High Frequency Trading, International Markets, and Regulation

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Table of Contents

Section I: Introduction 1
Abstract 1
Research Question and Significance 1
General Literature Review and Background 2
Anticipated Audience 2

Section II: Literature Review and Background 3
What Exactly is High Frequency Trading? 3
Barriers to Entry 5
High Costs to Build: An Amendment to the Time Value of Money 5
Co-location 7
Example of HFT in Action 7
Notable Events Attributed to HFT 8
1987 Market Crash: The Emergence of Programs Tied to Market Crashes 8
2010 Flash Crash 10
Black Swans in an Ever-Changing Financial Landscape 19
Flash Orders 21
Dark Pools 22

Section III: Algorithmic Trading Strategies 24
Algorithmic Techniques 24
Pairs Trading 24
Moving Large Volume and Predatory Algorithms (Sharks) 25
Quote Stuffing 26
Spoofing 27

Section IV: Elementary Policy Analysis 29
Understanding Existing Market Structure and Policy 29
Independent Policy Analysis of Five Proposed Options 30
Policy Option Comparison and Framework Review 34

Section V: Conclusion 36

Works Cited 37

Section I: Introduction

Abstract

In a recent interview with 60 Minutes (2014), prominent author Michael Lewis explained, "the United States stock market, the most iconic market in global capitalism, is rigged." Millions of unregulated transactions occur in fractions of a second on a daily basis, avoiding documentation. Several key players are paying hundreds of millions of dollars to gain unfair advantages at the expense of traditional game players. High frequency trading (HFT) has been publicly scrutinized for its adverse effects to the domestic market place. Nowadays, it is not uncommon to find an article about an investigation due to high frequency traders colluding and sharing private information in major news publications. This fascinating, evolutionary topic has gained mass attention, yet received limited regulation from authorities in charge of maintaining a fair market environment. With an ever-changing technological landscape, it is paramount to maintain the integrity upon which the stock exchanges and extended marketplaces were founded.

Research Question and Significance

The high frequency trading thesis project is aimed at answering the following question: what is the effect of electronic transactions (e.g. high frequency trading) on finance/microfinance and the associated global economies? In order to formulate policy intervention and analysis, a thorough understanding of high frequency trading characteristics, structure, and events is imperative.

Much research has led to hypotheses that markets become more liquid, stock prices are more efficient, and trading costs decrease as a result of high frequency trading. Au contraire, skeptics of high frequency trading have scrutinized the market, concluding that the stock market is rigged and manipulated to the advantages of money hungry institutions (Lewis, 2014).

After dozens of reports on a monthly basis from top news sources criticizing high frequency traders for collusion, rapidly increasing market volatility, and manipulating the marketplace, the future remains uncertain. As there is little analysis on future policy for high frequency trading, developing a thorough understanding of the topic to base future recommendations for regulation is critical. This should hopefully advance the field in a collaborative effort to establish a fair trading system for the worldwide marketplace.

In my undergraduate efforts, I have spread myself across many disciplines, in hopes of becoming a well-rounded individual. My skeptical analysis has focused on economics and statistics. High frequency trading draws on advanced principles from an array of subjects, all with great interest to me. This topic has allowed me to exercise the plethora of tools I have collected over the past three years, particularly within economics, statistics, and policy.

General Literature Review and Background

It has become increasingly apparent that this is an era controlled by machines. Some people would say that humans have created their own worst nightmare. As complex algorithms invade the marketplace, they carry unforeseen risks that have potential for catastrophe.

Algorithms are becoming smarter; they have the potential to read entire news stories from around the world within seconds of being released (Gourley, 2013). In the time that it takes a human to read just one article, the algorithms have developed an accurate perspective of what has occurred in each market around the world and how to efficiently trade to maximize profits. As algorithms are seemingly efficient, they are often so complex that humans have difficulty understanding them. Nonetheless, they buy and sell in micro and nanoseconds, a timescale inconceivable to humans. The Securities Exchange Act of 1934 was certainly incapable of predicting the potentially problematic implications of high frequency trading.

In order to establish an unbiased, fair system, illicit activity must be documented and punishable. Currently, there have been several reports on high frequency trading. Some of the most prestigious are "High Frequency Trading and Price Discovery" from The European Bank, "Equity Market Structure Literature Review" by the United States Securities and Exchange Commission, and "Recommendations for Equitable Allocation of Trades in High Frequency Trading Environments" from the Chicago Federal Reserve Bank. This thesis primarily draws from approximately fifteen academic reports surrounding high frequency trading events, strategies, and policy. Furthermore, Michael Lewis's most recent non-fiction book, *Flash Boys,* which has gained immense attention within the financial services industry, has aided in identifying particularly interesting aspects of high frequency trading.

Overall, a thorough analysis has been conducted to form an educated opinion surrounding the most important areas of the matter, leading to sound policy review.

Anticipated Audience

The nature of this thesis encompasses a narrow subset of the overarching financial markets. The intended audience for this thesis primarily includes academics with a foothold in traditional mathematics, economics, statistics, and policy. Engineers from traditional branches (i.e. electrical and computer) may also find the topic, results, and recommendations relevant to material within their respective field.

