Spring 5-2021

The Role of The IEX in a Fragmented Market System

Cameron Spicer

THE ROLE OF THE IEX IN A FRAGMENTED MARKET SYSTEM

by

Cameron Spicer

A Thesis Submitted in Partial Fulfillment
of the Requirements for Two Degrees with Honors
(Finance, Financial Economics)

The Honors College

University of Maine

May 2020

Advisory Committee:

Stephen Jurich, Assistant Professor of Finance, Advisor
Travis Blackmer, Lecturer in Economics
Ronald Nadeau, Associate Professor of Art & Honors Preceptor
Ronald Roope, Cooperating Faculty in Finance
Stefano Tijerina, Lecturer in Management

ABSTRACT

Over the past several decades, the secondary market system has evolved into a more complex and fragmented system than it once was. The Investor's Exchange (IEX) emerged in 2014 in rebellion of purportedly unethical High-Frequency Trading (HFT) behaviors in the markets. Using a novel, proprietary model for trade matching along with providing other services, the IEX has become a respectable player in the market system that prides itself on transparency and fairness. This paper explores the role that IEX has played in market fragmentation since its inception using empirical and historical analysis. The empirical analysis focuses primarily on a recent two-year time period spanning from August 13th, 2018 through August 13th, 2020. Using difference in means tests this paper makes comparisons between the IEX and NYSE American, the two most reputable "speed bump" models. Additionally, using ordinary least-squares regressions this paper does an extensive analysis of predictors of volume and market share. In-depth review of existing literature offers further insight about the IEX and its relationship to trends in market microstructure. I find that the IEX has been effective in deterring HFT behavior. This research supports the theory of a single market with multiple entry points described by O'Hara & Ye (2011) by highlighting how the IEX has become its own unique entry point for a well-connected market system.

DEDICATION

There hasn't been a single event, accomplishment, or moment in my life that came without substantial support from those around me. This Honors Thesis has certainly been no exception. This year was radically changed by the COVID-19 pandemic and led to profound struggle in my personal and professional life. Through it all my girlfriend Shanna Scribner has been my foundation and my support. Without her there is no way I would have survived this process, but I'm not sure I could survive without her in the first place. Thank you, Shanna, for your unending, unconditional love and support for me, especially during this difficult year.

I next owe great debts to the ones who have always been there for me: my family. Chuck, Linnea, Bailey, Paige, Jack, Tucker, & Opie, you have always been there and never wavered. Even being far from home for so many years, I still feel your love, support, and presence. Before you set me free into this world, you all shaped me into who I am.

An extension of my family during my time at the University of Maine has always been my teammates on the Men's Varsity Hockey Team. To my teammates, past and present, thank you for sharing my love for the game and supporting me in everything. I will never forget the time and sacrifices we have made together. Your encouragement for me in everything I have pursued at the University of Maine has been a tremendous highlight for my life and my memory of this place.

In the final weeks of developing my Thesis I began a remote consulting job with a Los Angeles-based company named Pitch Genius. This has been an amazing opportunity and would have been impossible without the support of the company's CEO, Jasmine

Foroutan. The level of flexibility and support she has offered me has been gracious beyond any expectation.

My thesis process was witness to the tragic passing of long-time Head Coach of the Men’s Hockey Team, Red Gendron. I was the first player that Red offered an athletic scholarship to during his tenure as Head Coach. Since I arrived to the University of Maine, I have seen and talked to him every day. Not only was he my teacher on the ice, but he was also one of the most intellectually driven people I have ever met in the hockey world. He had a passion for history and could speak on virtually any topic. We built a special relationship around my academic endeavors and his love and care for me a man always went beyond hockey, even when hockey was challenging. I am immensely proud to have known you, Coach. It will forever be a point of great sadness that you never got the opportunity to read this paper.

ACKNOWLEDGEMENTS

When I started this research process, I didn't know anything about researching. I had read a handful of peer-reviewed articles and that was pretty much it. Throughout the process I have spent most of my own time teaching myself, but none of it would have been possible without the time and support from several key people.

First and foremost, I am greatly indebted to my advisor, Dr. Stephen Jurich. He is one of the smartest people I have ever known and is a superb researcher. He had numerous opportunities to give up on me and never did. With outstanding patience and discernment, he encouraged me and held me accountable when I needed it. Despite many other responsibilities he always supported me and made time for me. There is no possible way I would have made it this far without him.

Near behind Dr. Jurich are my four committee members that committed to support me in this process from day one. Travis Blackmer, Ed Nadeau, Ron Roope, and Dr. Stefano Tijerina are four of the most influential people I have ever met. I view them all as both role models and friends. The past two semesters were met with exceptional challenges for everyone, but these exceptional men maintained their commitment to me throughout all the adversity. I am beyond thankful for their involvement in my thesis process, but even more grateful to have known and learned from them during my time as a student.

The Honors College and staff have created one of the best Honors programs in higher education. A number of my colleagues from other schools are instantly jealous when I have shared my experience with them. A huge part of the success of the Honors college at the University of Maine is the thesis and reading list process. They put an extraordinary amount of effort into making it a rewarding experience and have facilitated its importance with almost every program of study.

Finally, there are several additional people that deserve credit. Near the end of this process, I was fortunate enough to present my work to the Maine Masonic College and to the Wealth Management Team at Bangor Savings Bank. I would like to thank all the members of these institutions for their time and feedback on my research. Another person that was not involved with my thesis but played a huge role in encouraging me academically early on is Dr. David Townsend. He has always been one of my biggest supporters as a student-athlete and I am thankful to have had him as a role model. I would like to give a special thanks also to the Honors Associates from this year, Cara Doiron and Kim Crowley. Cara and Kim have been instrumental in helping dozens of students complete their theses this year, myself included.

PREFACE/FOREWORD

Writing a thesis has been the most difficult thing I have ever done in my life. More than just being difficult, it has been particularly humbling. Through the 100's of hours I have poured into this, my greatest fear has been answering a huge question about market microstructure. With the insight I now have, I realize that it is a rare and powerful thing for someone to use research to discover something revolutionary. I have continuously put pressure on myself to make this an exceptional contribution to the literature. The pressure I have put on myself has been so great that it both nearly broke me and nearly prevented the completion of my research. Trying to make this research a profound contribution distracted me from the fact that a contribution of any size is all it needs to be. My hope now is that this paper is part of the big picture of the fragmented market system and one day helps others learn more about the finance industry.

The equity market is one of the most delicate and important systems in our world. From retail investors all the way up to hedge fund managers, changes in the market can change peoples lives. This is what makes this research so important. The IEX started, and is part of, a huge trend of continued fragmentation of the market system. As the market system changes, people's lives also stand to be changed either implicitly or explicitly. The market matters because people matter. The market changes because people are different and because people also change. The truth behind finance, and this paper, is that human behavior is what underlies much of what we study.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF GRAPHS

LIST OF FIGURES

LIST OF ABBREVIATIONS

IEX	Investor’s Exchange
CBOE	Chicago Board Options Exchange
API	Application Programming Interface
Reg NMS	Regulation National Market System
NYSE	New York Stock Exchange
FINRA	Financial Industry Regulatory Authority
NBBO	National Bid or Best Offer
BATS	Better Alternative Trading System
CSV	Comma Separated Values
MEMX	Member’s Exchange
LTSE	Long-Term Stock Exchange
AT	Algorithmic Trading/Trader
NSX	National Stock Exchange
ATS	Alternative Trading System
SEC	Security Exchange Commission
HFT	High-Frequency Trading/Traders
ECN	Electronic Trading Network
CHX	Chicago Stock Exchange
TRF	Trade Reporting Facility

CHAPTER I

MARKET FRAGMENTATION

Overview

For years the secondary market system in the finance industry has been evolving into a prolific environment of exchanges, institutions, traders, brokers, and regulators. Around the year 1995, this same market system was predominantly made up of only 5 exchanges that each operated with analogous functions in relation to each other. In the United States there are currently 29 national securities exchanges available for trading stocks and options as well as 61 ATS exchanges[1]. This proliferation of exchanges can be attributed in theory to a diverse range of sources and long history of market microstructure evolution (O'Hara, 1996; O'Hara & Ye, 2011). The evolution of market microstructure is a dynamic blend of innovation, regulation, and interaction within and surrounding the markets themselves.

Many different changes in the financial securities market environment have contributed to the current status of market fragmentation for the system as a whole[2]. These trends have spread not only throughout domestic markets but can also be seen abroad (Gresse, 2017; O'Hara & Ye, 2011). The history of market fragmentation in the United States was a precursor to the formation of the IEX and the IEX is now a unique part of the fragmented market system. This chapter analyzes much of the theoretical and empirical

---

[1] Taken from official SEC lists of exchanges and ATS's. The list of SEC sanctioned exchanges can be found at: https://www.sec.gov/fast-answers/divisionsmarketregmrexchangesshtml.html & the list of SEC sanctioned ATS's can be found at: https://www.sec.gov/foia/docs/atslist.htm

[2] See Appendix A for more information on the history of market fragmentation

work in market microstructure that relates to the fragmentation of the equity market in the U.S. and abroad.

Radiation within the Market System

For a quarter of a century, the securities' market system has been categorized by rapid and novel change. An obvious and intuitive source of this expansion and evolution is the digital revolution (Hendershott et al., 2011), but the academic community has continued to identify other relevant sources. In the past 4 years alone, the number of stock and options exchanges has increased by 4, and 21 new SEC-sanctioned ATS exchanges have emerged[3].As these changes have occurred, a large portion of volume has moved to off-exchange venues since the admission of Reg NMS (Kwan et al., 2015; O'Hara & Ye, 2011).

With this rapid expansion there has been noticeable increases in competition between exchanges and between market participators(Boehmer et al., 2018; Hens et al., 2018; Wang, 2018). Bessembinder & Kaufman (1997) and Bennett & Wei (2006) discuss some of the costs to the increased levels of competition while many others have identified some of the benefits (Aitken et al., 2017; de Fontnouvelle et al., 2006; O'Hara & Ye, 2011). All the while, regulators have attempted to stay on top of protecting a fair market environment.

Regulation NMS was a huge tipping point for the fragmentation of equities markets (Aitken et al., 2017; Kwan et al., 2015; O'Hara & Ye, 2011; Woodward, 2018). In order for the IEX to become an exchange, the SEC had to grant an exception to Reg NMS[4] due

[3] Calculated using current values in comparison to a count done by author Matt Turner in a web article for Business Insider. This article can be found at https://www.businessinsider.com/firm58-graphic-on-stock-market-fragmentation-2016-3

[4] https://www.cnbc.com/2016/06/17/sec-gives-its-blessing-to-the-iexs-speed-bump-trading.html

to its new technical innovation: the access delay[5]. This is largely why the entrance of the IEX had such a profound impact on fragmentation. Not only that, but the new change to Reg NMS allowed for the entrance of NYSE American, the IntelligentCross dark pool, and other access delay venues making the market even more fragmented.

New competition between venues in the equity market has continued and evolved since the IEX emerged. In 2020 alone, the SEC granted exchange membership to two new exchanges: The Member's Exchange (MEMX) and the Long-Term Stock Exchange (LTSE). Both exchanges have mirrored the extensive effort from the IEX to brand themselves into a specific niche within the equity market system. Ironically, there is indication that the entry of MEMX has been a competitive response to the IEX and other venues. Similar to the critique assigned to the BATS exchange in *Flash Boys*, MEMX has received direct support from virtually all prominent market maker institutions known to participate heavily in Algorithmic trading, and potentially HFT behavior. In fact, one analyst even referred to the exchange as "Bats 2.0" in a Financial Times article[6]. There is a considerable likelihood that MEMX could use attractive fee structures to acquire market share so that supporting institutions can capitalize on that market share using HFT or other methods.

Changes in fragmentation have grown to show the signs of the evolutionary principle of adaptive radiation. As more changes arise in the market, there is potential that the theory of a single market with multiple entry points presented by O'Hara & Ye (2011) could be challenged if increased fragmentation undermines the functions of Reg NMS.

[5] Also referred to as a "speed bump" because it was designed to deter HFT behavior
[6] https://www-proquest-com.wv-o-ursus-proxy02.ursus.maine.edu/docview/2165970117?pq-origsite=summon

Beyond that, there is risk that predatory behavior could emerge due to a regulatory lag on top of existing risks such as flash crashes, deterioration of market quality, or other trends. Ultimately, it is difficult to predict what the ideal balance of consolidation versus fragmentation is best. The conclusions of Mendelson (1987) how theoretical analyses of different market organization to be comparable in quality, but in the presence of trading algorithms makes the future of the markets look like they will be fragmented for the foreseeable future.

Market Quality

New derivations of traders and strategies emerged in tandem with changes in the market system. These changes have had impacts on market quality. The degree and direction of each of these impacts is somewhat debated, but the general consensus is that market fragmentation improves market quality (Aitken et al., 2017). Multiple studies have shown that fragmentation reduces spreads, with O'Hara & Ye (2011) finding that "more fragmented stocks have lower transactions costs and faster execution speeds" and that "fragmentation is associated with higher short-term volatility but greater market efficiency". This paradigm study is the primary reference to the theory of the equity market acting fully cohesive with multiple points of entry despite fragmentation.

Interesting research has also been performed on the role that trading skills play in fragmentation as a way to measure market quality. Ladley et al. (2015) finds that as the intricate web of markets and exchanges has grown to include ECN's and ATS' that compete with traditional exchanges, the value of trading skills has increased. This research was valuable for providing more insight to how a retail investor fits into market fragmentation. Their findings are summarized well in this quote:

> “In centralized markets with many traders, transaction prices tend to be efficient, and small market orders tend to have little price impact. Therefore, the incentives to acquire skills are weak, and, in equilibrium, most traders are unskilled. In fragmented markets, market orders have more price impact. Consequently, skilled traders, who quote prices close to fundamental values, make money by trading with unskilled traders who do not, and therefore most traders are skilled in equilibrium. As a result, fragmented markets are more resilient. Inter-market price variation, defined as the variation in prices between trading venues is, however, increasing in market fragmentation.” (Ladley et al., 2015)

This study has many findings that are important to this thesis development because this thesis originated out of curiosity for how fragmentation impacts the retail investor. The discovery that small orders have a negligible impact on price is fundamental support for fragmentation’s positive effects since a fragmented market creates so much more liquidity in the market. Additionally, this research indicates that there could be a rising number of unskilled retail traders.

An area that is understudied when it comes to market quality is the impact of HFT on market quality. Foucault & Biais (2014) discuss the lack of evidence but point out the potential for many negative externalities. Their study investigates policy implications behind HFT, specifically as it relates to market quality. The IEX may have potentially introduced one of the purported negative externalities through the access because research has shown that it may “promote activity detrimental to market quality” (Wah et al., 2017). This would be a logical conclusion given that access delays work against the positive features of a fragmented market that is connected by electronic behavior. According to that research, access delays are a dangerous venue type in a world of make-take fees, execution instability and improbability, and long queues.

Lit and Dark Liquidity

A crucial aspect of market fragmentation is the growth of dark trading. Prevalence of ATSs and ECNs grows virtually every year and has a dramatic impact on the market. Conceptually, dark pools create a safe haven for block trades to occur without damaging price discovery for the rest of the market. However, over the past decade the average trade size in ATSs venues has decreased considerably (Biedermann, 2015; Kwan et al., 2015). In addition to this, dark pools have been the source of some illegal activity[7]. Despite this, dark pools have a distinct competitive advantage in the form of the Increment Rule, the part of Reg NMS that has allowed for fragmentation to truly take off (Kwan et al., 2015).

A concern with dark pools has been the impact it has on order flow and liquidity. Gresse (2017) indicates that dark trading and increased fragmentation does not have an impact on liquidity. In that study it was also shown that lit fragmentation harms the depth of smaller stocks and that HFTs affect the depth of large stocks. With such a large range of venue choices, routing choices are difficult to quantify.

One effect that dark pools have had is queue manipulation. There is evidence from multiple studies that "dark pools allow some traders to bypass existing limit order queues with minimal price improvement" (Kwan et al., 2015). In fact, 'queue jumping' is one of the main facilitators of the practice of frontrunning by HFT. This is the practice that the IEX was designed to fight against. Not only is frontrunning a predatory side effect of dark pools, they also undermine the value that is provided by queue positions for large tick-size stocks (Moallemi & Yuan, 2017). There have also been benefits to these trends, however. The trend of 'queue jumping' has been a source of increased competition between market

[7] https://www.tradersmagazine.com/flashback/flash-friday-turning-the-spotlight-on-dark-pools/

makers across venues and this is seen as a considerable benefit to fragmentation(Aitken et al., 2017).

Impacts of Fragmentation

The expansion of venues, participants, and entrants within the equity market system has created room for more frequent and delicate interactions in response to the many exogenous forces at play. There have been concerns voiced by academia that certain conditions of fragmentation could be leading markets to be more fractured than fragmented (O'Hara & Ye, 2011). This claim can be understood better through the hypothesis that there is "a tradeoff in market structure between order flow consolidation and competition among market centers" (Bennett & Wei, 2006). Ultimately, as in any evolutionary process, time is a huge factor. This is exactly why "the ability to circumvent time priority of displayed limit orders is one cause of the rapid rise in US equity market fragmentation" (Kwan et al., 2015). Digital technology has created time-minimizing processes that have sped up fragmentation unthinkable ways.

With so many changes happening so fast, it is quite logical why such claims have been made. A non-intuitive indicator of fragmentation is volume vs. liquidity because volume increases with more interactions in the market, but liquidity is more abstract and difficult to quantify. This concept is replicated in the information asymmetry between the stakeholders in the stock market. A more fragmented market leads to higher potential for information asymmetry which is facilitated by an increased number of interactions (Adrian, 2016). The number of interactions within every aspect of the market system have increased synchronously with the size of the system itself. This has occurred not just transactionally in the market, but also throughout the processes that lead to market transactions.

Regardless of these abstract trends of evolution in the market system, the general effect of fragmentation has been discovered to be a positive one. Fragmentation has been shown to improve market quality, even as fragmentation has increased (Aitken et al., 2017). Not only that, but fragmented markets have been seen to be more resilient than consolidated markets (Ladley et al., 2015). One of the most reputable and cited studies on fragmentation summarizes more of the effects in their paper's abstract:

> ""We find that fragmentation affects all stocks; more fragmented stocks have lower transactions costs and faster execution speeds; and fragmentation is associated with higher short-term volatility but greater market efficiency, in that prices are closer to being a random walk. Our results that fragmentation does not appear to harm market quality are consistent with US markets being a single virtual market with multiple points of entry"(O'Hara & Ye, 2011)

The hypothesis that the fragmented market has adopted the form of a single, cohesive market with multiple entry points has become a focus of this research. Under this hypothesis, the role of the IEX could be explained as a new form of entry for a select type or number of participants. Ultimately, O'Hara & Ye describe a more important detail about fragmentation that transcend the state of the market. That detail is that fragmentation has a large range of explicit and implicit costs.

CHAPTER II

HIGH-FREQUENCY TRADING

Introduction

High-frequency trading has become a controversial buzzword in the finance industry in the past several years. One of many testimonies for this is the emergence of the IEX and its corresponding novel, *Flash Boys* by Michael Lewis. To understand high-frequency trading better, and to use it to under the IEX the market system, it needs to be well-defined.

Computers have facilitated trading in numerous ways. Generally speaking, the use of computers to trade is referred to as 'algorithmic trading'. AT encompasses a wide variety of subcategories and has increased dramatically since its inception (Hendershott et al., 2011). One of the subcategories of AT is high-frequency trading. This is an important differentiation because HFT is uniquely based on speed and can often be predatory or distasteful.

