existence of dark orders can be both beneficial and detrimental to markets. On the one hand, providing (typically institutional) traders with the ability to submit large orders without pre-trade transparency can encourage latent liquidity to be expressed on market. Without pre-trade transparency, front-runners do not have an opportunity to "step in front" of the large traders' orders, reducing the cost of executing large orders. Once on-market, this liquidity may be accessed by other traders, increasing total market liquidity. On the other hand, if all traders use dark orders, the price discovery process breaks down, removing the very prices that are necessary for the dark pools to function - such a situation results in market failure.

Previous literature on dark pools has failed to reach a consensus as to whether the costs or benefits of dark pool trading dominate. This failure to definitively identify the impacts of dark trading on market quality is (at least) partially driven by the difficulties present in the analysis of dark trading. These difficulties include: the difficulty of obtaining sensitive data describing dark trading; the failure of previous studies to appropriately account for endogeneity concerns; the relatively recent establishment of dark trading; and the need for dark trading to be taken up by a substantial proportion of traders before its' impact can be ascertained. The final two chapters of this dissertation use unique experimental designs to overcome these limitations that have hindered the analysis of this topic thus far.

Chapter 5 investigates the impact of the introduction of dark trading on the TSX with regards to market quality and efficiency. The introduction of dark trading is found to increase quoted, effective, and realised spreads, indicating that traders are initially wary of how the introduction of hidden liquidity will impact trade executions. Once dark orders are established on all securities, increased levels of continuous dark trading are found to decrease transaction costs and improve measures of pricing efficiency. This is consistent with the finding that dark orders facilitate increased competition between market makers, allowing them to extract value from their knowledge of the true value of securities without disseminating that information to the market. This results in an increase in available liquidity without damaging the price discovery process.

In the final chapter of this dissertation, the introduction of rules to limit dark trading in Canada - the so called "Minimum Price Improvement" regulations - are used to identify the impact dark trading has on the market. The sharp decline in dark trading caused by this exogenous shock creates a unique set-up that is not biased by the limitation of endogenous dark movements, as is observed in previous studies. Consistent with the findings in Chapter 5, increased levels of dark trading are found to improve measures of transactions costs and market efficiency.

The findings of these two studies on dark pools are counter to previous empirical findings in markets such as Australia and the US. One important factor in this contrary result is that the levels of dark trading in Australia and the US are both around 15-20%, as compared to the 5-10% found in Canada. Thus, the finding that low levels of dark trading are beneficial while higher levels are detrimental is consistent with the idea that there is a tipping point in the level of dark trading in a market, up to which dark trading is beneficial, but beyond which dark trading becomes harmful to the price discovery process. With the low level of dark trading that exists in Canada, it is likely that this tipping point has not yet been reached in this market.

Taken together, Chapters 5 and 6 establish that low levels of dark trading are beneficial for a market. This result does come with the caveat that the benefits to dark trading may erode as the impact on the price discovery process becomes more marked. Further research should be conducted to establish the hypothesised tipping point at which dark trading becomes detrimental. Once established, this tipping point can be used as a reference point for regulation that aims to curb dark trading. Furthermore, the existence of a minimum price increment appears to have reduced the extent of undesirable conduct, including dark market-making. Overall, this has increased competition between market makers, resulting in improved liquidity in the lit Canadian market.

The recent introduction of minimum price improvement regulations by the Australian regulator should be carefully analysed to provide further evidence of the impacts such regulation has, especially in countries with high levels of dark trading, such as the US. Similarly, the compulsory immediate post-trade transparency required in Canada facilitates the study of dark pools, and efforts by national regulators to increase the transparency of dark pools for academic purposes should be encouraged.

This thesis shows that the recent developments in market microstructure have largely been beneficial for the quality of equity markets. While there is likely to always be some resistance to change, it is essential to utilise evidence to assess how new types of trading impact the market before regulation is introduced.