Certainly any working professional within the financial services industry, including traders and bankers, will directly be able to relate to the constantly changing markets due to the immergence of high frequency trading. The thesis further works to increase global market efficiency in electronically dependent times. Some information is presented at an elementary level, while other topics require intermediate and advanced knowledge and theory from specific fields.
The thesis will be summarized in a poster presentation at Carnegie Mellon University's 2015 Meeting of the Minds on May 6, 2015.

Section II: Literature Review and Background

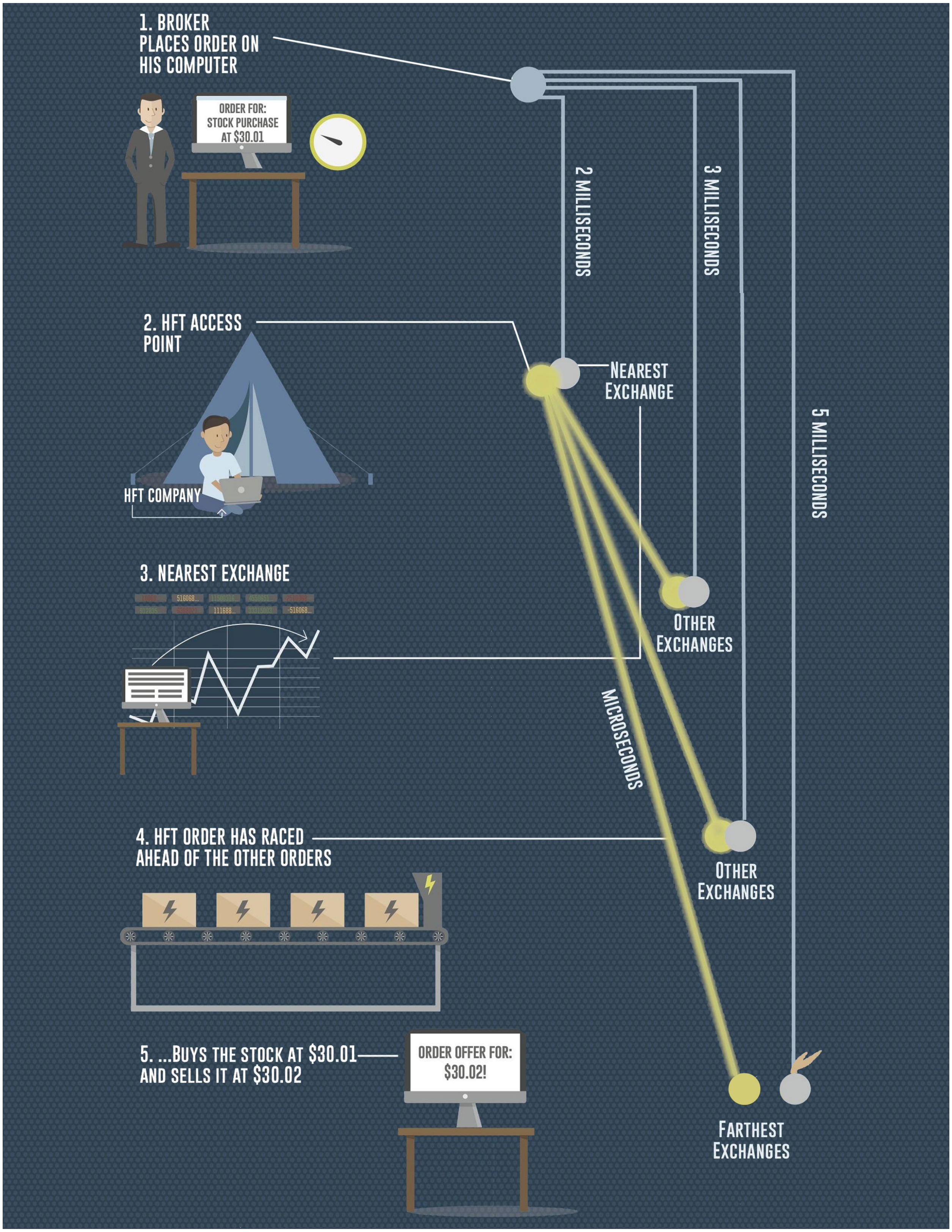
What Exactly is High Frequency Trading?

As Kirilenko and Lo (2014) describe HFT on the most fundamental level, it is, “a form of automated trading that takes advantage of innovations in computing and telecommunication to consummate millions upon millions of trades per day.”

Furthermore, high frequency trading is ubiquitous in the financial world nowadays: between 40-60% of trading (Kirilenko & Lo, 2014) is attributed to HFT with stocks, derivatives, and liquid foreign currencies. Although high frequency trading is so prominent and makes up for a substantial amount of daily financial transactions, a small number of entities regularly participate and “what is known about them is not particularly illuminating.”

A typical trade on a stock exchanged is outlined in Figure 1 (NBC News, 2014).

Figure 1: Typical Trade



Barriers to Entry

High frequency trading companies, or "shops" as they are often referred to, have been slow to emerge. This is because there are high barriers to entry for this market. The high barriers can primarily be attributed to one factor: the exorbitant cost due to fiber optic cable installation and co-location.