The founder of the IEX, Brad Katsuyama was particularly curious when he discovered the effects that HFT had on him as a trader on Wall Street. These effects of HFT led him to start the IEX and revolutionize the stock market industry. The IEX has largely been seen as a "band-aid fix" to HFT(Adrian, 2016), but still indicates that more regulation is necessary in the realm AT and HFT. According to St. John (2016), the entry of the IEX had less to do with the value proposition of the IEX and more to do with repairing the negative perception that had been created by HFT.

The Rise of Algorithmic Trading

The history of AT can be traced in theory all the way back to 1851 when Paul Julius Reuter used a cable beneath the English Channel to share stock market quotations. Since then, AT has continued to evolve and has increased its pace of growth since the onset of the digital revolution[8]. In the early 2000's AT had grown rapidly. By 2009 it was believed that nearly 73% of volume in the U.S. equity market occurred using AT (Hendershott et al., 2011). We now live in a world where our market is defined by, and reliant on the presence of ATs to act as market makers and bridge the gaps created by our fragmented market system.

When a fund manager searches for a broker-dealer to execute a trade or when a retail investor works with a financial institution to update their portfolio those interactions lead to the use of ATs. Prior to AT, these interactions would have led to a broker-dealer work the floor of the NYSE to execute the trade at the fairest prices. At codified that process. In fact, AT has come so far along that the NYSE was able to operate with an empty trading floor during the initial months of the COVID-19 pandemic[9]. Not only have ATs improved flexibility for investors, the have lowered transaction costs and increased volume across the board (Menkveld, 2016).

High-Frequency Infrastructure

As previously noted, speed is a crucial differentiator for an AT to be considered HFT. The phenomenon underlying the need for speed in HFT is an arm's race for faster connections to exchange matching centers. In *Flash* Boys, Katsuyama learned of this early

[8] See Appendix B for a concise and interesting history on AT since 1851.
[9] See this article from the NY Post about the COVID-19 shut-down at NYSE: https://nypost.com/2020/03/18/nyse-to-shut-down-trading-floor-monday-due-to-coronavirus/

on and it helped lead him to IEX co-founder, Ronan Ryan. The novel even begins with a primer on the HFT Arm's Race in the form of the Spread Networks dark fiber line Budish et. al (2015) finds that this is evidence of a flawed market design because the mechanical capabilities of a continuous limit order book break down at high-frequency time scales.

The mechanical flaw in market design as it relates to HFT occurs primarily because of the Order Protection Rule, which is part of the Reg NMS implemented by the SEC. The order protection rules requires that exchanges must route orders to other exchanges if those exchanges have better prices. Wang (2018) succinctly describes the impact that the HFT Arm's Race has on the market system and investors:

> "Faster exchanges attract more price-improving limit orders because the probability of being bypassed by trades with inferior prices on other exchanges is reduced. When all exchanges speed up, this probability can increase, potentially harming the welfare of investors. In contrast, increasing connection speeds between exchanges raises investor welfare by reducing this probability. Nevertheless, no exchange wants to improve connection speeds because this will reduce its trading volume

Similarly, Budish et. al (2015) provided a theoretical alternative in the form of batch auction matching in response to the issue of the mechanical infrastructure in market design. In their research, they compared time-series data using minutes as a standard versus 250 milliseconds to highlight the clear mechanical arbitrage available to the fastest HFT actors. They found that "arbitrage opportunities decline dramatically, from a median of 97 milliseconds in 2005 to a median of 7 milliseconds in 2011".

Front-Running

Prior references to 'mechanical arbitrage' are a reference to the practice of 'front-running' that is used by HFT firms for profits. Due to the implementation of Reg NMS, there is an unavoidable latency issue due to the travel times of trade signals. Although these latency times are typically faster than the blink of an eye—under 20 millionths of a second—it is still slow enough for very fast computers running HFT algorithms to shave pennies off millions of trades per day. Front running can be further defined as "using the knowledge of a large impending trade to take a favorable position in the market before that trade is executed." (Adrian, 2016).

Front running is what occurred behind the scenes of Katsuyama's trading desk that led him to create the IEX. The IEX has become a market response to the problem of HFT and front-running. Although this has been seemingly effective, a market-based solution to a regulated environment is certainly less than ideal. According to Menkveld (2016), "electronic markets without HFTs could [perhaps] produce an even better service at a lower cost." Unfortunately, it has become natural for the growth of fragmentation to happen in step with the growth of inefficiencies despite any associated benefits.

The SEC offers data visualization tools on a variety of market metrics. One of those metrics is the trade-to-order volume ratios on given dates. This metric indicates the number how many trades are actually executed versus placed. Intuitively, the number of trades is less than the number of orders. However, only roughly 70% of orders are executed compared to the number of orders canceled. Figure 1 shows

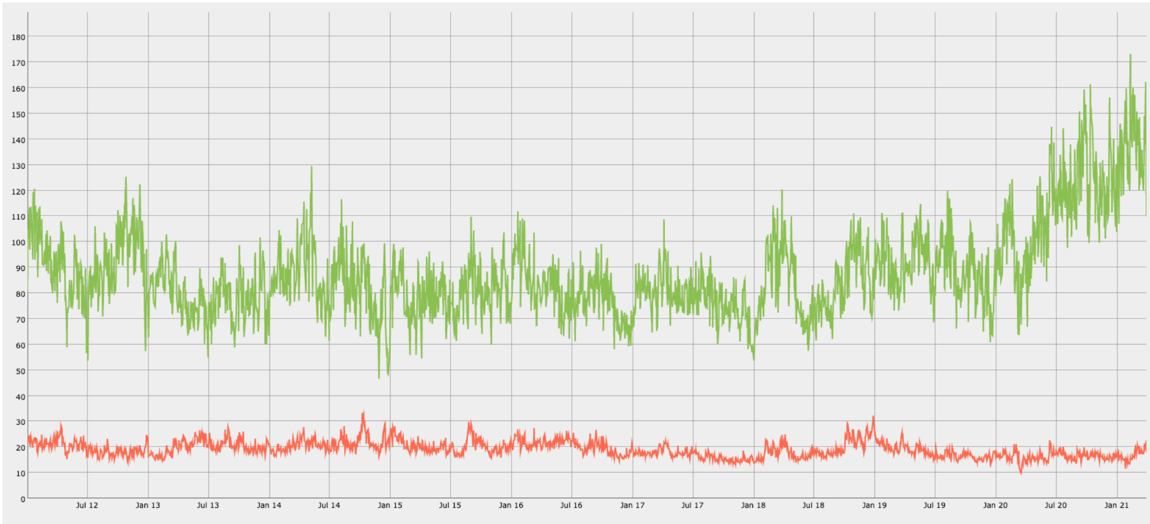


Figure 1 - Trade-to-Order Ratios in the U.S. (SEC)

A Discrete Issue with HFT

A blog post[10] by Economist David Glasner dives into one of the most interesting viewpoints about 'the real problem' with HFT: social waste and the economics of information. There are understandable truths behind the laments of Michael Lewis in his book about the IEX. HFT has been shown to lower costs, to lower bid-ask spreads, and add liquidity to the market. However, Glasner argues that it misses the point about HFT's shortcomings using classic economics articles. He first explains a book by Thorstein Veblen called *The Theory of the Leisure Class* which highlights the social waste that engineers create by using their skills to contribute to the luxury of the leisure class without adding true value to society (Veblen, 1994). Then, he brings up a paper by Jack Hirshleifer that discusses the economics of information (Hirshleifer, 1978).

What does the leisure class and the economics of information have to do with HFT? The answer is humbling. The essential theory is that the world's best and brightest minds are being used to shave millionths of second off trades using computer algorithms instead

[10] Read the opinion by Glasner here: https://uneasymoney.com/2014/04/08/the-real-problem-with-high-frequency-trading/

of being used to solve issues for society. HFT is the source of massive social waste and significant market efficiency. For example, Jurich et al. (2020) uncovered that ATs are more likely to cancel their orders in normal market conditions. The behavioral conditions from their study support the theory that ATs create inefficiencies in society for the benefit of those who create and own the algorithms.

Impact of AT & HFT

The truth about AT and HFT is that they have forever changed our market system. Algorithms provide a trading avenue that reaches volumes that would be impossible using archaic methods. HFT is estimated to be "responsible for around seventy percent of all equity trading volume on U.S. markets, HFT algorithms must be precision programmed to capture enormous amounts of data and to rapidly extract meaning from this input" (Yadav, 2014). Speed is hugely important and was directly related to the co-location of servers. The rest stakeholders in the market are subject to this either directly or indirectly.

Case Study: The 2015-2016 Stock Market Selloff

The flash crash of 2010 is often the most talked about event in the lifetime of HFT and AT. A highly interesting discovery that I made about the impact of HFT was the 2015-2016 stock market sell-off in the U.S. due to turbulence in the Chinese economy. During that time, the cancel-trade ratio spiked to an unprecedented level on the NSX and the CHX Exchanges. Figure 2 and Figure 3 show two different views of this data where it shows the dramatic cancel-to-trade ratio of over 400 cancels per single trade made.

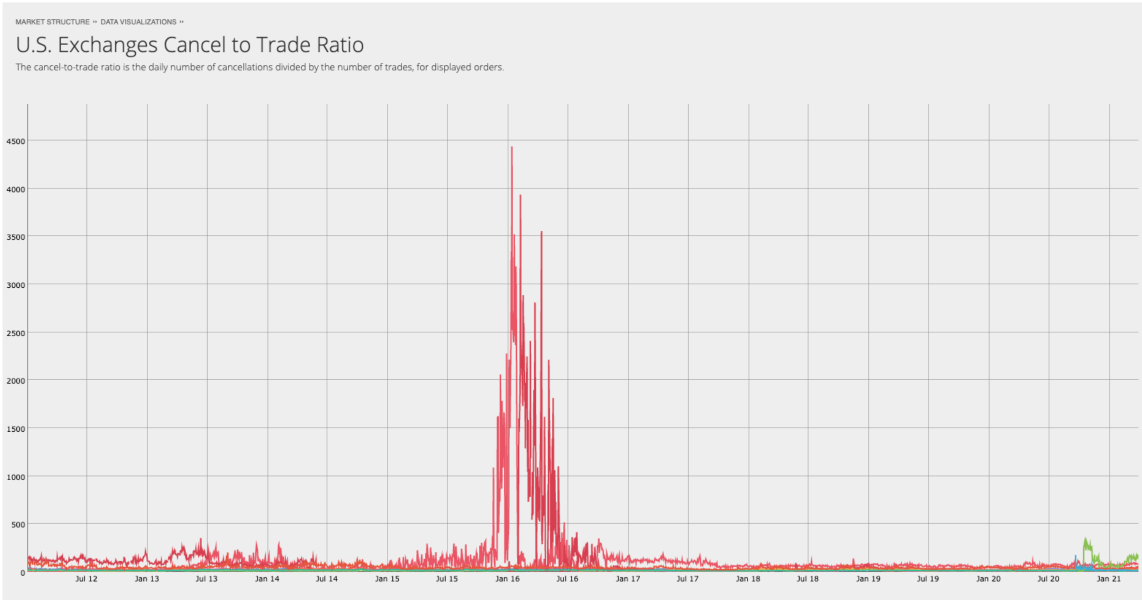


Figure 2 - U.S. Exchange Cancel-to-Trade Ratio View 1 (SEC)

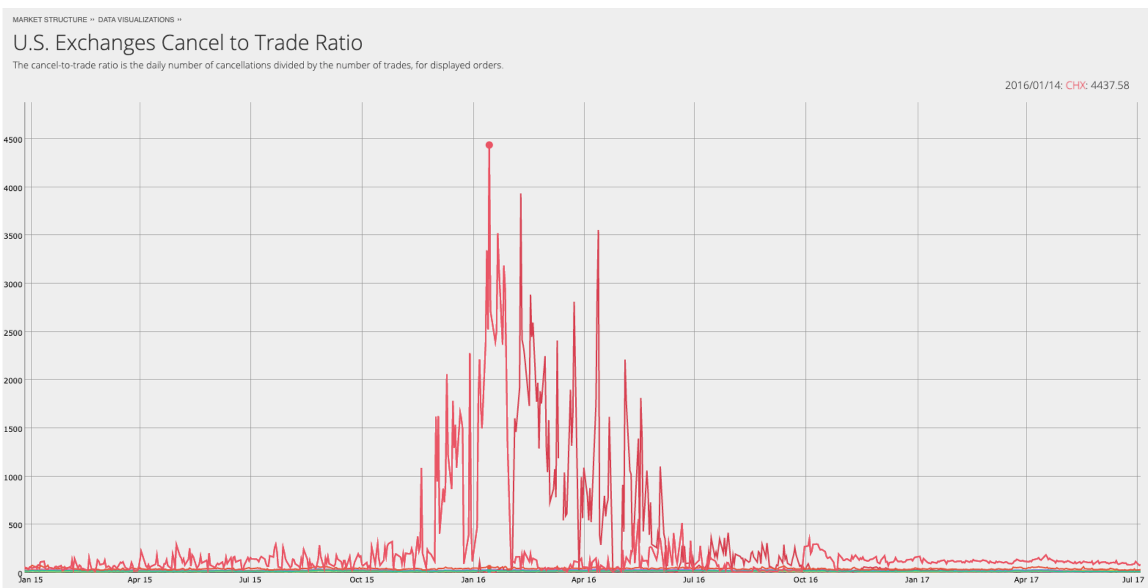


Figure 3 - U.S. Exchange Cancel-to-Trade Ratio View 2 (SEC)

This event is believed to be initiated by a Chinese policy where state owned banks were required to give a lot of loans to state-owned companies "even at the expense of risk-adjusted profitability"[11]. State owned banks ended up with a lot of bad loans on their books.

[11] https://www.wsj.com/video/what-led-to-china-stock-selloff/E787213B-A6FB-4626-AE6C-D8D6757C9B1D.html

This derived from a $600 billion stimulus bailout in 2008 that led to more state bank lending. Money supply grew like crazy, led to asset bubbles in market around the world. In the U.S. it was first a real estate bubble, then stock prices inflated. This also happened in the Shanghai exchange where the stock market jumped 150% in one year.

The interesting thing about this event is that the spike in U.S. cancel-to-trade occurred only on two exchanges in the U.S. markets while the rest of the markets remained largely unaffected in this statistic. Where it really gets interesting is the discovery that these two exchanges are two of the primary exchanges that have connection to the dark-fiber line laid by Spread Networks. Additionally, the CHX Exchange had been purchased by a number of high-profile Chinese investors[12] Although it is still only speculation, the two exchanges have undisputable connections to the realm of AT. These connections create logical skepticism about how the algorithms interacted with each other in light of the exogenous events in China.

[12] More info. Can be found here: https://money.cnn.com/2016/02/05/investing/china-buys-chicago-stock-exchange/index.html

CHAPTER III

EMERGENCE, MISSION, AND FUNCTION OF THE IEX

Emergence of the IEX

According to *Flash Boys*, the Investors Exchange arose out of Brad Katsuyama's serendipitous side-project of discovering why his trading screens were less predictable than they once were. Katsuyama's ventures took him into meetings with a large number of major players on Wall Street. Along the way, he was introduced to key figures that contributed to the exchange's emergence such as Ronan Ryan and Rob Park. Michael Lewis' novel is the primary existing account of the early development of the IEX, but it only tells one version of the story.

It has become commonplace to associate the IEX with HFT's in both the literature and in financial world. This connection is due largely to the effect of *Flash Boys* on the image of HFT. Regardless of *Flash Boys*, the motives behind creating the IEX were spurred along by the prevalence and impact of HFT's and algorithmic trading (Wah et al., 2017; Woodward, 2018). Research has extended beyond this to show that there are causal effects between speed and competition for market share among exchanges (Wang, 2018).

Exchange Function Innovation: The "Speed" Bump

Securities markets differentiate themselves based on their chosen set of trading variables. Liquidity provisions, fee structures, and auxiliary features of exchanges are decided upon and adjusted to maximize attraction to buyers and sellers. Every party in the market system is in search of a competitive advantage. Those not actively searching for a new advantage at least stand to gain from finding one.

Regardless of motive from Katsuyama or others, the IEX 'Speed Bump' was created in direction reaction to an "increasing prevalence of HFT" (Woodward, 2018). To address these concerns, the exchange did two primary things: created a fee structure that does not use rebates to attract liquidity[13], and created proprietary trade function in the form of the Discretionary Limit (D-Limit) Peg Order Type [14]. The IEX has taken a revolutionary stance in the market by not using rebates. Katsuyama stands by this choice because he believes it is a core part of their model not to use rebates to attract liquidity[15].

The D-Limit order type is a non-displayed order that rests on the IEX and waits for orders to be routed to their exchange. It is the primary proprietary technology that relies on the IEX access delay. Simply put, the D-Limit order uses its own algorithm that is modelled to combat HFT frontrunning. Bishop (2017), an employee of the IEX, explains the approach in an intuitive way: "Our approach instead is to shape the solution to match the problem: we can fight math with math! If others are leveraging short term prediction models to anticipate NBBO changes, than we can build such a model our-selves and deploy it to protect resting orders."

There is a notion about the IEX that instead of emerging from a crusade for a progressive competitive advantage in the secondary market system, the goodwill of an exclusive group of righteous martyrs took the initiative to fix the HFT problem. It is seeming to be more than a coincidence that the speed bump could be a competitive

---

[13] See Appendices D and E to view the fee schedule for the IEX
[14] See Appendix F for more information on the D-Limit Order Type from the IEX
[15] More about Katsuyama's position can be read here: https://www.marketwatch.com/story/iex-ceo-katsuyama-stands-firm-on-exchanges-fee-only-model-2016-06-21

advantage for exchanges, but research has yet to make concrete conclusions. Witness to this is the rise of IEX doppelgangers such as NYSE American, the Chicago Stock Exchange LEAD program, the Nasdaq Extended Life order designation, or the IntelligentCross dark pool[16].

There is great optimism in the belief that allowing the IEX's new model to exist in the secondary market system was an unintended benefit from the exchange's true ambition. With over 100% growth in their market share between 2016 and 2020[17], the lingering question is whether this nascent exchange created a true and effective innovation for investors or a bubble of belief that their venue provides the fairest experience.

---

[16] https://www.wsj.com/articles/steven-cohen-targets-high-frequency-trading-with-dark-pool-venture-1523994344

[17] https://iextrading.com/ at the bottom of page

CHAPTER IV

HYPOTHESES

Hypothesis Development

Originally this project began due to a high interest in the world of 'Finance Twitter' and the behavior of retail investors that use Twitter to network and learn from other traders. Along the way it was clear that the retail investor is only on the surface of the securities markets. Trends in equity market microstructure such as dark pools, payment for order flow, algorithmic trading and HFT, and fee structures uncovered where there is a deeper need for research. It was at this point that my advisor shared *Flash Boys* with me. This novel by Michael Lewis inspired discussions about the IEX, predatory behavior in HFT, the physical infrastructure of the markets, and many others. These discussions were a dynamic part of the financial world, and also a dynamic part of the hypotheses in this thesis.

A driving force behind this project has been the ethical discussion created by *Flash Boys*. How much HFT behavior is predatory? What is the relationship that has emerged between HFT's and opposing venues? How does this impact theories that HFT companies are marker makers? These discussions are subsidiary view of the entire fragmented system but they each explain more about how and where the IEX fits in. The trends of market microstructure that have been previously discussed are further dimensions of the story of the IEX and fragmentation. The hypothesis' in this section developed from various literature involving the IEX and venues with access delays. These are the testable predictions intended to assist in providing a substantive contribution to the literature.