Appendix A

Trading in Canada

A.1 Trading on the TSX

Trading on the TSX is organized in an upstairs-downstairs structure. Orders can be filled by upstairs brokers (usually these are very large orders), who have price improvement obligations, or they can be cleared via the consolidated (electronic) limit order book. The TSX limit order book generally follows the so called price, visibility, broker, time priority. This implies that the book is constructed by sorting incoming limit orders lexicographically: first by their price ("price priority") and then, in case of equality, by their visibility (visible orders have priority), then by broker (brokers enjoy priority for clearing against orders from the same brokerage), and finally by the time of the order arrival. Broker priority also applies, in the sense that active and passive *client* (not proprietary) orders submitted by the same broker at the same price and visibility have priority over earlier submitted orders at the same price and visibility.[68] Visibility priority implies that for the same price, dark orders, or the hidden portions of iceberg orders, have lower priority than visible orders. The limit order book relies on its users to voluntarily supply liquidity by posting limit orders. Transactions in the limit order book occur when active orders, that is, market orders (e.g., an order to buy at the best available ask price) or marketable limit orders (e.g., a buy limit order with a price higher

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[68] To invoke broker referencing, both orders must be client orders, implying that the broker cannot internalize an order in the sense of trading on its own inventory and invoke broker priority. Broker preferencing is, however, immaterial to the analysis. Notably, traders can also tag their order to switch off broker preferencing.

than the current best ask), are entered into the system. Unpriced market orders occur very infrequently on the TSX. The marketable portion of an order is commonly referred to as an "active order", and a "passive order" refers to a standing limit order that is hit by an active order. Active orders may "walk the book", that is, if the order size exceeds the number of shares available at the best bid or offer price, then the order continues to clear at the next best price, provided that order protection is maintained (i.e., no other visible marketplace posts at better prices).[69] All orders must be sent to the TSX by registered brokers (the Participating Organizations or POs), though direct market access by clients is possible by using a PO's broker number.

Dark orders can be entered in one of two ways. Firstly, they can be entered as standard limit orders, expect that the order is simply not displayed (aka "dark"). Alternatively, they can be entered as midpoint orders where these orders "floated" with the midpoint of the national best bid and offer price. Traders can also specify a number of additional options, including a limit price.[70] Passive dark orders that execute invoke no fee (and no rebate). Active visible orders that trade against a dark order invoke a fee of $0.001 per share. Active dark orders that trade against passive visible orders (these would not be midpointpegged orders) invoke a fee of $0.0035 per share. For comparison, "standard" fees for lit market transactions are as follows: active orders involve a fee between $0.0033 and $0.0035 per share (depending on the discount tier that the broker falls into), passive orders receive a rebate between $0.0031 to $0.0032 per share. Dark orders are excluded from the so-called ELP program which gives special deals to electronic (high-frequency) market makers.

A.2 Dealer Crosses

Dealer crosses, which are excluded from the analysis, are usually one-on-one arranged trades that have no pre-trade transparency, and can thus be considered "dark" trades. There are a number of regulations in Canada's Universal Market Integrity Rules (UMIR)

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[69] The onus is generally on the brokers to ensure order protection, however, all visible marketplaces, including the TSX, offer order routing services to ensure order protection; they also allow brokers to specify that orders are to be executed only on the TSX.

[70] Details are available at: http://www.tmx.com/en/pdf/TSX_TSXV_Dark_Liquidity_Guide_v1-1.pdf.

that relate to dealer crosses. Namely, the order exposure rule, UMIR 6.3, together with the client-principal trading rule, UMIR 8.1, specify that all orders of less than 50 standard trading units (henceforth, 5,000 shares) must be exposed to the market, unless the dealer provides meaningful (i.e., 1 tick) price improvement relative to the NBBO. Furthermore, the best execution rule, UMIR 5.1, ensures that dealer crosses for more than 5,000 shares are in the interest of the client. Finally, the best price (or, no trade-through) rule, UMIR 5.2, specifies that an order cannot trade through better-priced orders. Dealer crosses incur no exchange fees. Smith, Turnbull and White (2001) have shown that the upstairs market fulfills an important role by allowing, in particular, institutional investors to clear large orders in one trade.

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