High Costs to Build: An Amendment to the Time Value of Money

Lewis's *Flash Boys* book begins by describing the 205 crews composed of eight men each which began one of the most secretive big digs in history, hoping to connect a line of fiber optics from the Chicago Mercantile Exchange to the Nasdaq stock exchange in Carteret, New Jersey. With fiber optic cables, trade orders could make a round trip from Chicago to New York in a matter of approximately 12 milliseconds. The traditional telecommunications providers in the United States (e.g. AT&T, Verizon, etc.) were slower, making the same round trip in approximately 17 milliseconds. Furthermore, there was variation from company to company and inconsistent speed fluctuations. For example, it was discovered that Verizon had a route that took 14.65 milliseconds compared to the more common 15, 16 and 17 millisecond routes.

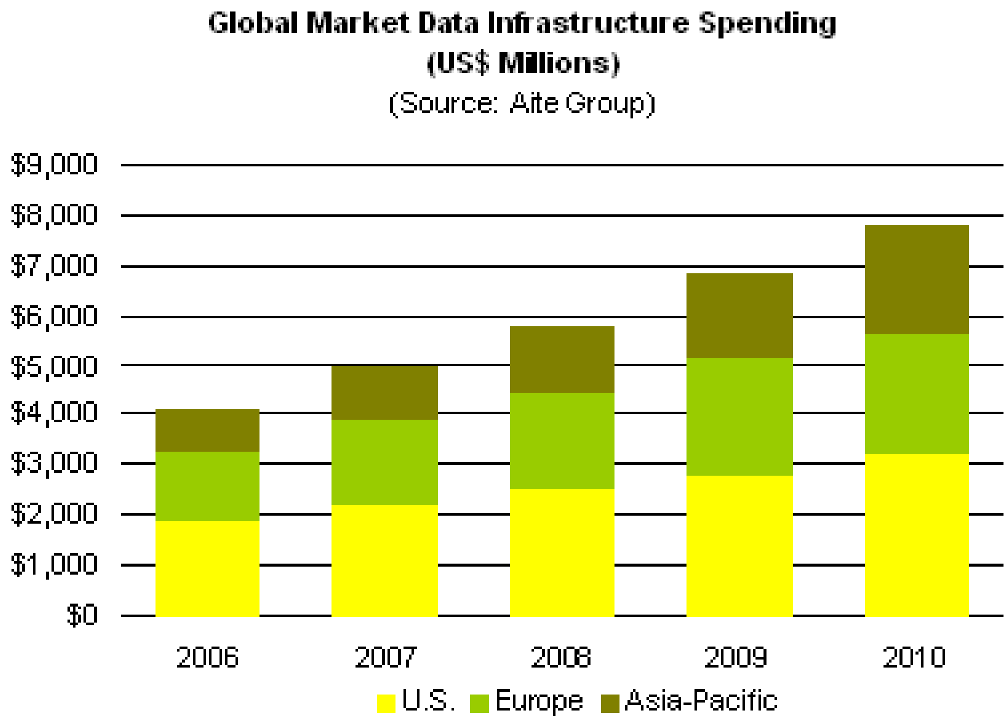
The reason time meant money was that there were price discrepancies in Chicago and New York, so timely access to a specific exchange in one area translated to substantial profits.

The 827-mile cable connecting the two cities cost approximately $300 million (Lewis, Flash Boys: A Wall Street Revolt, 2014). The problem was that the fiber optic cable could only support 200 traders. In total, the project to connect New York to Chicago via fiber optic lines would cost each trader $14 million, or $300,000 a month. This corresponded to a grand total of $2.8 billion dollars for a mere five-year lease on the line. At the time, this was the fastest route between the two cities, taking a mere 13-millisecond round-trip. The construction project spearheaded by Spread Networks ended in 2010, taking approximately one year to complete.

The promise of time reduction in the trading world meant a battle for inclusion in the exclusive cable lines. Wired Magazine published an article (Adler, 2012) noting, "Kevin McPartland of the Tabb Group, which compiles information on the financial industry, projected that companies would spend $2.2 billion in 2010 on trading infrastructure—the high-speed servers that process trades and the fiber-optic cables that link them in a globe-spanning network."

Figure 2 (Bailey, 2008) shows a summary of projected global expenditure on high performance trading infrastructure from the Aite Group.

Figure 2



From Figure 2 (Bailey, 2008) we see a consistent yearly increase in data infrastructure spending for the United States, Europe, and Asia-Pacific. This comes as no surprise given increased competition where everyone is trying to gain an edge and go to extremes. It is interesting, though, that the United States tends to spend a significant amount more than Europe and Asia-Pacific on data infrastructure. Although the United States spends the most cumulatively each year, Asia-Pacific has the highest, increased growth in spending over the five year time period.

Another comparable project to the aforementioned Chicago-New Jersey project is the transatlantic cable that connects UK traders to US traders (Phillps, 2012). The new path is supposed to save a mere 5 milliseconds off communication times.

Although there is data on infrastructure spending, it is interesting to think about, as Michael Lewis explains, the top-secret nature of these types of projects (Lewis, Flash Boys: A Wall Street Revolt, 2014). For example, even the construction workers working on the 827-mile fiber optic cable project connecting Chicago to New Jersey remained unaware of the reason behind their project. As "prop shops" and other companies in the financial services industry constantly seek advantages over their competitors, they obviously want to hide or disguise the steps they take. Therefore, although Figure 2 (Bailey, 2008) presents estimates for infrastructure spending, we conclude that the numbers are likely to be on the low end due to the inability to estimate other top-secret projects occurring.