Effectiveness and Integrity of the IEX

Since its inception, the IEX has attempted to differentiate itself by creating and marketing a high level of fairness and integrity. On their website they claim that "IEX sets new standards by raising the bar for performance, fairness, and transparency."[18] This standard they have set for themselves as an exchange is meant to go hand in hand with their access delay model. According to the IEX, the speed bump was created to "protect investors from potentially harmful trading that may involve the front-running of orders" (Pisani, 2016). This claim was genuine enough in the eyes of the SEC to permit the speed bump model to exist five years ago[19].

Since then, how has the speed bump faired against HFT? Chow et. al (2020) showed that the IEX provides a low realized half-spread and thus a low cost to investors indicating that the IEX has had success in their mission. Hu's (2019) findings showed that stocks that have spent a long-time trading on the IEX have higher decreases in trading costs than other stocks. This research indicated that the amount of frontrunning was reduced, supporting the IEX's goal of deterring HFT's as well. Besides these, there is little other research that supports or denies the theory.

Hypothesis 1 – The IEX has been successful in deterring HFT behavior on their exchange

Academic research on access delay exchanges is somewhat uncomprehensive given the novelty of the exchange design. The entry of the IEX allowed for research on market quality by examining various metrics such as price efficiency and transaction costs (Aldrich & Friedman, 2017; Chow et al., 2020; Hu, 2019; Wah et al., 2017). This research

[18] https://iextrading.com/about/
[19] https://www.sec.gov/rules/interp/2016/34-78102.pdf

has contributing to answering this hypothesis. To contribute further to the literature, the following sub-hypotheses are testable inquiries that have guided the empirical analysis of this work. Hypothesis 1 focuses on analyzing the interaction between HFT with the theory behind the IEX access delay model. Beyond this, there are also implications for the impacts seen by a retail investor on IEX. This hypothesis is similar to that of Chow et. al (2020) who used the entry of the IEX as an event to analyze market quality metrics.

Access Delay Benchmarking

In order for the IEX to enter as an exchange, the SEC adopted a new interpretation of the Order Protection Rule as part of Reg NMS. This interpretation was the basis for allowing venues to implement access delays. Access delays create intentional latency on orders and executions so that the exchange can improve its control over the transactions.

Hypothesis 2 – Of exchanges with speed bumps, the IEX has captured more market share than other exchanges

Now that many venues have adopted the model, who has had success? I posit that the IEX has captured the most market share for two reasons. First, they were the first exchange with an access delay, so they have had a head start on competitors. Second, the IEX has specifically adopted and marketed themselves as being the most transparent and fair exchange available to investors.

Ethical Exchange Design

Uncovering the role of the IEX in the market system is a task that prompts for more information about the integrity of their exchange. The emergence of the IEX was a highly poignant event in the history of financial markets. In fact, the SEC received over 500 comment letters in a 10-month period during the approval process (Wah et al., 2017). By comparison, the entry of BATS and EDGX resulted in only four total comment letters during their approval processes (Hu, 2019). The IEX sparked a tense discussion among community members and *Flash Boys* amplified the emotion behind the situation. This emotion was certainly tied to the financial implications behind the new exchange model. However, given the substantial and emotional response it would make sense that the IEX discussion went even deeper and probed the moral viewpoints of community members. The profound response to the IEX and the changes to Reg NMS that permitted access delays have inspired the penultimate hypothesis for this work.

<u>Hypothesis 3</u> – *There is a desire and/or incentive for investors to use a more "ethical" exchange design than an "unethical" exchange design*

It can be cleared seen from *Flash Boys* that there is a desire for a higher standard of ethics in the securities market. A more poignant view is that there is a desire to minimize unfair behavior. With the IEX mission being to create this type of investing environment it brings up the question of choice for investors. Does the access delay truly limit frontrunning and the informational inequality described by Adrian (2016). How does the effect of the access delay create incentives for consumers? Under the assumption that rational shareholders aim to maximize their return, a primary measure for this will be the degree that the IEX reduces slippage on trades (Bishop, 2017).

<u>Hypothesis 3a</u> – *The IEX has generally been more successful than NYSE American as an exchange.*

Although the NYSE American also has an access delay, the IEX is still the initial proprietor of the access delay. Additionally, the IEX started with a distinct vision and mission for their exchange. NYSE American was largely a market response to the traction the IEX built up in the industry, and to the opportunity created by the SEC's approval for access delays to exist. Ultimately, this can be tested softly by seeing which exchange grew faster in its early years, and which exchange is more effective in deterring HFT. Additionally, exchange volume and market share growth over time is a reasonable indicator.

In Flash Boys an adversarial narrative was created around the IEX and BATS. This narrative, widely controversial in the financial community, paints IEX as the hero and BATS as a villain. One of the striking historical events in this process is a fight that occurred between IEX founder, Brad Katsuyama, and BATS Global Markets' President, William O'Brien, live on CNBC[20]. The debate ensued on the CNBC set that is located on the trading floor of the NYSE. It is reported that the event completely halted trading on the NYSE trading floor as traders turned to listen in, and that 'Finance Twitter' slowed significantly as well[21]. Now that much of the drama has passed, analyzing the success of the IEX and NYSE American against BATS can offer insight to the discussion and where it led.

Critics of BATS claim that the exchange was founded with key support from firms participating in HFT behavior. After its inception, BATS purportedly structured their fee schedule and business plan in a way to siphon liquidity from the NYSE and NASDAQ to allow HFT firms to capitalize on the trades being made there. With the beliefs that the IEX has maintained the integrity that they have claimed to operate with and that investors desire

[20] Access to this argument can be viewed here: https://www.cnbc.com/video/2014/04/01/the-great-debate-combating-hfts-image.html
[21] https://www.cnbc.com/2014/04/01/katsuyama-vs-obrien--who-won-the-fight.html

ethical markets, it would be logical that the IEX has had more success during its early lifespan than BATS. These two sub-hypotheses were developed to help assess how each exchange's early success impacted the ethical narrative that *Flash Boys* and the IEX initiated around the presence of HFT.

<u>Hypothesis 4</u> – *The IEX has increased in their ability to capture liquidity by using their proprietary IEX signal under the protection of a discretionary peg order*

This hypothesis was incepted early in the research process but evolved later once its testability was discovered. The competitive advantage of the IEX revolves around their access delay. However, if a venue is trying to acquire more liquidity, why would it create intentional latency that limits the volume potential of their exchange? The answer lies in what happens during the 350-millisecond access delay used by the IEX, and that answer is the discretionary peg (D-Peg) order type. The D-Peg order on the IEX is a non-displayed, resting order that uses proprietary technology to prevent "slippage"[22] on trade executions. Their technology serves as an active price-updating tool that utilizes the time provided by their access delay to identify "crumbling quotes", quotes that indicate slippage on trades, and re-price the trade at the NBBO before the order executes at an unfavorable price. Since the IEX has invested significant resources into branding and marketing their transparent operations, they have provided educational resources that make it easier to conceptualize their value propositions to traders[23].

[22] Slippage refers to small loses on trades during their execution. HFT algorithms send odd-lot-sized trades to search for resting orders. During this first wave process, HFT algorithms progressively send larger orders to exchanges that have resting liquidity but do so at less favorable prices each time.
[23] Visit the IEX website for more insight: https://iextrading.com/behind-the-trade/

CHAPTER V

METHODOLOGY AND APPROACH

Introduction

The approach for this empirical analysis was chosen in attempt to answer the primary research question: how does the IEX play a role in market fragmentation? To properly address how the IEX fits into market fragmentation, it was essential to focus on the IEX relative to other exchanges. There were three focus exchanges in the study in addition to the IEX. NYSE American is the main comparison exchange to the IEX because it also has an access delay. The NYSE physical location is the iconic 'big board' and this exchange was used alongside the NASDAQ Book as a proxy for the displayed market. Focusing on these exchanges created a manageable scope for the analysis without sacrificing explanatory power. Conclusions on HFT behavior and the impact of access delays are also provided by this analysis since the data is divided into odd-lots and non-odd-lots, a proxy for HFT.

Part of addressing the primary research question is analyzing market fragmentation. Explaining fragmentation is a complex task because it draws from an intricate blend of events and phenomena, past and present. Understanding the role of the IEX within fragmentation is a challenge due to the how abstract a concept fragmentation is. The empirical approach for this analysis was created to contribute to the literature surrounding the IEX but also offers insight to market fragmentation.

Statistical methods used include first-difference t-tests and ordinary least squares regressions. These two methods were useful for the analysis because they allowed for numerous tests using the full selection of sample data. Market share and volume along with the odd-lots proxy offer a large amount of insight. There is even more insight for the IEX from combining market share and volume along with the IEX monthly and daily statistics. Additionally, there is further insight from the CBOE data because it was separated into Tape A, Tape B, and Tape C share types.

Sample Selection

Sample Period

The empirical analysis uses a sample period from August 13th, 2018 through August 13th, 2020. This sample period originated from dataset that was initially collected for a working paper that focuses on exchange fees (Jurich, 2021). The sample begins in the middle of the month to account for changes in fee structures. Changes in fee structures do not directly impact this analysis. This data was the basis for my sample selection to facilitate collaboration efforts with my advisor. Additionally, it was a recent time period that allowed for a relevant analysis of the IEX. There is no other association between the two research projects and their use of this sample period.

Data Selection

Numerous data points were chosen to address the IEX and market fragmentation. Data was chosen first for the entire market for use in analyzing market fragmentation during the sample period. Data from the IEX was then chosen in order to perform a focused analysis of the IEX during the sample period.

Market Share and Volume. The initial data selection included volume and market share for 13 exchanges and three TRFs. This data included volume and market share for Tape A, Tape B, and Tape C share types as well as for the total market. These data points were collected twice. First, they were collected with odd-lots included. Next, they were collected without including odd-lot shares. Odd-lots refers to trades made in a size of 100 shares or less.

IEX Daily and Monthly Statistics. After choosing data for the entire market, various data was gathered for the IEX in order to expand the sample. Various metrics were gathered on either a daily or monthly basis depending on what was available. Monthly metrics included: average routed volume, average matched volume, average market share, average order size, average aggregate fill size, the percentage of aggregate fills by trade size for nine different trade sizes[24], the number of block trades for three different block trade sizes[25], unique symbols traded, average daily symbols traded, the percentage of trades made in block sizes, the number of broker members, the percent of broker self-cross[26], first wave rate[27], and first wave fill rate[28]. Daily metrics include total shares handled, routed volume, matched volume, lit volume, and market share. For further information on these data points visit the IEX website[29]. Kwan, Masulis, and McInish (2015) used information about dark pools to discuss block trades which has inspired the use of block trade percentage.

---

[24] Trade sizes: Under 100 shares, 100-199 shares, 200-299 shares, 300-399 shares, 400-499 shares, 500-999 shares, 1,000-4,999 shares, 5,000-9,999 shares, over 10,000 shares.
[25] Block trade sizes: 10,000-19,999 shares, 20,000-49,999 shares, 50,000 shares.
[26] These are trades internalized by a broker member and then reported to the exchange.
[27] First wave trade fill weight is the percentage of routed trades in the total market that are routed to a given exchange on the trade's first routed signal.
[28] The first wave fill percentage is the number of shares that are filled out of either the order size or the number of quoted shares at the target venue depending on the smaller of the two denominator options.
[29] https://iextrading.com/stats/

Data Collection

Data Sources

The core dataset for this analysis was compiled using two sources: CBOE Global Markets and the IEX. CBOE Global Markets and IEX both offers a variety of public data through their websites. The IEX also has data that is accessible through their API. Market share and volume statistics for Tape A, Tape B, Tape C, and the total market were collected from CBOE Global Market's website. All IEX daily and monthly stats were collected from either the IEX website or through the IEX API using Python.

Data Tools

Data collection, storage, preparation, and analysis were performed using three primary tools: Python, IBM SPSS, and Microsoft Excel. Python was utilized for data collection through web scraping and IEX API calls. The coding language was also used to manipulate CSV files into a usable format for Excel or SPSS. Excel was used to store and prepare data that was collected through Python, CSV downloads, or copy and pasting. IBM SPSS was used to store prepared data and is the statistical package that was used for all data analysis.

Data Collection Methods

CBOE Global Markets Data[30]. Market share and volume data collected from CBOE Global Market was performed using CSV file downloads for each trading day in the sample period. These files were downloaded once with odd-lots and again without odd-lots.

---

[30] Collected from CBOE Global Markets at https://www.cboe.com/us/equities/market_share/market/

IEX Daily and Monthly Data[31]. Statistics for the IEX were collected using Python web scraping, through calls to the IEX API, and through copy and pasting from the IEX website[32]. Web scraping was used to collect the first wave weight and first wave fill data points from the IEX website. This method was used due to a bug encountered while trying to access the data through the IEX API. Historical monthly statistics for the IEX were collected using calls to the IEX API. Finally, daily statistics for the IEX were collected using a simple copy and paste into Excel. Daily statistic access on the IEX API was in a beta phase during data collection so copy and paste was the simplest solution.

Methodology

The empirical portion of this study was a quantitative analysis of the previously described data. To analyze the data in the sample I first reported descriptive statistics for each category of selected data. For my inferential analysis I utilized two statistical methods: first-difference t-tests and ordinary least squares regression. The basis for each analysis in this study is that volume and market share data is used with odd-lots and without odd-lots.

Market share and volume data from the CBOE shows a full picture of the fragmented market, including the IEX. This data also has been divided into Tape A, Tape B, and Tape C shares to analysis market trends based on listing venue. This data has also been collected without odd-lots because it serves as a proxy for High-Frequency traders (O'Hara et al., 2014; Roseman et al., n.d.). Monthly and daily statistics from the IEX allow for insight into which factors might explain changes in their volume or market share.

[31] Collected from the IEX. Data can be viewed on their website at https://iextrading.com/stats/

[32] The program written to perform web scraping and API calls was mistakenly overwritten after the data collection process and are not available for viewing in the appendices.

Creating a scope for the analysis involved focusing on a select number of exchanges. The analysis uses the NYSE and NASDAQ as constants for the overall market since they make up such a large amount of total displayed market volume. Additionally, the NYSE American exchange is used in the analysis as a comparison exchange for the IEX because it is the other major access delay exchange. Much of the analysis is done between the IEX and NYSE American. Odd-lots were used for each exchange to investigate and compare HFT behavior. Monthly and daily statistics were used solely for the IEX.

Difference tests in this analysis are used in the univariate and ordinary least squares regression are used in the multivariate. Each dependent variable (either volume or market share in every model) is used both with and without odd-lots. O'Hara, Yao, and Ye (2014) explain that odd lots are increasingly used in algorithmic and high frequency trading. Similarly, Johnson, Van Ness, and Van Ness (2017) analyze odd-lot transactions by order submission type. Menkveld (2013) shows that HFT activity is higher on volatile, high-growth stocks relative to large, blue chip stocks by using odd-lot data.

CHAPTER VI

DATA ANALYSIS

Data Preparation

Assembly of the master dataset for this analysis was a long and somewhat unconventional process. The data was prepared as it was collected and was done so in sequential order. First, the market share and volume data from the CBOE was collected followed by the monthly IEX data and then the daily IEX data. After data collection, the data was prepared in Excel and then exported to SPSS. Within SPSS the data was used to compute new variables and code binary dummy variables for use in the statistical analysis.

Preparing the market share and volume data from CBOE Global Markets involved downloading CSV files, writing and running Python code to combine and organize the data within those files, cross-checking the output in Excel, and then exporting the data to SPSS. Each CSV file from the CBOE represented one day of trading in the market. These files could only be downloaded containing odd-lots or omitting odd lots so two CSV files were downloaded for each trading day in the sample. These files were placed in separate folders so that all CSVs for the odd-lots data was in one folder and all non-odd-lots data was in a different folder. Using the pandas library and glob module in Python, I wrote a program[33] that parsed through each folder and combined all of the files into a single data frame. To divide the data into appropriate categories, I wrote another program[34] to separate Tape A,

[33] See Appendix C
[34] See Appendix C

Tape B, and Tape C categories from the total market. The final program[35] I wrote created a separate data frame that removed the TRF categories of volume and market share to display only equity exchanges. After exporting the final data frame to Excel, I manually checked that the program executed properly by examining the data. Finally, I imported the data into SPSS for analysis.

Data from the IEX required extensive preparation. Since the data was collected in both daily and monthly forms and was collected using three separate methods, the preparation process varied. Most of the data preparation occurred manually to circumvent the need for a complex program or external assistance. The primary challenge with preparing the IEX data was matching data with appropriate dates. For the daily IEX statistics, each data point was manually checked and aligned with its appropriate date. For the monthly IEX statistics, data points were duplicated across every date within the corresponding month. It is important to note that all monthly data points in the master dataset were duplicated and used on a daily basis for the corresponding month. As with the CBOE data, IEX statistics were prepared in Excel before being imported into SPSS.

Final preparation for the dataset required computing adjusted variables and creating binary variables. Since the dataset included both volume and market share, volume had to be adjusted using the natural logarithm of each data point. This occurred for each data point representing volume. Interaction variables were also computed for use in the multivariate analyses. Interaction variables were computed by taking the product of two other data points. Finally, binary dummy variables were coded for each exchange.

[35] See Appendix C

The final dataset contained 88 variables using all the collected data. Every variable contained up to 7935 total observations. There were 20 nominal variables and 68 ordinal variables. The final dataset is available via the University of Maine Digital Commons[36]

[36] https://digitalcommons.library.umaine.edu/

Descriptive Statistics

Table I – Volume by Exchange

These tables contain descriptive statistics for volume the four sample exchanges in the empirical portion of this study: the IEX, NYSE American, NYSE, and NASDAQ. This data is listed in Panels A-D below with each panel representing a respective exchange. Volume is measured as the single-counted sum of shares traded on an exchange. Odd-lots refers to trades made in a size of 100 shares or less and the data is reported with odd lots and without odd-lots. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations ($N = 7935$) across 505 trading days. This sample selection includes two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Each panel in this table displays one of these four exchanges.