Co-location

From Figure 1 (NBC News, 2014) we note the proximity of the HFT access point to the exchange in step two. Lewis repeatedly highlighted that every trader wanted to trade faster than the other trader (Lewis, 2014), obviously because there were large profits to be made and time was the limiting factor. He notes, "to be faster, [traders] needed to find shorter routes for the signals to travel... they needed the newest hardware, stripped down to its essentials." The location of traders' computers and the computers inside stock exchanges reduced distance, ultimately cutting more time. All of a sudden, a virtual battle broke out over cable length and computer location.

"Prop shops" were willing to pay millions to be placed inside an exchange (Lewis, 2014). In fact, arguments broke out over location inside remote data centers. The HFT shops were regularly replacing data switches and entire servers and enhancing the quality of their fiber optic cable; all these seemingly ridiculous upgrades were to shave microseconds off transaction times.

Pressure to beat other firms demonstrates the hostile and expensive competition within the industry. Yet, the rewards were enormous.

The term "co-location" was coined due to this obsessive fight to be as close as possible to the exchanges (Lewis, 2014). In summary, infrastructure spending and co-location expenses amounted to enormous sums of upfront money, demonstrating the high barriers of entering the market.

Example of HFT in Action

On August 18, 2011, Bloomberg released the headline "Hewlett-Packard Said To Plan Spinoff of PC Business" at 12:08:12.679 (Gourley, 2013). Almost instantaneously the market jumped approximately 14%, as shown in Figure 3.

Figure 3

In reality, it took four seconds from the time of the article publication for the market to react (Gourley, 2013). Nearly four years later, algorithms in high frequency trading have gotten much smarter. They have the ability to read the multitude of news articles to determine the gravity of an event that occurred and plug variables into a mathematical model. Once this has happened, the algorithm can buy and sell assets accordingly.

Obviously as we saw in 2011, a 14% increase in stock price can happen in a mere four seconds (Gourley, 2013); nowadays, that amount of time is drastically decreasing. Furthermore, the algorithms can behave in smarter ways, emitting "noise" for other algorithms to sort through, perhaps creating time disadvantages for market players.

It is important to highlight that the transactions that have the ability to control market prices worldwide are occurring automatically on timescales we cannot conceive.

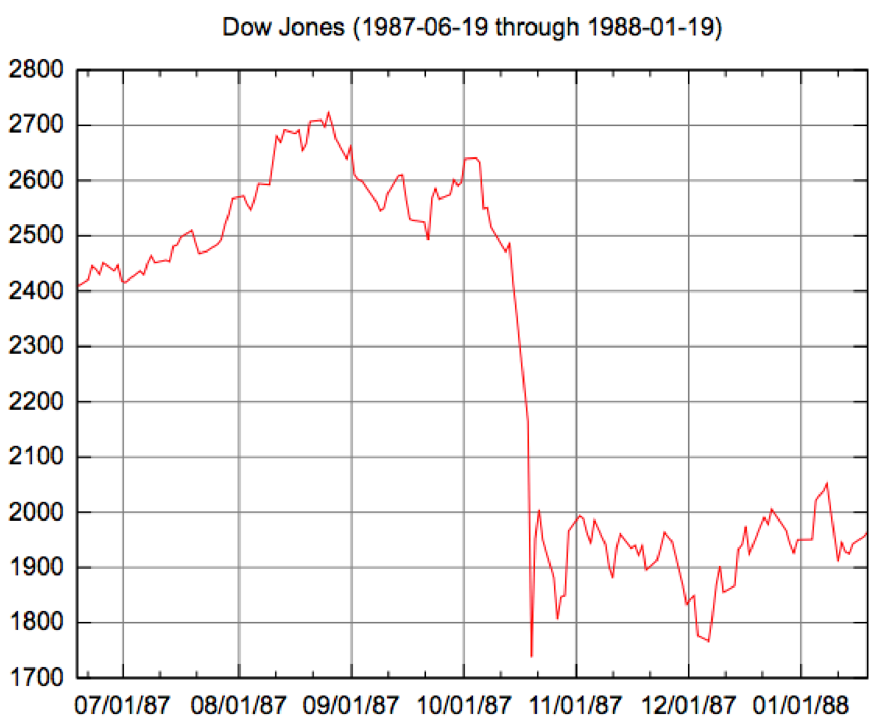
Notable Events Attributed to HFT

Over the past 30 years, two important market crashes have occurred where high frequency trading was somehow involved. This section explains the 1987 Market Crash as well as the 2010 Flash Crash in detail.

1987 Market Crash: The Emergence of Programs Tied to Market Crashes

On Monday, October 19, 1987 the financial markets experienced a shockwave that resonated worldwide. The Dow Jones Industrial average tumbled approximately by 508 points during a single day of trading, or roughly 22.61% as depicted in Figure 4 (Gourley, 2013).

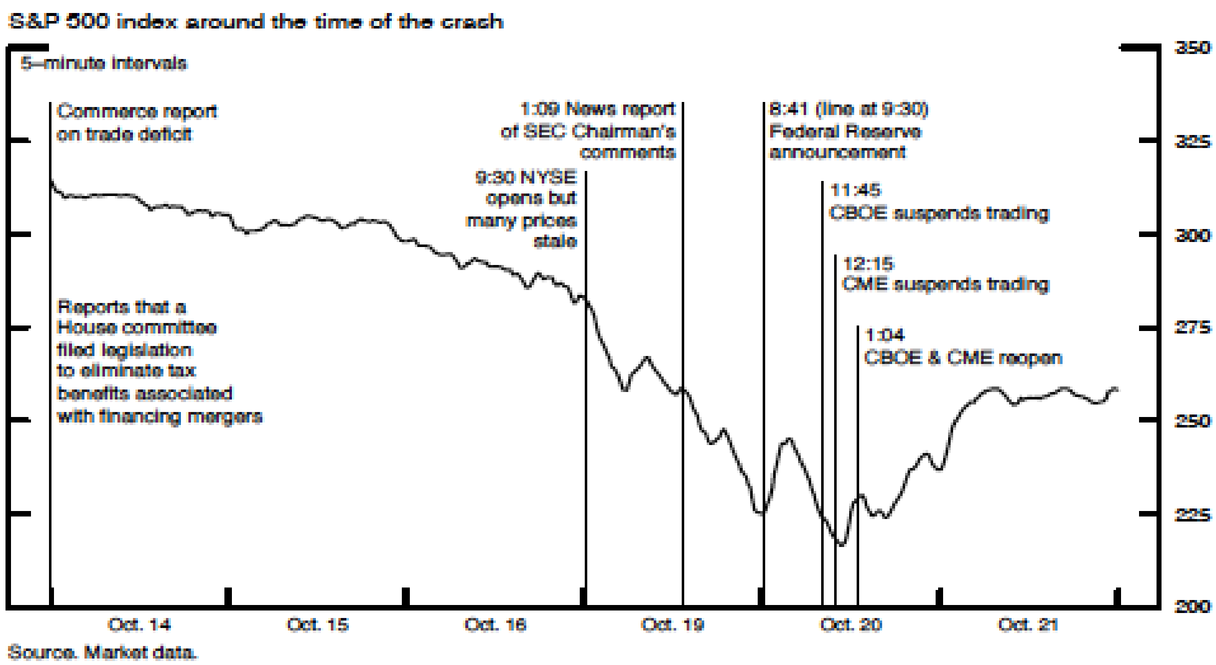
Figure 4



The S&P 500 and associated futures and options markets also crashed to similar degrees. The week leading up to Monday, October 19 recorded significant losses of nine percent (Carlson, 2006). Events leading to the crash are summarized in Figure 5. In the past several decades, this particular week, October 12-16, was one of the largest weekly declines, triggering anxiety, uncertainty, and questioning throughout the global marketplace for sound explanation.

Some key events in the October 12-16 week that aided in creating market uncertainty were the filings of legislation aimed at eliminating tax benefits associated with financial mergers and the dollar losing value (Carlson, 2006). An increase in interest rates subsequently placed downward pressure on equity prices. Abnormally high selling volumes were recorded in the last half hour of Thursday, October 15.

Figure 5



Friday morning, stock markets continued to plunge amidst market fear, forcing investors to hedge with futures contracts. Index arbitrage traders contributed to the NYSE's downward pressures by buying futures and selling stocks because of resulting price discrepancies in the two markets.

Trade volume was high on Monday the 19th, and technological problems led to trade executions taking over an hour. For example, a single firm recorded sales of $1.1 billion in selling large blocks of stock (Carlson, 2006). The preceding week's events combined with the newly created, unexplainable glitches and behavior on the 19th had disastrous results.

The severity of the crash can be attributed to three main reasons:

1. Margin Calls
2. Program Trading
3. Difficulty obtaining information

As we are primarily interested in program trading, it is certainly worth briefly discussing the other two points. Margin calls ultimately reduced market liquidity (Carlson, 2006). On the 19th, approximately ten times the normal size of margin calls were needed due to high price volatility in the futures market. Ultimately, retail investors could not meet margin calls, requiring liquidation in options markets that contributed to the aforementioned selling pressures. Technological problems led to difficulty obtaining information regarding current market conditions. Herd behavior ensued and traders sold and closed their positions, as they could not retrieve reliable price quotes for stock and stock indexes due to technological troubles. Rumors spread causing concern, which led to high selling volumes of stock.

Pertaining most to the topic of this thesis, program trading, especially portfolio insurance, is theorized to have also led to the crash (Carlson, 2006). According to the CME report summarizing the 1987 market crash, "portfolio insurance did contribute significantly to selling in the futures markets… however, this strategy was only one of many sources of selling, and does not by itself explain the magnitude of the crash." Individual investors used portfolio insurance to protect themselves from losses. The unknown effect of simultaneous portfolio insurance use by many investors may have created a feedback loop, causing systemic, downward price fluctuations. Furthermore, as portfolio insurers prefer using futures markets, 40% of futures sales that day were attributed to them. As previously highlighted, price discrepancies resulted between the futures and stock markets as a result.

The Federal Reserve was forced to immediately intervene to provide liquidity, restoring investor confidence in an efficient, reliable, and stable financial system.