Panel A: *IEX Volume with Odd-Lots and Without Odd-Lots*

IEX Volume		*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
With Odd Lots	*Tape A*	505	123,741,927	38,156,866	37,994,990	354,821,017
	Tape B	505	22,731,102	10,168,228	8,476,227	81,420,230
	Tape C	505	64,700,435	17,001,450	21,895,529	169,483,798
	Market Total	505	211,173,465	63,525,934	69,347,850	585,149,555
Without Odd Lots	*Tape A*	505	118,601,154	37,199,743	35,916,277	344,274,411
	Tape B	505	22,276,583	10,026,254	8,270,128	80,424,447
	Tape C	505	61,541,148	16,352,674	20,845,869	162,638,103
	Market Total	505	202,418,885	61,822,831	65,692,601	566,889,380

Table 1 - IEX Volume with Odd-Lots and Without Odd-Lots

Panel B: *NYSE American Volume with Odd-Lots and Without Odd-Lots*

	NYSE American Volume	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
With Odd Lots	*Tape A*	505	7,728,425	3,903,127	2,117,862	28,095,666
	Tape B	505	15,058,628	7,810,282	5,310,685	58,475,358
	Tape C	505	3,977,312	1,981,022	1,371,621	12,296,252
	Market Total	505	26,764,365	13,111,237	9,551,257	98,867,276
Without Odd Lots	*Tape A*	505	6,918,151	3,547,325	1,864,050	27,863,926
	Tape B	505	14,431,443	7,541,253	5,165,493	56,464,277
	Tape C	505	3,548,604	1,768,273	1,216,985	11,196,129
	Market Total	505	24,898,198	12,084,741	9,037,634	92,265,155

Table 2 - NYSE American Volume with Odd-Lots and Without Odd-Lots

Panel C: *NYSE Volume with Odd-Lots and Without Odd-Lots*

	NYSE Volume	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
With Odd Lots	*Tape A*	505	607,218,125	179,172,751	202,703,417	1,559,868,639
	Tape B	505	46,666,551	19,956,791	13,635,105	174,426,101
	Tape C	505	41,951,205	12,510,134	13,112,207	96,991,248
	Market Total	505	695,835,881	206,586,489	229,450,729	1,831,285,988
Without Odd Lots	*Tape A*	505	549,192,212	167,824,713	143,844,007	1,448,105,623
	Tape B	505	55,651,452	58,576,193	13,329,077	674,556,026
	Tape C	505	47,026,182	42,044,267	12,042,900	339,418,541
	Market Total	505	651,869,847	190,133,080	212,967,717	1,707,250,303

Table 3 - NYSE Volume with Odd-Lots and Without Odd-Lots

Panel D: *NASDAQ Volume with Odd-Lots and Without Odd-Lots*

NASDAQ Volume		*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
With Odd Lots	*Tape A*	505	500,844,645	165,457,690	127,333,847	1,143,726,077
	Tape B	505	217,750,887	102,812,082	58,980,002	817,897,193
	Tape C	505	559,627,488	199,213,937	201,357,028	1,294,372,787
	Market Total	505	1,278,223,019	443,281,594	387,670,877	3,118,315,141
Without Odd Lots	*Tape A*	505	434,678,771	143,663,456	106,871,418	1,017,658,914
	Tape B	505	209,478,750	98,127,876	56,727,627	787,771,142
	Tape C	505	486,288,375	174,063,362	172,288,389	1,163,979,193
	Market Total	505	1,130,445,896	391,641,515	335,887,434	2,755,338,113

Table 4 - NASDAQ with Odd-Lots and Without Odd-Lots

Table II – Market Share by Venue

These tables contain descriptive statistics for market share the four sample exchanges in the empirical portion of this study: the IEX, NYSE American, NYSE, and NASDAQ. This data is listed in Panels A-D below with each panel representing a respective exchange. Odd-lots refers to trades made in a size of 100 shares or less and the data is reported with odd lots and without odd-lots. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations ($N = 7935$) across 505 trading days. This sample selection includes two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Each panel in this table displays one of these four exchanges.

Panel A: *IEX Market Share with Odd-Lots and Without Odd-Lots*

IEX Market Share		*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
With Odd Lots	*Tape A*	505	3.325%	0.410%	2.132%	4.369%	-0.465
	Tape B	505	1.435%	0.210%	0.782%	1.986%	-0.536
	Tape C	505	2.664%	0.539%	1.135%	3.914%	-0.922
	Market Total	505	2.728%	0.406%	1.556%	3.616%	-0.878
Without Odd Lots	*Tape A*	505	3.420%	0.427%	2.178%	4.587%	-0.364
	Tape B	505	1.442%	0.209%	0.783%	1.995%	-0.519
	Tape C	505	2.741%	0.570%	1.133%	4.141%	-0.849
	Market Total	505	2.786%	0.418%	1.571%	3.762%	-0.829

Table 5 - IEX Market Share with Odd-Lots and Without Odd-Lots

Panel B: *NYSE American Market Share with Odd-Lots and Without Odd-Lots*

	NYSE American Market Share	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
With Odd Lots	*Tape A*	505	0.199%	0.045%	0.130%	0.375%	1.548
	Tape B	505	0.955%	0.317%	0.323%	2.164%	0.852
	Tape C	505	0.152%	0.033%	0.085%	0.269%	0.798
	Market Total	505	0.330%	0.074%	0.199%	0.682%	0.969
Without Odd Lots	*Tape A*	505	0.192%	0.046%	0.123%	0.480%	2.104
	Tape B	505	0.940%	0.318%	0.320%	2.147%	0.888
	Tape C	505	0.148%	0.041%	0.081%	0.477%	3.058
	Market Total	505	0.327%	0.075%	0.198%	0.689%	1.029

Table 6 - NYSE American Market Share with Odd-Lots and Without Odd-Lots

Panel C: *NYSE Market Share with Odd-Lots and Without Odd-Lots*

	NYSE Market Share	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
With Odd Lots	*Tape A*	505	16.271%	1.280%	12.455%	23.948%	-0.148
	Tape B	505	2.947%	0.568%	1.515%	4.627%	-0.099
	Tape C	505	1.684%	0.278%	1.114%	2.577%	0.151
	Market Total	505	8.921%	0.941%	6.042%	13.237%	-0.794
Without Odd Lots	*Tape A*	505	15.914%	2.451%	4.998%	23.948%	-2.665
	Tape B	505	3.466%	2.483%	1.532%	18.483%	4.91
	Tape C	505	1.972%	1.276%	1.093%	8.867%	4.108
	Market Total	505	8.922%	0.977%	5.963%	13.539%	-0.729

Table 7 - NYSE Market Share with Odd-Lots and Without Odd-Lots

Panel D: *NASDAQ Market Share with Odd-Lots and Without Odd-Lots*

	NASDAQ Market Share	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
With Odd Lots	*Tape A*	505	13.259%	1.219%	9.808%	16.606%	0.14
	Tape B	505	13.484%	1.407%	9.852%	18.451%	0.428
	Tape C	505	21.960%	1.431%	18.103%	25.990%	-0.041
	Market Total	505	16.069%	0.983%	12.770%	18.761%	0.024
Without Odd Lots	*Tape A*	505	12.360%	1.182%	8.874%	15.583%	0.076
	Tape B	505	13.338%	1.402%	9.675%	18.349%	0.392
	Tape C	505	20.604%	1.339%	16.885%	24.377%	-0.068
	Market Total	505	15.149%	0.943%	11.771%	17.872%	-0.082

Table 8 - NASDAQ Market Share with Odd-Lots and Without Odd-Lots

Table III – IEX Volume

The table here displays descriptive statistics for different sub-categories of volume on the IEX. Volume is measured by the single-counted sum of shares traded daily on the IEX. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations (N = 505) accounting for all trading days on the IEX during the sample period.

Volume by Type on IEX

Volume Type	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Total Volume	505	244,900,402	73,885,664	77,453,934	678,665,029
Routed Volume	505	34,061,269	10,655,123	8,106,084	93,515,474
Matched Volume	505	210,839,133	64,348,784	69,347,850	585,149,555
Displayed Volume	505	41,463,696	15,114,474	8,783,027	90,278,928

Table 9 - Volume by Type on IEX

Table IV – IEX Trade Size

This table displays descriptive statistics for monthly aggregate trade sizes on the IEX. Trade size is determined in the sample as being the percentage of filled orders in each range of share amounts on an aggregate basis. The sample period spans from August 2018 to August 2020. This sample contains observations (*N* = 505) accounting for all trading days on the IEX during the sample period.

Percent of Aggregate Fills by Trade Size

Share Size	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
< 100	505	73.634%	1.419%	70.100%	76.480%	-0.551
100 - 199	505	2.308%	0.470%	1.540%	3.200%	0.315
200 - 299	505	10.744%	0.608%	9.280%	12.930%	1.648
300 - 399	505	4.516%	0.232%	4.060%	4.990%	0.106
400 - 499	505	2.324%	0.168%	1.960%	2.820%	0.318
500 - 999	505	3.974%	0.273%	3.560%	4.510%	0.284
1000 - 4999	505	2.260%	0.199%	1.970%	2.740%	0.777
5000 - 9999	505	0.162%	0.017%	0.140%	0.210%	1.246
10000 <	505	0.083%	0.010%	0.070%	0.110%	0.907

Table 10 - IEX Trade Sizes

Table V – IEX Block Trade Size

This table displays descriptive statistics for the monthly number of trades made in block sizes. A block size trade is a very large trade that is measured as being over 10,000 shares. The sample period spans from August 2018 to August 2020. This sample contains observations ($N = 505$) accounting for all trading days on the IEX during the sample period.

Number of Trades in Block Sizes

Trade Metric	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
% of Block Trades	505	5.50%	0.58%	4.63%	6.76%	0.828
Block Trades Between 10,000 - 19,999 Shares	505	5,762	2,308	3,873	14,911	2.857
Block Trades Between 20,000 - 49,999 Shares	505	1,652	852	1,094	5,223	3.279
Block Trades Over 50,000 Shares	505	252	127	142	697	2.099

Table 11 - Block Trades on the IEX

Table VI – IEX Monthly Statistics

The table below reports descriptive statistics for various exchange metrics for the IEX measured monthly. Each statistic has been measured monthly for the IEX. Average order size, average aggregate fill size, and the number of unique symbols traded are all intuitively named for the data they represent. First wave trade fill weight is the percentage of routed trades in the total market that are routed to a given exchange on the trade's first routed signal. The first wave fill percentage is the number of shares that are filled out of either the order size or the number of quoted shares at the target venue depending on the smaller of the two denominator options. The sample period spans from August 2018 to August 2020. This sample contains observations (N = 505) accounting for all trading days on the IEX during the sample period.

Monthly Trade Statistics on the IEX

Exchange Metrics	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
Average Order Size	505	454.84	102.65	266	674	0.329
Average Aggregate Fill Size	505	175.65	14.02	140	201	-0.550
Number of Unique Symbols Traded	505	8122.46	229.47	7818	8600	0.730
First Wave Trade Fill Weight	505	7.69%	9.23%	0.03%	47.02%	1.534
First Wave Fill Percentage	505	96.03%	5.18%	55.03%	99.53%	-3.644

Table 12 - Monthly Trading Statistics for the IEX

Table VII – Exchange Fill Weights and Fill Rates

The tables below report descriptive statistics for the fill weights and fill rates of each exchange in the US. First wave trade fill weight is the percentage of routed trades in the total market that are routed to a given exchange on the trade's first routed signal. The first wave fill percentage is the number of shares that are filled out of either the order size or the number of quoted shares at the target venue depending on the smaller of the two denominator options. Each statistic has been measured monthly for the sample period which spans from August 2018 to August 2020. This sample contains observations (N = 7935) accounting for 505 trading days during the sample period.

Panel A: *Fill Weights for US Venues*

Fill Weight by Exchange

Venue	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
IEX	7935	16.570%	1.961%	12.620%	20.920%	-0.135
NYSE American	7935	0.316%	0.080%	0.210%	0.510%	0.903
NYSE	7935	16.507%	5.533%	9.230%	23.840%	0.080
NASDAQ	7935	29.248%	8.208%	21.020%	47.020%	0.959
NYSE Arca	7935	13.003%	3.328%	7.590%	16.830%	-0.239
EDGX	7935	6.866%	0.947%	4.940%	8.960%	-0.242
BATS (Z)	7935	10.133%	5.188%	4.950%	20.940%	0.832
BATS (Y)	7935	2.631%	1.153%	0.590%	4.930%	-0.174
NYSE National	7935	0.900%	0.711%	0.230%	2.180%	0.720
EDGA	7935	1.773%	0.555%	0.780%	2.920%	0.102
NASDAQ BX	7935	1.105%	0.808%	0.170%	3.130%	0.698
NASDAQ PSX	7935	0.767%	0.161%	0.480%	1.030%	-0.403
NYSE Chicago	7935	0.180%	0.196%	0.030%	0.840%	1.900

Table 13 - Fill Weights for US Venues

Panel B: *Fill Rates for US Venues*

Fill Rate by Exchange

Venue	*N*	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*	*Skewness*
IEX	7935	98.638%	1.464%	91.980%	99.530%	-4.086
NYSE American	7935	97.994%	0.608%	95.780%	98.960%	-1.684
NYSE	7935	97.506%	1.199%	93.070%	98.640%	-1.961
NASDAQ	7935	98.583%	0.554%	96.750%	99.200%	-1.654
NYSE Arca	7935	97.999%	0.742%	95.200%	98.830%	-2.041
EDGX	7935	99.111%	0.247%	98.170%	99.350%	-2.308
BATS (Z)	7935	98.862%	0.207%	98.190%	99.110%	-1.357
BATS (Y)	7935	98.429%	0.292%	97.680%	99.030%	-0.333
NYSE National	7935	90.122%	3.283%	79.740%	94.210%	-1.478
EDGA	7935	97.015%	1.174%	93.830%	98.200%	-1.306
NASDAQ BX	7935	92.847%	1.297%	89.170%	94.590%	-1.309
NASDAQ PSX	7935	95.503%	1.128%	93.330%	97.340%	-0.342
NYSE Chicago	7935	85.804%	11.483%	55.030%	98.510%	-0.741

Table 14 - Fill Rates for US Venues

Inferential Statistics

Table VIII – Comparison of HFT Presence on Exchanges by Volume[37]

These tables report first difference test results between an exchange's mean volume with odd-lots versus without odd-lots. Volume is measured as the single-counted sum of shares traded daily on an exchange. Odd-lots refers to trades made in a size of 100 shares or less. This data reports values containing and odd-lots and omitting odd-lots as a proxy for HFT. The difference is calculated by subtracting non-odd-lots values from odd-lots values. The sample period spans from August 13th, 2018, to August 13th, 2020. This sample contains observations (*N* = 7935) across 505 trading days. This sample selection includes two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Each panel in this table displays one of these four exchanges. Significant levels are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

Panel A: HFT Presence on the IEX by Volume

IEX Volume

Classification		*HFT Proxy*		*Difference*	*Odd Lots / Volume*	*T-Stat*
		With Odd Lots	Without Odd Lots			
IEX	*Tape A*	123,741,927	118,601,154	5,140,773	4.15%	21.91***
	Tape B	22,731,102	22,276,583	454,519	2.00%	16.4***
	Tape C	64,700,435	61,541,148	3,159,287	4.88%	12.01***
	Market	211,173,465	202,418,885	8,754,580	4.15%	20.65***

Table 15 - HFT Presence on the IEX

[37] This table is aggregated in Appendix # to facilitate comparison between exchanges

Panel B: HFT Presence on NYSE American by Volume

NYSE American Volume

Classification		HFT Proxy		Difference	Odd Lots / Volume	T-Stat
		With Odd Lots	Without Odd Lots			
NYSE American	*Tape A*	7,728,425	6,918,151	810,274	10.48%	3.57***
	Tape B	15,058,628	14,431,443	627,185	4.16%	2.44***
	Tape C	3,977,312	3,548,604	428,708	10.78%	3.11***
	Market	26,764,365	24,898,198	1,866,167	6.97%	5.5***

Table 16 - HFT Presence on NYSE American

Panel C: HFT Presence on NYSE by Volume

NYSE Volume

Classification		HFT Proxy		Difference	Odd Lots / Volume	T-Stat
		With Odd Lots	Without Odd Lots			
NYSE	*Tape A*	607,218,125	549,192,212	58,025,913	9.56%	7.48***
	Tape B	55,651,452	46,666,551	8,984,901	19.25%	34.87***
	Tape C	47,026,182	41,951,205	5,074,977	12.10%	47.74***
	Market	695,835,881	651,869,847	43,966,034	6.32%	7.64***

Table 17 - HFT Presence on NYSE

Panel D: HFT Presence on NASDAQ by Volume

NASDAQ Volume

	Classification	*HFT Proxy*		*Difference*	*Odd Lots / Volume*	*T-Stat*
		With Odd Lots	Without Odd Lots			
NASDAQ	*Tape A*	500,844,645	434,678,771	66,165,874	13.21%	0.85
	Tape B	217,750,887	209,478,750	8,272,137	3.80%	7.23***
	Tape C	559,627,488	486,288,375	73,339,112	13.10%	2.56***
	Market	1,278,223,019	1,130,445,896	147,777,123	11.56%	0.12

Table 18 - HFT Presence on NASDAQ

Table IX – Comparison of HFT Presence on Exchanges by Market Share[38]

These tables report first difference test results between an exchange's mean market share with odd-lots versus without odd-lots. Market share for an exchange is measured as the quotient of volume for the exchange divided by total volume in the market. Market share is measured daily in this sample. Odd-lots refers to trades made in a size of 100 shares or less. This data reports values containing and odd-lots and omitting odd-lots as a proxy for HFT. The difference is calculated by subtracting non-odd-lots values from odd-lots values. A negative difference indicates an increase when accounting for odd-lots. The sample period spans from August 13th, 2018, to August 13th, 2020. This sample contains observations (N = 7935) across 505 trading days. This sample selection includes two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Each panel in this table displays one of these four exchanges. Significant levels are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

Panel A: HFT Presence on the IEX by Market Share

IEX Market Share

Classification		*HFT Proxy*		*Difference*	*T-Stat*
		With Odd Lots	Without Odd Lots		
IEX	*Tape A*	3.325%	3.420%	-0.0949%	-4.67***
	Tape B	1.435%	1.442%	-0.0075%	-5.62***
	Tape C	2.664%	2.741%	-0.0767%	-12.64***
	Market	2.728%	2.786%	-0.0579%	-4.59***

Table 19 - HFT Presence on the IEX by Market Share

[38] This table is aggregated in Appendix # to facilitate comparison between exchanges

Panel B: HFT Presence on NYSE American by Market Share

NYSE American Market Share

	Classification	*HFT Proxy*		*Difference*	*T-Stat*
		With Odd Lots	Without Odd Lots		
NYSE American	*Tape A*	0.199%	0.192%	0.0074%	8.67***
	Tape B	0.955%	0.940%	0.0151%	4.32***
	Tape C	0.152%	0.148%	0.0044%	17.02***
	Market	0.330%	0.327%	0.0020%	5.45***

Table 20 - HFT Presence on NYSE American by Market Share

Panel C: HFT Presence on NYSE by Market Share

NYSE Market Share

	Classification	*HFT Proxy*		*Difference*	*T-Stat*
		With Odd Lots	Without Odd Lots		
NYSE	*Tape A*	16.271%	15.914%	0.3569%	37.38***
	Tape B	2.947%	3.466%	-0.5194%	-66.12***
	Tape C	1.684%	1.972%	-0.2871%	-71.69***
	Market	8.921%	8.922%	0.0010%	16.07***

Table 21 - HFT Presence on NYSE by Market Share

Panel D: HFT Presence on NASDAQ by Market Share

NASDAQ Market Share

Classification		*HFT Proxy*		*Difference*	*T-Stat*
		With Odd Lots	Without Odd Lots		
NASDAQ	*Tape A*	13.259%	12.360%	0.8991%	7.96***
	Tape B	13.484%	13.338%	0.1459%	4.06***
	Tape C	21.960%	20.604%	1.3563%	1.61*
	Market	16.069%	15.149%	0.9200%	4.23***

Table 22 - HFT Presence on NASDAQ by Market Share

Table X – Regression by Exchange Volume

This table reports the results of an ordinary least squares regression that uses exchange volume as the dependent variable. This dependent variable was used in two forms, one containing odd-lot trades and one omitting odd-lot trades. Volume is measured as the single-counted sum of shares traded daily on an exchange. Odd-lots refers to trades made in a size of 100 shares or less. The reason this data reports values containing and odd-lots and omitting odd-lots is because it serves as a proxy for HFT. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations (*N* = 7935) across 505 trading days. The test parameters include the two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Beta coefficients for each test parameter are stacked above the corresponding test statistic.Test statistics include significant levels which are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

$$Total\ Market\ Volume\ = \beta_0 + \beta_1 V + \ \beta_2 A + \ \beta_3 N + \beta_4 Q + \epsilon$$