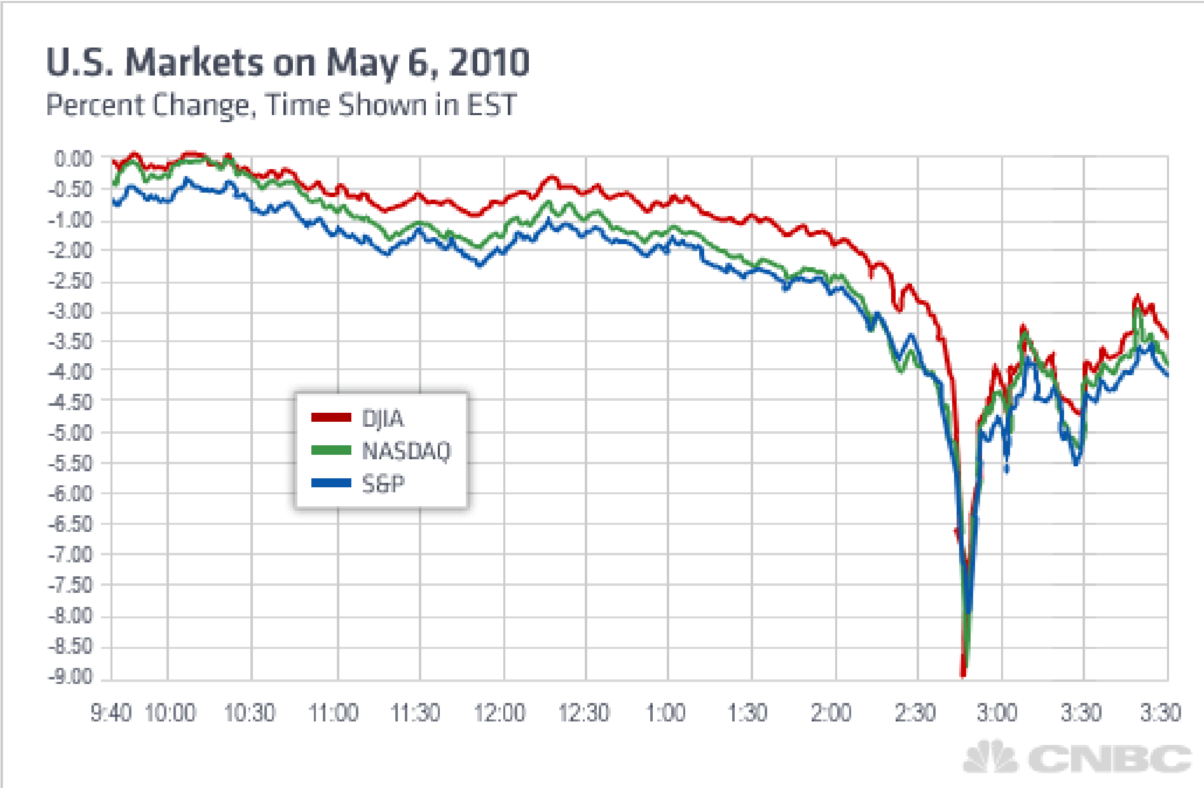
2010 Flash Crash

An Elementary Analysis

Thursday May 6, 2010 – starting at approximately 2:32pm EST, it took a mere 33 minutes for United States financial markets to undergo immense volatility that had never before been witnessed.

The Dow Jones Industrial Average recorded an approximately 9% or 1010.14 point loss within a matter of minutes (Kirilenko & Lo, 2014). The market would recover shortly after as shown in Figure 6.

Figure 6



Historically, this was the largest point decline in a single day ever recorded. A joint investigation led by the United States Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC) concluded that this was the effect of a perfect financial storm.

The investigation attributed this event to "an automated execution algorithm on autopilot, a game of 'hot potato' among high frequency traders, cross-market trading, and a practice by market makers to keep placeholder bid-offer 'stub-quotes" (Kirilenko & Lo, 2014).
Kirilenko and Lo (2014) explain that a later analysis seemed to attribute the event to a "rapid automated sale of 75,000 E-mini S&P 500 June 2010 stock index futures contracts (worth about $4.1 billion) over an extremely short time period) [which] created a large order imbalance that overwhelmed the small risk-bearing capacity of financial intermediaries –that is, the high frequency traders and market makers." Trading volume during this time period skyrocketed.

SEC interviews confirmed that, "arbitrage firms 'purchased the E-Mini and contemporaneously sold Standard & Poor's Depository Receipts S&P 500, baskets of individual securities, or other equity index products.'" In short, high frequency traders' automatic algorithms tried to exploit liquidity in the futures market but instead triggered a black swan event.

More generally, flash crash type events have the characteristics of "extreme short-term volatility combined with a rapid spike in trading volume" (Kirilenko & Lo, 2014). These black swan events seek to take advantage of seemingly favorable market conditions.

A Synopsis of an Expert Analysis

As these results were released in 2010, Kirilenko, Kyle, Samadi, and Tuzun later published a report in 2011 further investigating the roots of this particular market failure. They strived to answer the following three questions:

- "How did high frequency traders trade on May 6?
- What may have triggered the Flash Crash?
- What role did HFTS play in the flash Crash?"

We first analyze the audit trail, transaction-level data trading volume for regular transactions in the June 2010 E-mini S&P futures contract before and after the Flash Crash. The audit trail, transaction-level data for June 2010 E-mini S&P 500 futures contracts upon which the trader designation occurs hails from the Computerized Trade Reconstruction (CTR) data set. The CME is obligated to submit this dataset to the CFTC. Results are summarized in Table 1 (Kirilenko & Lo, 2014).

Table 1

	Panel A: May 3-5			
	DOWN		UP	
	Sell	Buy	Sell	Buy
High Frequency Traders	23,746	23,791	40,524	40,021
Intermediaries	6,484	6,328	11,469	11,468
Fundamental Buyers	3,064	7,958	6,127	14,910
Fundamental Sellers	8,428	3,118	15,855	5,282
Opportunistic Traders	20,049	20,552	37,317	39,535
Small Traders	232	256	428	504
	Panel B: May 6th			
	DOWN		UP	
	Sell	Buy	Sell	Buy
High Frequency Traders	152,436	153,804	191,490	189,013
Intermediaries	32,489	33,694	47,348	45,782
Fundamental Buyers	28,694	78,359	55,243	165,612
Fundamental Sellers	94,101	10,502	145,396	35,219
Opportunistic Traders	189,790	221,236	302,417	306,326
Small Traders	1,032	947	1,531	1,473

In Panel A results are shown for May 3-5, during down and up periods where the average number of contracts bought and sold are recorded (Kirilenko, Kyle, Samadi, & Tuzun, 2011). The down period is from 13:32:00 until 13:45:28 CT. The up period is from 13:45:33 until 14:08:00. Panel B explores the same volumes for both periods during May 6.

Comparing Panel A to Panel B, we immediately see an enormous increase in contracts bought and sold on May 6. It does not necessarily surprise experts that HFT constituted a sizeable portion of trades before and during the May 6 crash, but the significant upward swing in volume from the previous three-day period to May 6 is astounding. May 6 yielded 1,455,000 contracts traded by HFTs, or roughly one third of all trades that day (Kirilenko, Kyle, Samadi, & Tuzun, 2011).

Because holding horizons and trading strategies vary from trader to trader, trading accounts are organized into six categories as shown in Table 1 based on trading activity. They are generally defined as follows:

1. High Frequency Traders: "A subset of Intermediaries, who individually participate in a very large number of transactions…" ranking in the top 7%.

2. Intermediaries: "Short horizon investors who follow a strategy of buying and selling a large number of contracts to stay around a relatively low target level of inventory."

Fundamental Traders fall in one of the two following categories: buyers and sellers. Fundamental Traders are defined as "trading accounts which mostly bought or sold in the same direction during May 6." Buyers and Sellers are separated on the criterion of end of the day net position. If this is positive, they are buyers, and if this is negative, they are sellers.

3. Fundamental Buyers
4. Fundamental Sellers

5. Opportunistic Traders: "May behave like Intermediaries (both buying and selling around a target net position) and at other times may behave like Fundamental Traders (accumulating a directional long and short position)."

6. Small Traders: "Trading accounts which traded no greater than 9 contracts on May 6."'

It was found (Kirilenko, Kyle, Samadi, & Tuzun, 2011) that these six categories of traders have some overlap in terms of functionality in a liquid market "eco-system," yet each has a distinct goal. Most notably, however, the structure of overlap between May 3-5 and May 6 in terms of trader volume and net position scaled by market trading does not change. Table 2 (Kirilenko, Kyle, Samadi, & Tuzun, 2011) shows market descriptive statistics for the June 2010 E-Mini S&P 500 futures contracts for May 3-6, 2010.

Table 2

	May 3-5	May 6th
Volume	2,397,639	5,094,703
# of Trades	446,340	1,030,204
# of Traders	11,875	15,422
Trade Size	5.41	4.99
Order Size	10.83	9.76
Limit Orders % Volume	95.45%	92.44%
Limit Orders % Trades	94.36%	91.75%
Volatility	1.54%	9.82%
Return	-0.02%	-3.05%

The numbers for May 3-5 are averages for a specific day within that time frame. We again see the massive influx of traders participating in the market on May 6. It is concluded that HFTs must have dramatically changed their trading strategies yet preserved their trading behavior on May 6 (Kirilenko, Kyle, Samadi, & Tuzun, 2011). Strategies changed due to exacerbated selling pressures from Fundamental Sellers, while traditional HFT behavior of taking "liquidity from the market when prices were about to change and actively keep inventories near a target inventory level" remained consistent. It is notable that trade size, order size, limit orders % volume, and limit orders % trades do not fluctuate immensely. This provides further evidence that behavior of an individual trader did not necessarily change, however strategy changed.

Table 3 (Kirilenko, Kyle, Samadi, & Tuzun, 2011) separates summary statistics for each trader category, where the results for May 3-5 are again averages. Aside from the traditional, self-explanatory categories, the experts created two columns "Agg Ratio Trade-Weighted" and "Agg Ratio Vol-Weighted" which measure aggressiveness in orders. In this futures market, an "aggressive" order is categorized when "it is executed against a 'passive' order that was resting in the limit order book." Aggressive orders take market liquidity while passive orders provide market liquidity. The ratios point to which type of traders removed market liquidity.