Exchange Volume Using Odd-Lots Proxy

Model Specifications	*With Odd Lots*			*Without Odd Lots*		
	Model A	*Model B*	*Model C*	*Model A*	*Model B*	*Model C*
	β	*β*	*β*	*β*	*β*	*β*
	T-Stat	*T-Stat*	*T-Stat*	*T-Stat*	*T-Stat*	*T-Stat*
Intercept/Constant	19.187***	19.346***	19.128***	19.113***	19.272***	19.057***
	1100.39	1157.54	1134.80	1108.23	1167.75	1143.81
IEX (V)	-0.053	-0.212***	0.006	-0.023	-0.181***	0.034
	-0.77	-3.31	0.11	-0.33	-2.87	0.57
NYSE Am (A)		-2.337***	-2.119***		-2.334***	-2.119***
		-36.49	-35.29		-36.90	-35.71
NYSE (N)			1.198***			1.204***
			19.95			20.29
NASDAQ (Q)			1.79***			1.738***
			0.29			29.29
Observations	504	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920	7920
R-Squared	0.000	0.144	0.257	0.000	0.147	0.258
Adj. R-Squared	0.000	0.144	0.256	0.000	0.147	0.257

Table 23 - Exchange Volume Using Odd-Lots Proxy

Table XI – Regression by Exchange Market Share

This table reports the results of an ordinary least squares regression that uses exchange market share as the dependent variable. This dependent variable was used in two forms, one containing odd-lot trades and one omitting odd-lot trades. Market share for an exchange is measured as the quotient of volume for the exchange divided by total volume in the market. Market share is measured daily in this sample. Odd-lots refers to trades made in a size of 100 shares or less. The reason this data reports values containing and odd-lots and omitting odd-lots is because it serves as a proxy for HFT. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations (*N* = 7935) across 505 trading days. The test parameters include the two primary access delay venues (IEX & NYSE American), and the two largest venues by market share (NYSE & NASDAQ). Panel A uses only the four exchanges as test parameters. Panel B contains the same analysis but includes the first wave trade fill weight as the initial parameter. Panel C replicates the previous analysis again but adds an interaction variable between first wave trade fill weight and total market volume (with odd-lots). First wave trade fill weight is the percentage of routed trades in the total market that are routed to a given exchange on the trade's first routed signal Beta coefficients for each test parameter are stacked above the corresponding test statistic. Test statistics include significant levels which are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

$Panel\ A$:

$$\frac{Exchange\ Volume}{Total\ Market\ Volume} = \beta_0 + \beta_1 V + \beta_2 A + \beta_3 N + \beta_4 Q + \epsilon$$

Panel B:

$$\frac{Exchange\ Volume}{Total\ Market\ Volume} = \beta_0 + \beta_1 F + \beta_2 V + \beta_3 A + \beta_4 N + \beta_4 Q + \epsilon$$

Panel C:

$$\frac{Exchange\ Volume}{Total\ Market\ Volume} = \beta_0 + \beta_1 F + \beta_2 V + \beta_3 A + \beta_4 N + \beta_4 Q + \beta_4 (F * \lambda_{t,w}) + \epsilon$$

Panel A: Exchange Market Share Using Odd-Lots Proxy

Exchange Market Share Using Odd-Lots Proxy

Model Specifications	*With Odd Lots*			*Without Odd Lots*		
	Model A	*Model B*	*Model C*	*Model A*	*Model B*	*Model C*
	β / *T-Stat*	*β* / *T-Stat*	*β* / *T-Stat*	*β* / *T-Stat*	*β* / *T-Stat*	*β* / *T-Stat*
Intercept / Constant	0.066***	0.071***	0.061***	19.113***	19.272***	19.057***
	71.56	75.49	63.86	1108.23	1167.75	1143.81
IEX (V)	-0.039***	-0.043***	-0.034***	-0.023***	-0.181***	0.034***
	-10.61	-12.09	-9.96	-0.33	-2.87	0.57
NYSE Am (A)		-0.067***	-0.058***		-2.334***	-2.119***
		-18.76	-16.95		-36.90	-35.71
NYSE (N)			0.028***			1.204***
			8.10			20.29
NASDAQ (Q)			0.099***			1.738***
			0.30			29.29
Observations	504	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920	7920
R-Squared	0.014	0.056	0.149	0.013	0.052	0.125
Adj. R-Squared	0.014	0.056	0.149	0.013	0.052	0.124

Table 24 - Exchange Market Share Using Odd-Lots Proxy

Panel B: Exchange Market Share Using Odd-Lots Proxy with First Wave Weight

Exchange Market Share Using Odd-Lots Proxy and First Wave Weight

Model Specifications	With Odd-Lots				Without Odd-Lots			
	Model A	*Model B*	*Model C*	*Model D*	*Model A*	*Model B*	*Model C*	*Model D*
	β T-Stat	β T-Stat	β T-Stat	β T-Stat	β T-Stat	β T-Stat	β T-Stat	β T-Stat
Intercept/Constant	0.014***	0.015***	0.017***	0.02***	0.014***	0.015***	0.017***	0.019***
	37.01	54.37	58.92	69.67	38.77	55.87	60.60	68.35
First Wave Weight (F)	0.004***	0.005***	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
	128.36	190.87	187.24	90.45	128.95	188.43	184.93	89.93
IEX (V)		-0.063***	-0.064***	-0.051***		-0.06***	-0.06***	-0.048***
		-76.53	-78.96	-57.74		-74.08	-76.56	-55.84
NYSE Am (A)			-0.015***	-0.017***			-0.015***	-0.017***
			-18.93	-23.39			-19.40	-22.85
NYSE (N)				0.011***				0.013***
				13.08				15.27
NASDAQ (Q)				0.038***				0.032***
				31.24				26.17
Observations	504	504	504	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920	7920	7920	7920
R-Squared	0.715	0.849	0.857	0.876	0.717	0.846	0.854	0.868
Adj. R-Squared	0.715	0.849	0.857	0.876	0.717	0.846	0.854	0.868

Table 25 - Exchange Market Share Using Odd-Lots Proxy & First Wave Weight

Panel C: Exchange Market Share Using Odd-Lots Proxy, First Wave Weight, and Interaction Variable

Exchange Market Share Using Odd-Lots Proxy and Routing Weights with Interaction Variable

Model Specifications	*With Odd Lots*				*Without Odd Lots*			
	Model A	*Model B*	*Model C*	*Model D*	*Model A*	*Model B*	*Model C*	*Model D*
	β	β	β	β	β	β	β	β
	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat
Intercept/Constant	0.014***	0.017***	0.02***	0.018***	0.014***	0.017***	0.019***	0.018***
	37.014	58.916	69.671	60.191	38.767	60.596	68.349	58.999
First Wave Weight (F)	0.004***	0.004***	0.004***	0.015***	0.004***	0.004***	0.003***	0.015***
	128.36	187.236	90.453	16.89	128.952	184.934	89.929	16.693
IEX (V)		-0.064***	-0.051***	-0.062***		-0.06***	-0.048***	-0.059***
		-78.956	-57.739	-50.318		-76.556	-55.841	-48.831
NYSE Am (A)		-0.015***	-0.017***	-0.017***		-0.015***	-0.017***	-0.016***
		-18.93	-23.389	-22.383		-19.403	-22.849	-21.847
NYSE (N)			0.011***	0.011***			0.013***	0.013***
			13.08	12.704			15.272	14.924
NASDAQ (Q)			0.038***	0.047***			0.032***	0.04***
			31.24	33.964			26.168	29.379
*First Wave Weight * Total Volume WOL ($F * \lambda_{t,w}$)*				-0.001***				-0.001***
				-12.978				-12.805
Observations	504	504	504	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920	7920	7920	7920
R-Squared	0.715	0.857	0.876	0.879	0.717	0.854	0.868	0.871
Adj. R-Squared	0.715	0.857	0.876	0.879	0.717	0.854	0.868	0.871

Table 26 - Exchange Market Share Using Odd-Lots Proxy, Routing Weights, & Interaction Variable

Table XII – Regression by IEX Monthly Statistics Volume

This table reports the results of an ordinary least squares regression that uses adjusted exchange volume for the IEX as the dependent variable. Volume is measured as the single-counted sum of shares traded daily on the IEX and has been adjusted using the natural logarithm of the statistic. This dependent variable was used in two forms, one containing odd-lot trades and one omitting odd-lot trades. Odd-lots refers to trades made in a size of 100 shares or less. This data reports values containing and odd-lots and omitting odd-lots as a proxy for HFT. The reason this data reports values containing and odd-lots and omitting odd-lots is because it serves as a proxy for HFT. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations (N = 7935) across 505 trading days. The test parameters include multiple different market statistics from the IEX. Panel A uses each metric along with the odd-lot trade percentage. Panel B contains the same analysis but removes odd-lot trade percentage because the dependent variable omits odd-lots. Beta coefficients for each test parameter are stacked above the corresponding test statistic. Test statistics include significant levels which are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

$Panel\ A$: $\ln(Exchange\ Volume) = \beta_0 + \beta_1 P + \beta_2 O + \beta_3 S + \beta_4 B + \beta_5 F + \epsilon$

$Panel\ B$: $\ln(Exchange\ Volume) = \beta_0 + \beta_1 O + \beta_2 S + \beta_3 B + \beta_4 F + \epsilon$

Panel A: IEX Volume Regression Using Monthly Statistics with Odd-Lots

IEX Volume with Odd-Lots Using IEX Stats

Model Specifications	*Model A*	*Model B*	*Model C*	*Model D*	*Model E*
	β	β	β	β	β
	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat
Intercept/Constant	23.11***	24.25***	-30.92***	-18.42***	-8.71***
	41.73	40.63	-5.18	-2.75	-1.38
Odd-Lot Trade % (P)	-5.4***	-5.25***	-2.5***	-1.68***	1.33***
	-7.18	-7.10	-3.36	-2.20	1.70
Order Size (O)		-0.21***	0.31***	0.11***	-0.32***
		-4.60	4.44	1.35	-3.54
Unique Symbols Traded (S)			5.56***	4.18***	3***
			9.28	6.07	4.62
% Traded in Block (B)				8.63***	16.1***
				3.90	7.32
First Wave Weight (F)					0.06***
					9.23
Observations	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920
R-Squared	0.093	0.130	0.258	0.280	0.385
Adj. R-Squared	0.091	0.126	0.253	0.274	0.379

Panel B: IEX Volume Regression Using Monthly Statistics without Odd-Lots

IEX Volume without Odd-Lots Using IEX Stats

Model Specifications	*Model A*	*Model B*	*Model C*	*Model D*
	β	*β*	*β*	*β*
	T-Stat	T-Stat	T-Stat	T-Stat
Intercept/Constant	20.39***	-41.07***	-22.05***	-6.51***
	70.49	-7.61	-3.35	-1.03
Order Size (O)	-0.21***	0.39***	0.13***	-0.3**
	-4.5	5.72	1.47	-3.29
Unique Symbols Traded (S)		6.42***	4.42***	2.86***
		11.40	6.43	4.34
% Traded in Blocks (B)			10.52***	15.23
			4.86	7.38
First Wave Weight (F)				0.05***
				9.28
Observations	504	504	504	504
Trading Days	7920	7920	7920	7920
R-Squared	0.039	0.236	0.271	0.378
Adj. R-Squared	0.037	0.233	0.267	0.373

Table XIII – Regression by IEX Monthly Statistics Market Share

This table reports the results of an ordinary least squares regression that uses market share for the IEX as the dependent variable. Market share for an exchange is measured as the quotient of volume for the exchange divided by total volume in the market. Market share is measured daily in this sample. Odd-lots refers to trades made in a size of 100 shares or less. The reason this data reports values containing and odd-lots and omitting odd-lots is because it serves as a proxy for HFT. The sample period spans from August 13th, 2018 to August 13th, 2020. This sample contains observations (*N* = 7935) across 505 trading days. The test parameters include multiple different market statistics from the IEX. Panel A uses each metric along with the odd-lot trade percentage. Panel B contains the same analysis but removes odd-lot trade percentage because the dependent variable omits odd-lots. Beta coefficients for each test parameter are stacked above the corresponding test statistic. Test statistics include significant levels which are represented by *, **, & *** for 10%, 5%, and 1%, respectively.

$$Panel\ A: \quad \frac{Exchange\ Volume}{Total\ Market\ Volume} = \beta_0 + \beta_1 P + \beta_2 O + \beta_3 S + \beta_4 B + \beta_5 F + \epsilon$$

$$Panel\ B: \quad \frac{Exchange\ Volume}{Total\ Market\ Volume} = \beta_0 + \beta_1 O + \beta_2 S + \beta_3 B + \beta_4 F + \epsilon$$

Panel A: IEX Market Share Regression Using Monthly Statistics with Odd-Lots

IEX Market Share with Odd-Lots Using IEX Stats

Model Specifications	*Model A*	*Model B*	*Model C*	*Model D*	*Model E*
	β	β	β	β	β
	T-Stat	T-Stat	T-Stat	T-Stat	T-Stat
Intercept/Constant	0.06***	-0.01***	0.7***	0.44***	0.64***
	6.12	-0.78	9.02	5.22	9.35
Odd-Lot Trade % (P)	-0.04***	-0.05***	-0.08***	-0.1***	-0.04***
	-3.20	-5.16	-8.75	-10.46	-4.77
Order Size (O)		0.01***	0.01***	0.01***	0***
		19.79	5.50	8.31	0.03
Unique Symbols Traded (S)			-0.07***	-0.04***	-0.07***
			-9.14	-4.91	-9.45
% Traded in Block (B)				-0.18***	-0.03***
				-6.29	-1.05
First Wave Weight (F)					0***
					17.16
Observations	504	504	504	504	504
Trading Days	7920	7920	7920	7920	7920
R-Squared	0.02	0.45	0.528	0.563	0.725
Adj. R-Squared	0.018	0.448	0.526	0.56	0.723

Table 27 - IEX Market Share Regression Using Monthly Statistics with Odd-Lots

Panel B: IEX Volume Regression Using Monthly Statistics without Odd-Lots

IEX Market Share without Odd-Lots Using IEX Stats

Model Specifications	*Model A*	*Model B*	*Model C*	*Model D*
	β	*β*	*β*	*β*
	T-Stat	T-Stat	T-Stat	T-Stat
Intercept/Constant	-0.04***	0.35***	0.18*	0.59***
	-10.8	4.45	1.90	8.16
Order Size (O)	0.01***	0.01***	0.01***	0
	18.18	7.77	7.88	-1.27
Unique Symbols Traded (S)		-0.04***	-0.02**	-0.06***
		-4.99	-2.32	-8.51
% Traded in Blocks (B)			-0.09***	0.03
			-2.8	1.40
First Wave Weight (F)				0***
				21.1
Observations	504	504	504	504
Trading Days	7920	7920	7920	7920
R-Squared	0.397	0.425	0.434	0.702
Adj. R-Squared	0.395	0.423	0.431	0.7

Table 28 - IEX Volume Regression Using Monthly Statistics without Odd-Lots

CHAPTER VII

RESULTS

Sample Overview

Table 1 Results

All four of the sample exchanges used displayed higher volume when accounting for odd-lots trades than without odd-lots trades. The IEX had nearly ten times as much volume as NYSE American. Volume on the NYSE big board is triple that of the IEX and the volume on the NASDAQ Book is six times the amount of the IEX. The IEX volume was comprised mostly in Tape A stocks while the NYSE American volume occurred most in Tape B stocks. The NYSE big board displayed an increase in Tape B and Tape C volume when accounting for odd-lots and these were the only two cases where volume increased when removing odd-lots from the sample.

Table 2 Results

Of each sample exchange, the IEX was the only exchange that displayed a considerable increase in market share when removing odd lots. The NYSE big board also displayed an increase at a negligible 1/100th of a percent. The majority of market share for the IEX is in Tape A stocks similar to the results for IEX volume. Likewise for NYSE American, their market share was dominated by Tape B stocks. The NYSE big board and NASDAQ Book exchanges combine to account for roughly 30% of the market during this sample period[39].

[39] This is roughly half of the typical amount of displayed market share based on recent years.

Table 3 Results

The volume reported by IEX is slightly lower than was reported by CBOE Global Markets. This is due to the number of broker self-cross that occurs on their exchange. Of the 244.9 million shares traded on the IEX, 41.5 million were displayed order types and 34 million were routed orders.

Table 4 Results

The majority of aggregate fills executed by the IEX were fills under 100 shares in size (73.634%). With the exception of trades between 100 and 199 shares, the average percentage of fills decreases as the size of trades increases. Every data point except for odd-lot-sized trades has a positive skewness indicating a potential for large positive outliers in the dataset. As trade size increases, the level of positive skewness of the data also increases. Under 1% of aggregates fills were made in block sizes or fills above 10,000 shares in size (0.083%).

Table 5 Results

The IEX handled 5.50% of their volume in block sizes during the sample period. The majority of these trades were between 10,000 and 19,999 shares (5,762 trades). Only a small number of trades exceeded 50,000 shares (252 trades). All block trade statistics had a very high level of positive skewness indicating large positive outliers.

Table 6 Results

The IEX had a mean order size of 455 shares and a mean aggregate fill size of 175 shares. These values are roughly in line with many dark pools including the IntelligentCross dark pool, which operates using an access delay[40]. The IEX trades an

[40] Dark pool FINRA quarterly reports available at https://www.finra.org/filing-reporting/otc-transparency/ats-quarterly-statistics

average of 8122 stocks out of roughly 11,500 publicly listed companies[41] in the U.S. and this value has a considerable positive skewness (0.730). The first wave trade fill weight for the IEX is 7.69% and this value has a high positive skewness since this value has increased over the sample period. First wave fill percentage has a mean of 96.03% and this value has very high negative skewness indicating negative outliers in the dataset.

Table 7 Results

Of all exchanges in the U.S. market system during the sample period, the IEX (16.57%) ranked second behind the NASDAQ Book (29.248%) in their first wave fill weights. When measuring the rankings of first wave fill rates, the IEX (98.638%) landed in third place behind EDGX (99.111%) and BATS (98.862%). All fill rates had negative skewness, likely due to time of volatility in the market. Smaller exchanges had large positive skewness in their first wave fill weights.

Difference Tests Results

Table 8 Results

This table contains the results from a difference in means test between volumes for each one of the four sample exchanges. Each exchange showed a statistically significant difference in Tape A, Tape B, Tape C, and Total volume at the 1% level except for the NASDAQ Book which did not show a statistically significant difference in Tape A volume or Total volume. Of all the exchanges, the IEX had the lowest percent of odd-lots per share of volume in Tape A, Tape B, Tape C, and Total volume.

Table 9 Results

---

[41] Value taken from this article: https://www.benzinga.com/news/20/10/18026067/the-number-of-companies-publicly-traded-in-the-us-is-shrinking-or-is-it

This table contains the results from a difference in means test between market share for each one of the four sample exchanges. Market share is already a relative value because it quantifies volume relative to total volume in the market so an extra calculation was not required. The IEX showed a considerable increase in total market share (0.0579%) when odd-lots were removed from the dataset. Both the NYSE big board (0.001%) and NYSE American (-0.002) showed negligible change in total market share when odd-lots were removed. The NASDAQ Book had the largest change (-0.920%) with nearly a 1% decrease in total market share when removing odd-lots from the data.

Regression Results

Table 10 Results

This table reports the results for an ordinary least squares regression that uses exchange volume as the dependent variable. The coefficient for the IEX alternates between negative and positive and is only significant in Model B for odd-lots and non-odd-lots regressions. NYSE American had negative and significant coefficients across the board. Conversely, the NYSE big board and the NASDAQ Book both had positive, significant coefficients both including and omitting odd-lots from the dependent variable. The explanatory power of the model increases with more independent variables as shown by the increase in r-squared values.

Table 11 Results

This table reports the results for an ordinary least squares regression that uses market share as the dependent variable. The coefficient for the IEX is negative and significant in every model. The coefficient for NYSE American is also negative and significant across the board. Each model in each panel displays an increase in explanatory power from the previous as indicated by the increases in r-squared. Conversely to the IEX and NYSE American, the NYSE big board and NASDAQ Book exchanges both have positive, significant coefficients in every model.

Panel A shows a comparable analysis to Table 10 because it only differs in that the dependent variable is market share as opposed to volume. Panel B include First Wave Weight because this variable is a proxy for the amount of liquidity that an exchange can capture (Bishop, 2017). First Wave Weight is significant and positive for both Panel's B and C. Panel C adds an interaction variable to the analysis. The interaction variable combines First Wave Weight with Total Volume to create a new explanatory variable. This interaction variable describes the effect based on the combined changes in First Wave Weight and Total Volume. In Panel C, the interaction variable is negative and significant. It shows that market share decreases in cases where First Wave Weight and Total Volume without odd-lots both increases.

<u>Table 12 Results</u>

This table reports the results for an ordinary least squares regression that uses IEX volume as the in dependent variable. In Panel A, the dependent variable contains odd-lots and all coefficients are significant at the 1% level. Panel B uses the dependent variable without odd-lots. Independent variables in this analysis are market statistics about the IEX that act as a proxy for a market trend. Odd-lot trade percentage is a proxy for HFT, order size is useful for exchange comparisons, unique symbols traded is a proxy for market involvement, block trade percentage is a proxy for investor time and dark pool competition, and first wave weight is a proxy for liquidity.

Panel A shows that the odd-lot percentage has a negative coefficient across each model, except for in the final model that adds first wave weight. Order size flips between negative and positive coefficients. Unique symbols traded and block trade percentage both have positive coefficients across the board.

Panel B did not contain odd-lot trade percentage because the dependent variable omits odd-lots. Order size was significant, but the last model was at the 5% level and not the 1% level. Order size had negative and positive coefficients and carried the same signs as in the prior panel. Unique symbols traded were all significant and positive across the board. Block trade percentage were positive, but only significant in Model C. Finally, first wave weight was positive and significant.

<u>Table 13 Results</u>

Table 14 replicates Table 13 using a new independent variable: market share instead of volume. Each independent metric can be thought of in the same way as described above. In Panel A, market share contains odd-lots and in Panel B odd-lots were omitted from the dependent variable.

Panel A shows that the odd-lot percentage has negative coefficients across the board and are all significant. The coefficient for order size differed from Table 13 in that it was positive across the entire board. Order size coefficients were all statistically significant. Unique symbols traded showed opposite results from the analysis in Table 13 using volume because all coefficients were negative. Similarly, block trade percentage was negative across the board. Finally, first wave weight was not a large enough coefficient to interpret. Unique symbols traded, block trade percentage, and first wave weight were all significant.

Auxiliary Hypotheses Data Analysis and Results

The empirical analysis and dataset discussed so far was unable to address some of the auxiliary hypotheses that compared the emergence of IEX and NYSE American with the BATS exchange. For reference, the following 3 sub-hypotheses look to test a time-series analysis of the IEX and NYSE American:

Hypothesis 3b – Market share and volume has increased over time on IEX and NYSE American

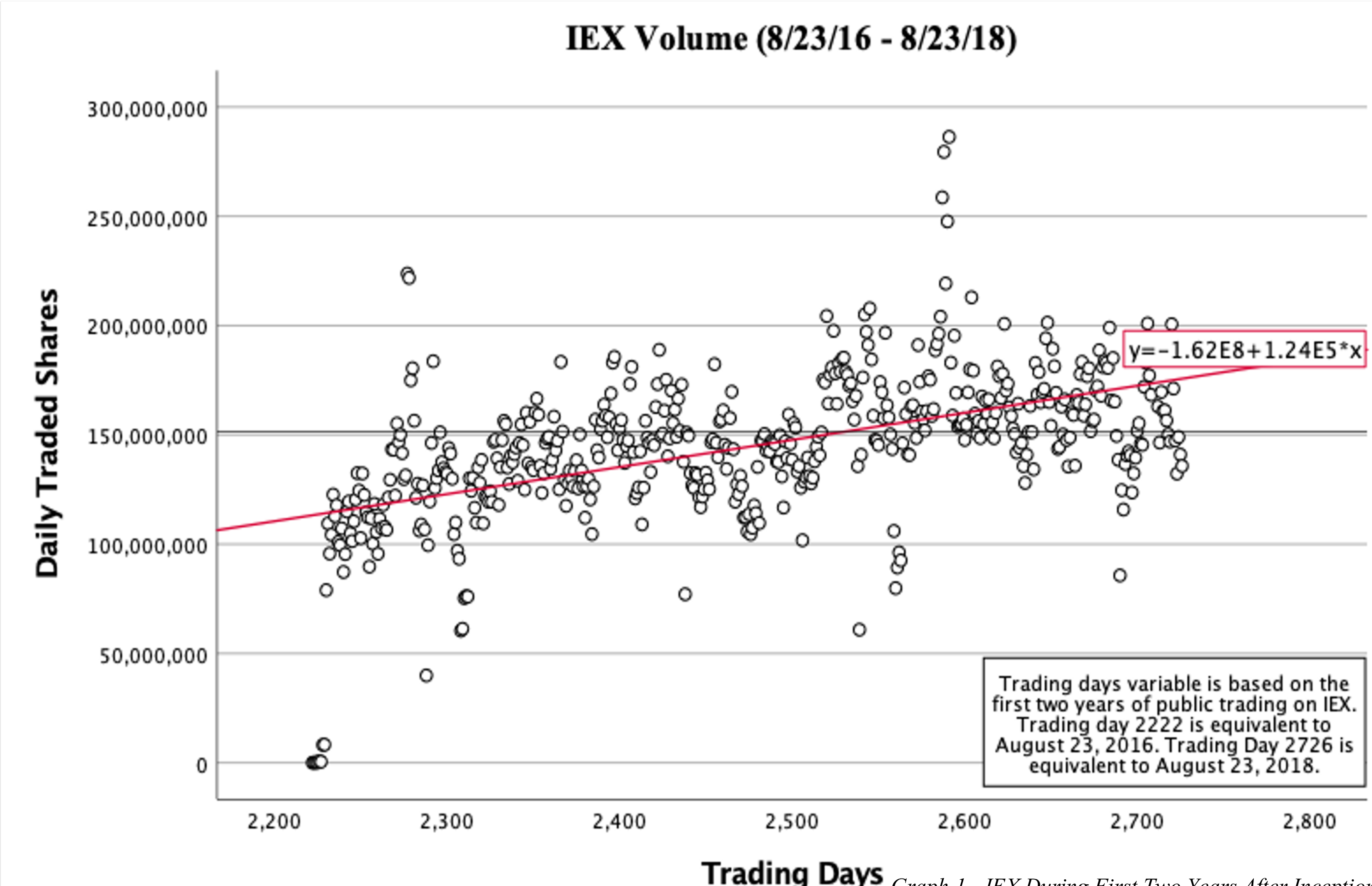
Hypothesis 3c – The market share of the IEX increased faster in its first year than the market share of BATS did in its first year

Hypothesis 3d – The market share and volume of the NYSE American increased faster in its first two years than the market share of BATS did in its first two years

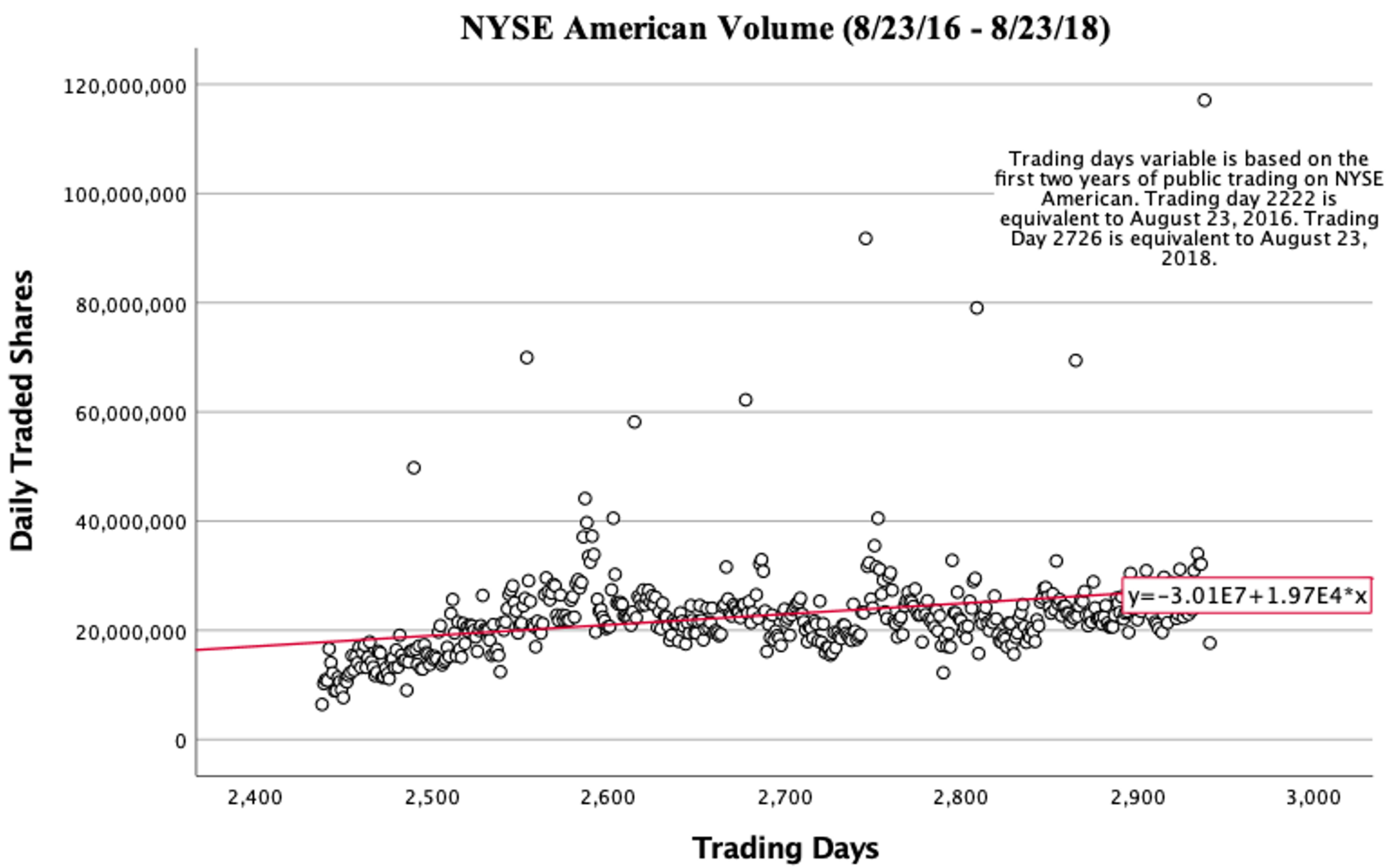
Answering these hypotheses was simplest to do using an ordinary least squares regression via a line of best fine on a scatterplot of the data. The following data was collected and prepared separately from the primary dataset. Data was collected from the CBOE by downloading a pre-formatted CSV file of all volume for every exchange from the 2007-2020. After downloading this file, the data could be simply moved into SPSS for analysis.

Preparing the data was slightly more challenging. First, the dates for the first day of recorded traded needed to be identified manually in the data set. After discovering the first day of trading for each exchange listed in the hypotheses the end date for each sample was set 2 years following that date. Each sample date range then needed to be indexed into numerical values so that the data could be divided and analyzed individually.

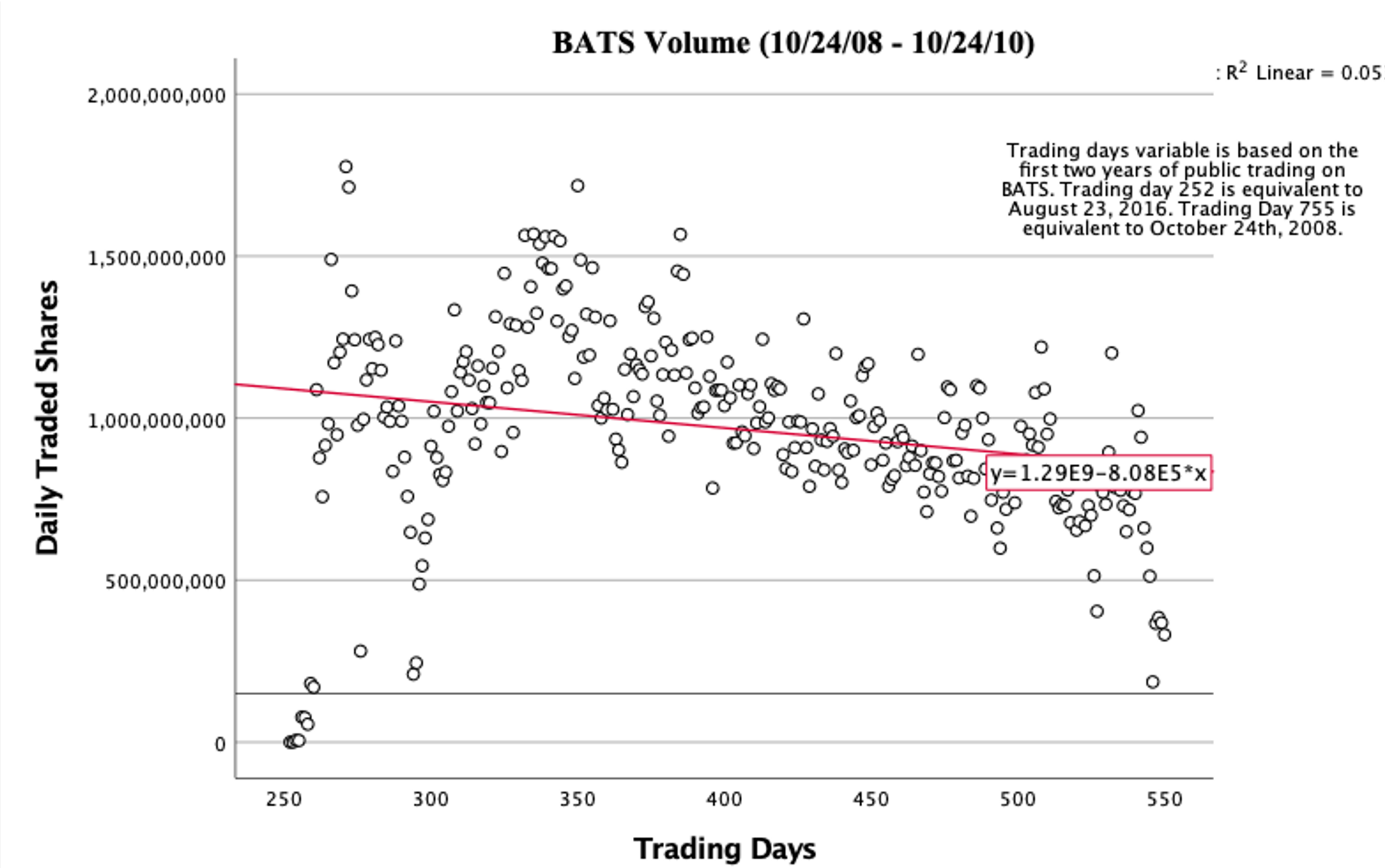
Analyzing the data was a simple process. Once the data had been prepared, it was transferred into SPSS. Through SPSS the data was plotted into a scatterplot for a single exchange. Once the scatterplot was built, a line of best fit was calculated and added along with the regression equation. A final note is that the BATS exchange emerged during the 2007-2008 recession which undoubtedly hurts the analysis overall. Due to this exogenous event, the analysis was replicated for the first two years of trading beginning with the official end of the recession.



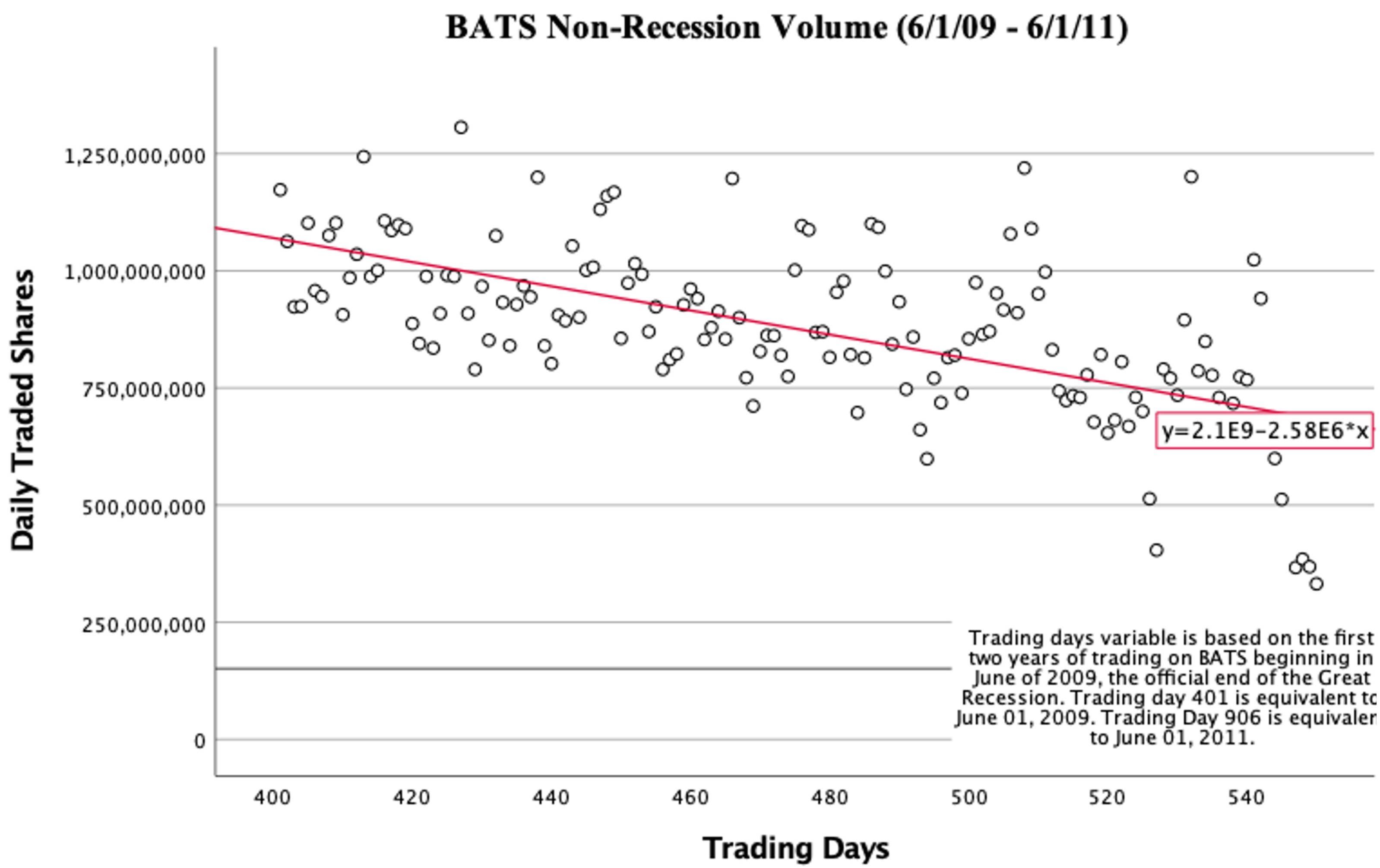
Graph 1 - IEX During First Two Years After Inception



Graph 2 - NYSE American During First Two Years After Inception



Graph 3 - BATS During First Two Years After Inception



Graph 4 - BATS During First Two Years After Inception (Non-Recession)

CONCLUSIONS

This research draws information from existing research and an empirical analysis to show that the IEX fills a unique niche in the market system and has generally achieved its goal of deterring HFT behavior. Based on the theory from O'Hara & Ye (2011) that the market functions as one cohesive exchange with multiple points of entry, the IEX has become yet another entry point. The IEX as an entry point to the market services many investor types, but ultimately has grown to serve the function that a dark pool is intended to create: protection for large orders for broker-dealers. Additionally, my findings show that the IEX is effective in deterring HFT behavior so odd-lots volatility on the IEX is less of a concern for retail investors.

The fact that access delay exchanges are permitted to interact with the NBBO in a different way is naturally unfair, but does it create a significant advantage for the IEX? The fact is that the IEX is truly a market response to the HFT problem. Every exchange has access to the same rules that permit the IEX to function with an access delay. The NYSE has implemented an access delay on NYSE American and found less success than the IEX during a similar time period. Ultimately, the growth and success of the IEX can certainly be somewhat attributed to their innovations and their initiative with the SEC to admit their business model to the industry.

The IEX grown year over year in its market share and has been more successful in its operation than its competitor, the NYSE American. The IEX has a significant portion of aggregate fills in the odd-lots size, but has minimal slippage as trade size increases. This could explain why IEX market share increases when accounting for HFT behavior on their exchange. Their ability to fill block-size routed orders speaks to their liquidity provision as an exchange also. However, only 5.5% of their total volume is made in block sizes. The exchange trades in 70-80% of the market in terms of symbols traded each year so their market penetration could certainly improve in the years to come.

The IEX has found substantial success in the exchange design when analyzing from the view of routed trades. The IEX ranks near the top of all exchanges in terms of its first wave fill rate and first wave fill weight. These values indicate that the IEX captures a high level of liquidity in the market despite having lower market share.

My findings show that the IEX is effective in deterring HFT behavior on their exchange. In my first-difference analysis of the four sample exchanges, the IEX had the lowest percent of odd-lots per share of volume in every category of stocks. Additionally, their market share increased when accounting for odd-lots. This is even more substantial given that roughly 73% of trades were made in odd-lots sizes on the IEX during the sample period. Of each sample exchange, the IEX was the only exchange to show a considerable increase in market share when accounting for odd-lots. This also supports the conclusion that the IEX has become a niche for large trades to occur at a more favorable price.

Volume on the IEX does not have considerable predictive power over volume in the market. Compared to NYSE big board and the NASDAQ Book which both significantly predict total volume. This confirms that using the NYSE big board and NASDAQ book was a proper choice for comparing the IEX to the market. Market share for the IEX on the other hand decreases relative to total volume in the sample period.

This indicates that the IEX is less capable of handling moments of high volatility and that volume moves off their exchange to larger venues at those times.

In every model, the first wave weight for exchanges has a positive relationship with market share. This supports the claim that the IEX can capture liquidity better than other exchanges despite low market share. When using interaction terms to analyze the first wave weight with total volume, I discovered that first wave weight decreases when volume increases. This indicates that less orders are routed during times of high volume. The high value of first wave weight that the IEX has shows that it has created an effective model using its access delay because it can capture a high amount of routed shares even if volume is changing in the market.

The final model used in this analysis is highly insightful to the IEX. It reinforces the deterrence of HFT as discovered in the difference tests because of the negative coefficient for odd-lots. Volume increases on the IEX lead to more market penetration and block share trade percentages. The first wave weight for the IEX has a positive relationship with both volume and market share despite evidence that the IEX struggles during times of volatility.

When using market share in the final model the results are mostly the same but differ slightly. Odd-lot trade percentage has a negative relationship with market share indicating again that the IEX deters HFT behavior. Order sizes on the IEX generally increase with market share. This also supports the theory that the IEX has become a good place for large trades to occur without slippage. Market share decreases, however, relative to the number of symbols traded on the exchange. This indicates that core investors who trade on the IEX may have a smaller risk appetite, or that the IEX has not been able to fully penetrate the available market. Block trades also have a negative relationship with market share in this model. This counters the claim that the IEX is a safe place for large trades to occur, but should be taken in context with the rest of the analysis.

Overall, the IEX has been a topic of high emotion for the equity market. From the passionate story told in *Flash Boys* to the intense debate between Brad Katsuyama and William O'Brien, stakeholders in the market have become divided as fragmentation continues for venues. Based on the available research and the analysis here, fragmentation has generally good effects on the market. The IEX is another point of an entry for the cohesive market system. Although the IEX has been seen as a proponent against HFT, it is important to remember that AT differs from HFT. The market system relies on AT to connect what has become such a fragmented system. Future analysis of the IEX would benefit more targeted, event-based datasets to explore how the IEX functions in the wake of changes in the market, regulation, or other phenomena.

BIBLIOGRAPHY

Adrian, J. (2016). *Informational Inequality: How High Frequency Traders Use Premier Access to Information to Prey on Institutional Investors*. http://ssrn.com/abstract=1858626.

Aitken, M., Chen, H., & Foley, S. (2017). The impact of fragmentation, exchange fees and liquidity provision on market quality. *Journal of Empirical Finance*, *41*, 140–160. https://doi.org/10.1016/j.jempfin.2016.10.002

Aldrich, E. M. ;, & Friedman, D. (n.d.). *Order Protection Through Delayed Messaging*. Retrieved October 22, 2020, from http://hdl.handle.net/10419/173265www.econstor.eu

Aldrich, E. M., & Friedman, D. (2017). *A Theoretical Model of the Investors Exchange*. http://hdl.handle.net/10419/197764www.econstor.eu

Aldridge, Irene. *High-Frequency Trading a Practical Guide to Algorithmic Strategies and Trading Systems*. Wiley, 2013.

Bayona, A., Dumitrescu, A., & Manzano, C. (2018). Information and Optimal Trading Strategies with Dark Pools. SSRN Electronic Journal, November, 60–62. https://doi.org/10.2139/ssrn.2995956

Bennett, P., & Wei, L. (2006). Market structure, fragmentation, and market quality. *Journal of Financial Markets*, *9*(1), 49–78. https://doi.org/10.1016/j.finmar.2005.12.001

Bessembinder, H., & Kaufman, H. M. (1997). A Comparison of Trade Execution Costs for NYSE and NASDAQ-Listed Stocks. In Source: The Journal of Financial and Quantitative Analysis (Vol. 32, Issue 3).

Biedermann, Z. (2015). Off-exchange Trading, Dark Pools and their Regulatory Dilemmas. *Public Finance Quarterly*, *60*(1), 78–94.

Bishop, A. (2017). *The Evolution of the Crumbling Quote Signal*.

Bizzozero, P., Flepp, R., & Franck, E. (2018). The effect of fast trading on price discovery and efficiency: Evidence from a betting exchange. Journal of Economic Behavior and Organization, 156, 126–143. https://doi.org/10.1016/j.jebo.2018.09.020

Boehmer, E., Li, D., & Saar, G. (2018). The competitive landscape of high-frequency trading firms. *Review of Financial Studies*, *31*(6), 2227–2276. https://doi.org/10.1093/rfs/hhx144

Brownlees, C. T., & Gallo, G. M. (2006). Financial econometric analysis at ultra-high frequency: Data handling concerns. Computational Statistics and Data Analysis, 51(4), 2232–2245. https://doi.org/10.1016/j.csda.2006.09.030

Budish, E., Lee, R. S., & Shim, J. J. (2019). A Theory of Stock Exchange Competition and Innovation: Will the Market Fix the Market. http://www.nber.org/data-appendix/w25855

Budish, E. et al. (2015). The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. 130 (November), 1547–1621. https://doi.org/10.1093/qje/qjv027.Advance

Buti, S., Rindi, B., & Werner, I. (2011). Diving Into Dark Pools. http://www.ssrn.com/abstract=1630499

Cantillon, E., & Yin, P. L. (2011). Competition between exchanges: A research agenda. International Journal of Industrial Organization, 29(3), 329–336. https://doi.org/10.1016/j.ijindorg.2010.12.001

Chen, D et al. (2020). Market Fragmentation. http://www.nber.org/papers/w26828

Chow, A., Lahtinen, K. D., & Lawrey, C. (2020). The Investors Exchange's (IEX) impact on investors. Journal of Asset Management, 1–11. https://doi.org/10.1057/s41260-020-00194-x

Christian, M. (2016). Spoilt for choice: Order routing decisions in fragmented equity markets.

Comerton-Forde, C. (2017). Shedding light on dark trading in Europe Background : Where are now and how did we get here ? In Working Paper (Issue MiFID I).

Comerton-Forde, C., Grégoire, V., & Zhong, Z. (2019). Inverted fee structures, tick size, and market quality. Journal of Financial Economics, 134(1), 141–164. https://doi.org/10.1016/j.jfineco.2019.03.005

Comerton-Forde, C., & Putniņš, T. J. (2015). Dark trading and price discovery. Journal of Financial Economics, 118(1), 70–92. https://doi.org/10.1016/j.jfineco.2015.06.013

De Fontnouvelle, P., Dejesus-Rueff, V., Jordan, J. S., & Rosengren, E. S. (2006). Capital and Risk: New Evidence on Implications of Large Operational Losses. Journal of Money, Credit, and Banking, 38(7), 1819–1846. https://doi.org/10.1353/mcb.2006.0088

Elliott, W. B., & Warr, R. S. (2003). Price Pressure on the NYSE and Nasdaq: Evidence from S&P 500 Index Changes. Financial Management, 32(3). https://ideas.repec.org/a/fma/fmanag/elliottwarr03.html

FinancialTimes. (2018). How high-frequency trading hit a speed bump | Financial Times. Financial Times, 1–5. https://www.ft.com/content/d81f96ea-d43c-11e7-a303-9060cb1e5f44

Foley, S. D. V., Malinova, K., & Park, A. (2012). Dark Trading on Public Exchanges. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2182839

Foucault, T., & Biais, B. (2014). HFT and Market Quality. Bankers, Markets, and Investors, 128.

Geranio, M. (2016). Evolution of the exchange industry: From dealers' clubs to multinational companies. In Evolution of the Exchange Industry: From Dealers' Clubs to Multinational Companies. Springer International Publishing. https://doi.org/10.1007/978-3-319-21027-8

Gresse, C. (2017). Effects of lit and dark market fragmentation on liquidity. Journal of Financial Markets, 35. https://doi.org/10.1016/j.finmar.2017.05.003

Haas, M., Khapko, M., & Zoican, M. (2020). Speed and learning in high-frequency auctions. Journal of Financial Markets, 100583. https://doi.org/10.1016/j.finmar.2020.100583

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does Algorithmic Trading Improve Liquidity? The Journal of Finance, 66(1), 1–33. https://doi.org/10.1111/j.1540-6261.2010.01624.x

Hens, T., Lensberg, T., & Schenk-Hoppé, K. R. (2018). Front-Running and Market Quality: An Evolutionary Perspective on High Frequency Trading. International Review of Finance, 18(4), 727–741. https://doi.org/10.1111/irfi.12159

Hirshleifer, J. (1978). The Private and Social Value of Information and the Reward to Inventive Activity. Uncertainty in Economics, 61(4), 541–556. https://doi.org/10.1016/b978-0-12-214850-7.50038-3

Hsiao, R. L. (2003). Technology fears: Distrust and cultural persistence in electronic marketplace adoption. Journal of Strategic Information Systems, 12(3), 169–199. https://doi.org/10.1016/S0963-8687(03)00034-9

Hu, E. (2019). Intentional Access Delays, Market Quality, and Price Discovery: Evidence from IEX Becoming an Exchange. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3195001

John, J. S. (2016). Slowing Down High-Speed Trading : Why the SEC Should Allow a New Exchange a Chance to Compete. Tulane Journal of Technology and Intellectual Property, 19. https://journals.tulane.edu/TIP/article/view/2671/2493

Jurich, S. (University of M. (2021). Agility and diversity in a web of fees: How can exchange operators gain an edge in fragmented markets?

Jurich, S., Mishra, A. K., & Parikh, B. (2020). Indecisive algos: Do limit order revisions increase market load? Journal of Behavioral and Experimental Finance, 28, 100408. https://doi.org/10.1016/j.jbef.2020.100408

Kirilenko, A. A., Kyle, A. S., Samadi, M., & Tuzun, T. (2012). The Flash Crash: The Impact of High Frequency Trading on an Electronic Market. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1686004

Kwan, A., Masulis, R., & McInish, T. H. (2015). Trading rules, competition for order flow and market fragmentation. Journal of Financial Economics, 115(2), 330–348. https://doi.org/10.1016/j.jfineco.2014.09.010

Ladley, D., Lensberg, T., Palczewski, J., & Schenk-Hoppé, K. R. (2015). Fragmentation and stability of markets. Journal of Economic Behavior and Organization, 119, 466–481. https://doi.org/10.1016/j.jebo.2015.09.013

Macey, J., & Swensen, D. (n.d.). Recovering the Promise of the Orderly and Fair Stock Exchange.

Madhavan, A. (2000). Market microstructure: A survey. Journal of Financial Markets, 3(3), 205–258. https://doi.org/10.1016/S1386-4181(00)00007-0

Mendelson, H. (1987). Consolidation, Fragmentation, and Market Performance. In Source: The Journal of Financial and Quantitative Analysis (Vol. 22, Issue 2).

Menkveld, A. J. (2013). High frequency trading and the new market makers. Journal of Financial Markets, 16, 712–740. https://doi.org/10.1016/j.finmar.2013.06.006

Menkveld, A. J. (2016). The Economics of High-Frequency Trading: Taking Stock HFT: high-frequency trader. https://doi.org/10.1146/annurev-financial-121415-033010

Moallemi, C. C., & Yuan, K. (2017). A Model for Queue Position Valuation in a Limit Order Book *. https://ssrn.com/abstract=2996221

Nikolsko-Rzhevska, O., & Nikolsko-Rzhevskyy, A. (2017). Disappearing Liquidity: Why It Matters and How to Deal with It. SSRN Electronic Journal, 1(832). https://doi.org/10.2139/ssrn.3083287

Noia, C. Di. (1998). Stock Exchanges in Europe : Network Effects , Implicit Mergers and Remote Access.

O'Hara, M. (1996). Market Microstructure Theory. https://doi.org/10.2307/2329383

O'Hara, M., Yao, C., & Ye, M. (2014). What's Not There: Odd Lots and Market Data. In Source: The Journal of Finance (Vol. 69, Issue 5).

O'Hara, M., & Ye, M. (2011). Is market fragmentation harming market quality? Journal of Financial Economics, 100, 459–474. https://doi.org/10.1016/j.jfineco.2011.02.006

Pisani, B. (2016). SEC gives its blessing to the IEX's "speed bump" trading. https://www.cnbc.com/2016/06/17/sec-gives-its-blessing-to-the-iexs-speed-bump-trading.html

Roseman, B. S., Van Ness, B. F., & Van Ness, R. A. (n.d.). Odd-Lot Trading in U . S . Equities Odd-Lot Trading in U . S . Equities.

Roth, A. E., & Wilson, R. B. (n.d.). How Market Design Emerged from Game Theory: A Mutual Interview. Journal of Economic Perspectives, 33. https://doi.org/10.1257/jep.33.3.118

Upson, J., & Van Ness, R. A. (2017). Multiple markets, algorithmic trading, and market liquidity. Journal of Financial Markets, 32, 49–68. https://doi.org/10.1016/j.finmar.2016.05.004

Van Kervel, V., & Menkveld, A. J. (2019). High-Frequency Trading around Large Institutional Orders. The Journal of Finance, 74(3), 1091–1137. https://doi.org/10.1111/jofi.12759

Wah, E., Feldman, S., Chung, F., Bishop, A., & Aisen, D. (2017). A Comparison of Execution Quality across U.S. Stock Exchanges. www.iextrading.com.

Wang, X. (2018). Why Do Stock Exchanges Compete on Speed, and How?

Woodward, M. (2018). Bumping Up the Competition: The Influence of IEX's Speed Bump in US Financial Markets. https://ssrn.com/abstract=3202843

Yadav, Y. (2014). How Algorithmic Trading Undermines Efficiency in Capital Markets. Vanderbilt Law Review, 68(6), 1607–1671. https://cdn.vanderbilt.edu/vu-wp0/wp-content/uploads/sites/278/2015/11/28001226/How-Algorithmic-Trading-Undermines-Efficiency-in-Capital-Markets.pdf

Ye, L. (2018). Understanding the Impacts of Dark Pools on Price Discovery. SSRN Electronic Journal, 1–67. https://doi.org/10.2139/ssrn.2874957

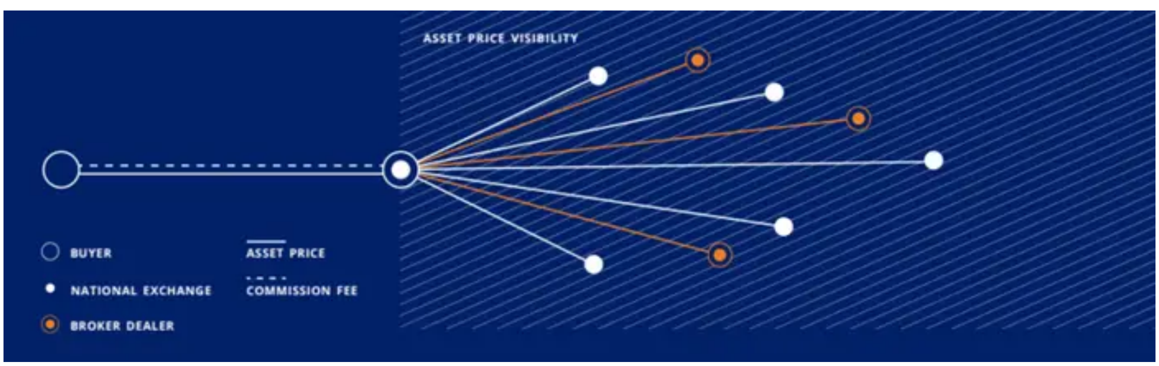
APPENDICES

APPENDIX A: HISTORY OF MARKET FRAGMENTATION

“Pre-1995 — ‘Before the digital revolution, a handful of exchanges, including NYSE, AMEX, NASDAQ, CBOE and the CME dominated the industry. Markets were highly controlled, with nearly all orders executed on an exchange floor.’”

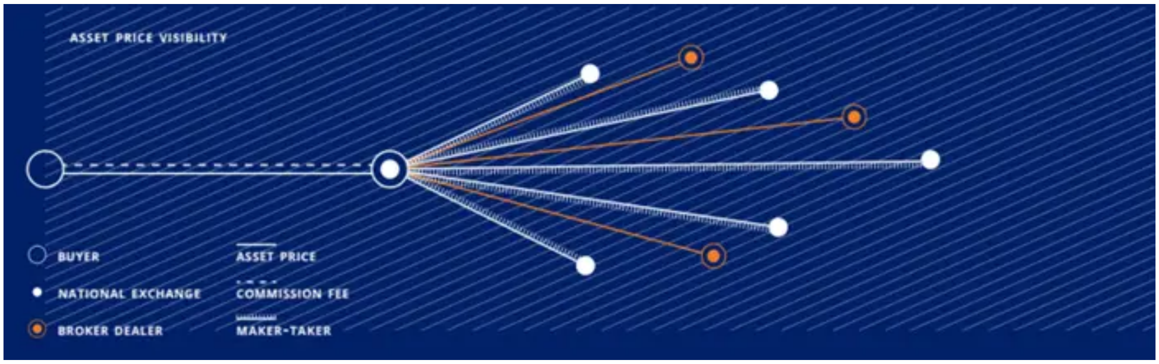
Source: Firm 58 via Business Insider

“1996 — ‘The SEC adopts Order Handling Rules, bringing the nascent electronic trading markets into the national market system and making them accessible to the public.’”



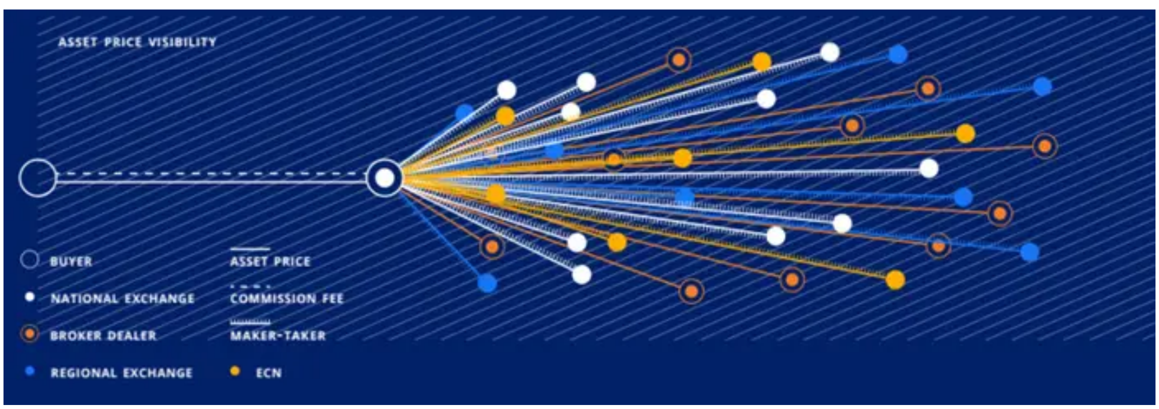
Source: Firm 58 via Business Insider

“2000 — ‘The maker-taker pricing model becomes the standard pricing model in US equities markets.’”



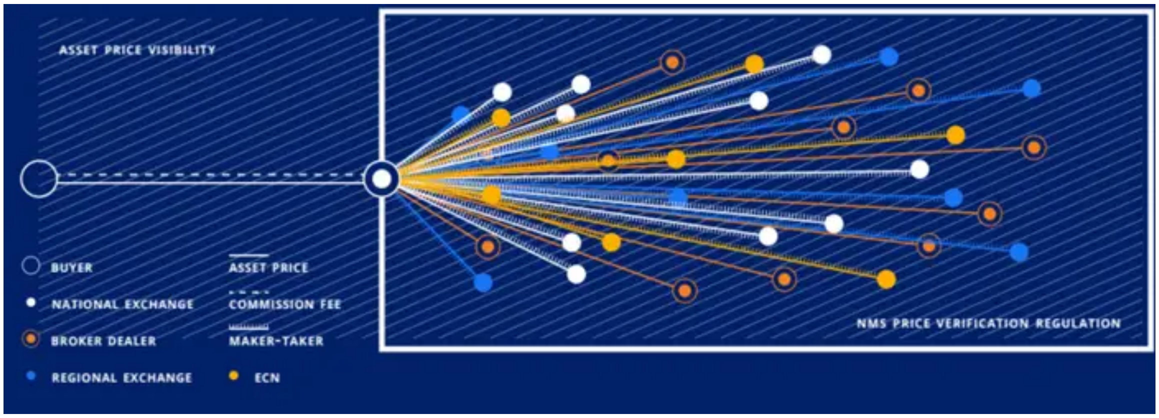
Source: Firm 58 via Business Insider

“2003 — ‘Exchange interest in new pricing and billing models soars, with exchanges creating more complex and frequently changing fee schedules.’”



Source: Firm 58 via Business Insider

“2005 — ‘The SEC adopts Regulation NMS in August, requiring brokers to verify that they have made an effort to execute their client's trade at the best possible price.’”



Source: Firm 58 via Business Insider

“2015 — ‘Markets have diversified to include 13 equities exchanges, 12 options exchanges and 40 dark pools.’”

Source: Firm 58 via Business Insider

APPENDIX B: BRIEF HISTORY OF ALGORITHMIC TRADING

"1851 - Paul Julius Reuter begins sending stock market quotations between London and Paris via a cable beneath the English Channel, having previously deployed pigeons to carry stock prices in Europe.

1990s - The rise of electronic marketplaces such as Archipelago, acquired by the New York Stock Exchange, Island ECN, now a part of Nasdaq, and Globex at the Chicago Mercantile Exchange enable algorithms to read market data and automatically execute trades.

2000 - Decimalization of US stock prices allows investors to buy and sell in penny increments, cutting the price spreads that underpinned profit margins for market-makers and encouraging traders to increase volumes to make up the difference.

Mid-2000s - Exchanges let traders pay to co-locate computers inside data centers, enabling them to receive and act on market data faster than those outside.

2005 - Regulation National Market System in the US increases competition among stock trading venues and turbocharges a race for the fastest technology between exchanges.

2010 - Spread Networks opens a fibre-optic link between New York and Chicago, reducing round-trip latency to 13.3 milliseconds, or thousandths of a second. Speeds are soon eclipsed by microwave networks that convey market data in about 8 milliseconds.

2012 - An electronic trading glitch causes Knight Capital to mistakenly purchase billions of dollars of shares in 148 NYSE stocks, causing more than $400m in losses and precipitating its takeover by Getco, a rival HFT company. The merged company, KCG Holdings, was later acquired by Virtu Financial.

2018 - Go West to go live between Chicago and Tokyo, speeding the flow of futures-market data over wireless towers, fiber-optic lines and submarine cables. It is a joint venture of big trading firms such as DRW, IMC and Jump Trading."[42]

[42] This article was sourced via the University of Maine to access the Financial Times. That article may be accessed here: https://search-proquest-com.wv-o-ursus-proxy02.ursus.maine.edu/docview/1992790298?pq-origsite=summon

APPENDIX C: DATA COLLECTION CODE

The code below was written in Python and used to combine the CSV files download from CBOE Global Markets. This program is described in greater detail in the Methodology chapter.

```
import os, glob
import pandas as pd

path = '/Users/cam/PyCharmProjects/HistoricalCBOEDataAppend'

all_files = glob.glob(os.path.join(path, "market_history_*.csv"))
df_from_each_file = (pd.read_csv(f, sep=',') for f in all_files)
df_merged = pd.concat(df_from_each_file, ignore_index=True)
df_merged.to_csv("merged.csv")
```

```
import os, glob
import pandas as pd

path = '/Users/cam/PyCharmProjects/CBOEwithoddlots/Odd Lots
Volume CSV Files'

all_files = glob.glob(os.path.join(path, "mktshare_v_exc_*.csv"))
df_from_each_file = (pd.read_csv(f, sep=',') for f in all_files)
df_merged = pd.concat(df_from_each_file, ignore_index=True)
df_merged.to_csv("Odd Lots Volume.csv")
```

The code below was written in python and used to manipulate the CSV files download from CBOE Global Markets. It was used to separate Tape A from Tape B from Tape C. This program is described in greater detail in the Methodology chapter.

```
import pandas as pd

df = pd.read_csv('Odd Lots Volume With TRFs.csv')
trf = df[(df['Trading Market Centre'] == 'NASDAQ TRF
Carteret')].index
df.drop(trf, inplace = True)
df.to_csv('Odd Lots No Carteret.csv')
df = pd.read_csv('Odd Lots No Carteret.csv')
trf = df[(df['Trading Market Centre'] == 'NYSE TRF')].index
df.drop(trf, inplace = True)
df.to_csv('Odd Lots No Carteret or NYSE.csv')
df = pd.read_csv('Odd Lots No Carteret or NYSE.csv')
trf = df[(df['Trading Market Centre'] == 'NASDAQ TRF
Chicago')].index
df.drop(trf, inplace = True)
df.to_csv('Odd Lots No TRFs.csv')
```

The code below was written in python and used to organize the data after it was combined and manipulated using the first two programs. This program is described in greater detail in the Methodology chapter.

```
import pandas as pd

df = pd.read_csv('Odd Lots No TRFs.csv')

totalmv = df.groupby('Date')['% of Mkt'].sum().reset_index()
totalmv_tapea = df.groupby('Date')['Tape A'].sum().reset_index()
totalmv_tapeb = df.groupby('Date')['Tape B'].sum().reset_index()
totalmv_tapec = df.groupby('Date')['Tape C'].sum().reset_index()
totalms = df.groupby('Date')['Market'].sum().reset_index()
totalms_tapea = df.groupby('Date')['Tape A Market
Share'].sum().reset_index()
totalms_tapeb = df.groupby('Date')['Tape B Market
Share'].sum().reset_index()
totalms_tapec = df.groupby('Date')['Tape C Market
Share'].sum().reset_index()


dftotals = pd.DataFrame([totalmv['% of Mkt'],
                         totalmv_tapea['Tape A'],
                         totalmv_tapeb['Tape B'],
                         totalmv_tapec['Tape C'],
                         totalms['Market'],
                         totalms_tapea['Tape A Market Share'],
                         totalms_tapeb['Tape B Market Share'],
                         totalms_tapec['Tape C Market Share']])
dftotals = dftotals.transpose()
print(dftotals)

dftotals.to_csv('Odd Lots No Trfs Totals.csv')
```

APPENDIX D: BASE RATES (IEX)

Base Fee Codes	Description	Executions at or above $1.00	Executions below $1.00
MI	Add non-displayed liquidity	$0.0009	0.30% of TDV
ML	Add displayed liquidity	FREE	0.30% of TDV
TI	Remove non-displayed liquidity	$0.0009	0.30% of TDV
TL	Remove displayed liquidity	$0.0006	0.30% of TDV
X	Opening Process for Non-Listed Securities (“Opening Process”)	$0.0009	0.30% of TDV
O, C, H, P	Auction Match Fee	$0.0003	0.30% of TDV
Alpha	Routing and removing liquidity (all routing options)	Cost + $0.0001	

APPENDIX E: FEE CODE COMBINATIONS AND ASSOCIATED FEES (IEX)

Fee Codes	Description	Fee
MI	Adds non-displayed liquidity	$0.0009
ML	Adds displayed liquidity	FREE
TI	Removes non-displayed liquidity	$0.0009
TL	Removes displayed liquidity	$0.0006
MIS	Member adds resting non-displayed liquidity that executes against the Member's removing interest	FREE
MLS	Member adds resting displayed liquidity that executes against the Member's removing interest	FREE
TIS	Member removes resting non-displayed liquidity added by such Member	FREE
TLS	Member removes resting displayed liquidity added by such Member	$0.0006
TIR[1]	Retail order removes non-displayed liquidity	FREE
MIA	Retail Liquidity Provider order adds non-displayed liquidity that executes against a Retail order	FREE
TLR[1]	Retail order removes displayed liquidity	FREE
TISR[1]	Retail order removes non-displayed liquidity added by such Member	FREE
MISA	Retail Liquidity Provider order adds non-displayed liquidity to a Retail order added by such Member	FREE
TLSR[1]	Retail order removes displayed liquidity added by such Member	FREE
X	Opening Process for Non-Listed Securities ("Opening Process")	$0.0009
XD	Displayed interest resting on the Continuous Book executes in the Opening Process	FREE
O	Opening Auction, IEX-listed security	$0.0003
OD	Displayed interest resting on the Continuous Book executes in the Opening Auction	FREE
C	Closing Auction, IEX-listed security	$0.0003
CD	Displayed interest resting on the Continuous Book executes in the Closing Auction	FREE
H	Halt or Volatility Auction, IEX-listed security	$0.0003
P	IPO Auction, IEX-listed security	$0.0003

iex exchange | iex

D-LIMIT

Designed to improve displayed liquidity for all market participants

Overview

Discretionary Limit (D-Limit) behaves like a regular limit order, except when the IEX Signal (i.e., the Crumbling Quote Indicator or CQI) predicts the price is about to change. This triggers D-Limit orders to automatically reprice to 1 MPV (minimum price variant, $0.01 for most stocks) outside that level.

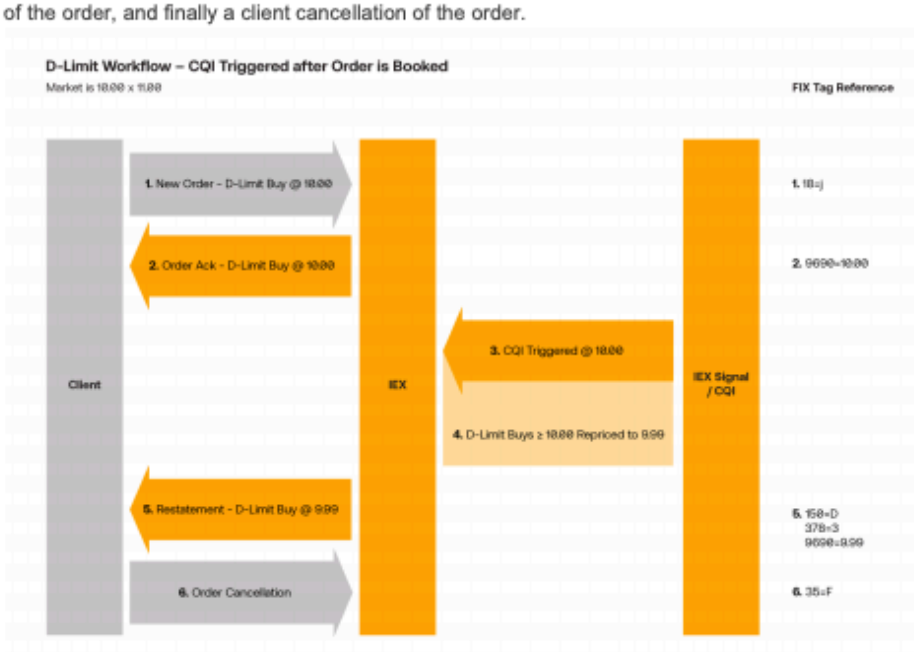
Repricing Details

When the CQI predicts that the price is about to change (i.e., the NBB is moving down or the NBO is moving up), D-Limit buy (sell) orders are repriced to 1 MPV below (above) the CQI price level. Under normal trading conditions, the order stays at the new price unless the CQI is triggered again or the Member updates the limit price.

Incoming orders can still interact with D-Limit orders after they have been repriced if their limits are priced equal to or more aggressive than the D-Limit order's new price.

D-Limit FIX Messaging Example

The diagram below details a base case messaging flow for a client sending a D-Limit order to IEX, the CQI triggering, repricing of the order, and finally a client cancellation of the order.



Source: IEX

APPENDIX G: T-TESTS AGGREGATED

Odd-Lots Volume by Venue

Classification		HFT Proxy		Difference	Odd Lots / Volume	T-Stat
		With Odd Lots	Without Odd Lots			
IEX	*Tape A*	123,741,927	118,601,154	5,140,773	4.15%	21.91***
	Tape B	22,731,102	22,276,583	454,519	2.00%	16.4***
	Tape C	64,700,435	61,541,148	3,159,287	4.88%	12.01***
	Market	211,173,465	202,418,885	8,754,580	4.15%	20.65***
NYSE American	*Tape A*	7,728,425	6,918,151	810,274	10.48%	3.57***
	Tape B	15,058,628	14,431,443	627,185	4.16%	2.44***
	Tape C	3,977,312	3,548,604	428,708	10.78%	3.11***
	Market	26,764,365	24,898,198	1,866,167	6.97%	-5.5***
NYSE	*Tape A*	607,218,125	549,192,212	58,025,913	9.56%	7.48***
	Tape B	46,666,551	55,651,452	(8,984,901)	-19.25%	34.87***
	Tape C	41,951,205	47,026,182	(5,074,977)	-12.10%	47.74***
	Market	695,835,881	651,869,847	43,966,034	6.32%	-7.64***
NASDAQ	*Tape A*	500,844,645	434,678,771	66,165,874	13.21%	0.85
	Tape B	217,750,887	209,478,750	8,272,137	3.80%	-7.23***
	Tape C	559,627,488	486,288,375	73,339,112	13.10%	2.56***
	Market	1,278,223,019	1,130,445,896	147,777,123	11.56%	0.12

Odd-Lots Market Share by Venue

Classification		*HFT Proxy*		*Difference*	*T-Stat*
		With Odd Lots	Without Odd Lots		
IEX	*Tape A*	3.325%	3.420%	0.0949%	4.67***
	Tape B	1.435%	1.442%	0.0075%	-5.62***
	Tape C	2.664%	2.741%	0.0767%	12.64***
	Market	2.728%	2.786%	0.0579%	4.59***
NYSE American	*Tape A*	0.199%	0.192%	-0.0074%	8.67***
	Tape B	0.955%	0.940%	-0.0151%	4.32***
	Tape C	0.152%	0.148%	-0.0044%	17.02***
	Market	0.330%	0.327%	-0.0020%	5.45***
NYSE	*Tape A*	16.271%	15.914%	-0.3569%	37.38***
	Tape B	2.947%	3.466%	0.5194%	66.12***
	Tape C	1.684%	1.972%	0.2871%	71.69***
	Market	8.921%	8.922%	0.0010%	16.07***
NASDAQ	*Tape A*	13.259%	12.360%	-0.8991%	7.96***
	Tape B	13.484%	13.338%	-0.1459%	4.06***
	Tape C	21.960%	20.604%	-1.3563%	1.61*
	Market	16.069%	15.149%	-0.9200%	4.23***

AUTHOR'S BIOGRAPHY

Cameron Spicer was born in Louisville, Colorado on February 22nd, 1996. He grew up in Erie, Colorado where he attended Centaurus High School. He left home at 16 years old to pursue his dream of playing Division 1 hockey in New Hampshire. After committing to the University of Maine in the Fall of his senior year he traveled the U.S. playing Junior A hockey in Nebraska, Illinois, and Massachusetts. At the University of Maine, he has pursued degrees in Finance and Financial Economics. During this time, he has played three seasons for the Men's Varsity Hockey Team. He was involved in the Student Athlete and Honors Student Advisory Committees, helped start the American Sign Language Club, and was active at the Newman Center. He also worked as a tutor for the Athletic Department after his freshman year. He currently works for a consulting company called Pitch Genius that specializes in helping start-ups raise funding.

After graduation, Cam is returning to the University of Maine to continue playing for the hockey team. He plans to pursue a Master's degree in Information Systems. Cam intends to continue to pursue hockey while working in start-up consulting. He lives in Orono with his girlfriend, and they spend their summers together in Colorado