Table 3

Panel A: May 3-5

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	34.22%	32.56%	15	5.69	14.75	100.000%	100.000%	49.91%	45.68%
Intermediaries	10.49%	11.63%	189	4.88	7.92	99.614%	98.939%	43.10%	41.62%
Fundamental Buyers	11.89%	10.15%	1,013	6.34	14.09	91.258%	91.273%	66.04%	64.09%
Fundamental Sellers	12.11%	10.10%	1,088	6.50	14.20	92.176%	91.360%	62.87%	61.13%
Opportunistic Traders	30.79%	33.34%	3,504	4.98	8.80	92.137%	90.549%	55.98%	54.71%
Small Traders	0.50%	2.22%	6,065	1.22	1.25	70.092%	71.205%	59.04%	59.06%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	2,397,639	446,340	11,875	5.41	10.83	95.45%	94.36%	1.54%	-0.02%

Panel B: May 6th

Trader Type	% Volume	% of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Agg Ratio Trade-Weighted	Agg Ratio Vol-Weighted
High Frequency Traders	28.57%	29.35%	16	4.85	9.86	99.997%	99.997%	50.38%	45.53%
Intermediaries	9.00%	11.48%	179	3.89	5.88	99.639%	99.237%	45.18%	43.55%
Fundamental Buyers	12.01%	11.54%	1,263	5.15	10.43	88.841%	89.589%	64.39%	61.08%
Fundamental Sellers	10.04%	6.95%	1,276	7.19	21.29	89.985%	88.966%	68.42%	65.68%
Opportunistic Traders	40.13%	39.64%	5,808	5.05	10.06	87.385%	85.352%	61.92%	60.28%
Small Traders	0.25%	1.04%	6,880	1.20	1.24	63.609%	64.879%	63.49%	63.53%
	Volume	# of Trades	# Traders	Trade Size (Avg.)	Order Size (Avg.)	Limit Orders % Volume	Limit Orders % Trades	Volatility	Return
All	5,094,703	1,030,204	15,422	4.99	9.76	92.443%	91.750%	9.82%	-3.05%

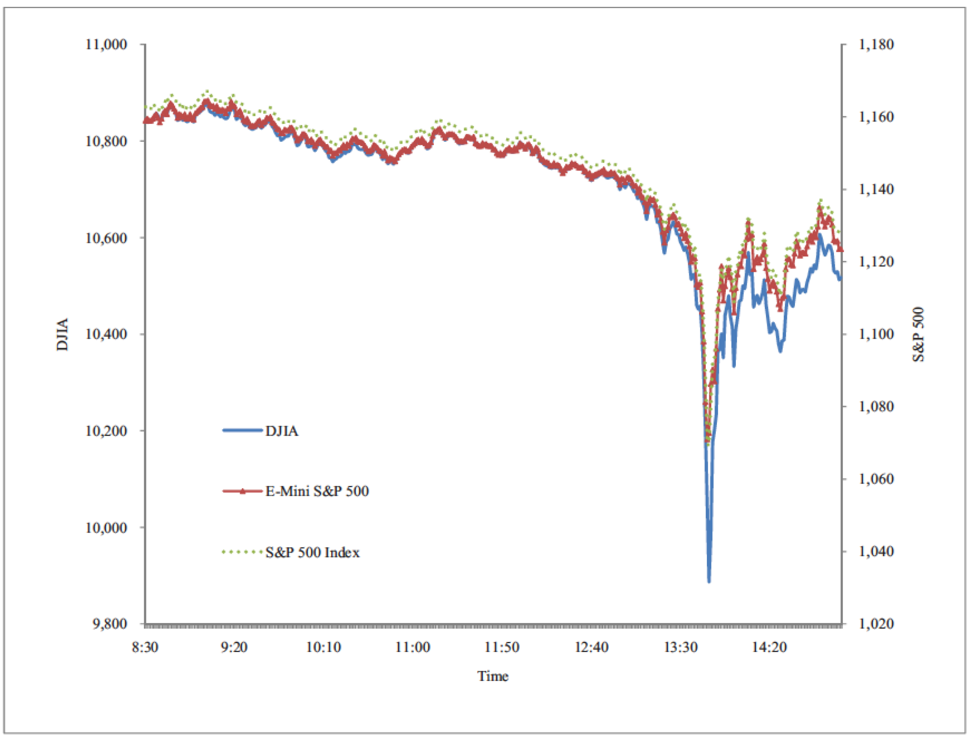
The findings from this data carry immense importance for the financial services industry and uphold certain hypotheses that did not stem from empirical or quantitative evidence. The first key point, which is consistent with a 2009 Menkveld et al. report, is that HFTs and Intermediaries add market liquidity while Fundamental Traders reduce market liquidity (Kirilenko, Kyle, Samadi, & Tuzun, 2011).

As reported earlier, the severe drop in market prices is attributed to two factors (Kirilenko, Kyle, Samadi, & Tuzun, 2011):

1. HFTs continuing to compete for market liquidity with Fundamental Sellers.
2. The 'hot potato' effect of rapidly buying and selling contracts solely between HFTs until Fundamental Buyers eventually intervened and took the contracts off the market.

Pertaining more to this expert analysis, we start by reviewing the U.S. Equity Indices on May 6, 2010 in Figure 7 (Kirilenko, Kyle, Samadi, & Tuzun, 2011), which specifically includes the timeline of the E-Mini S&P 500 time series.

Figure 7

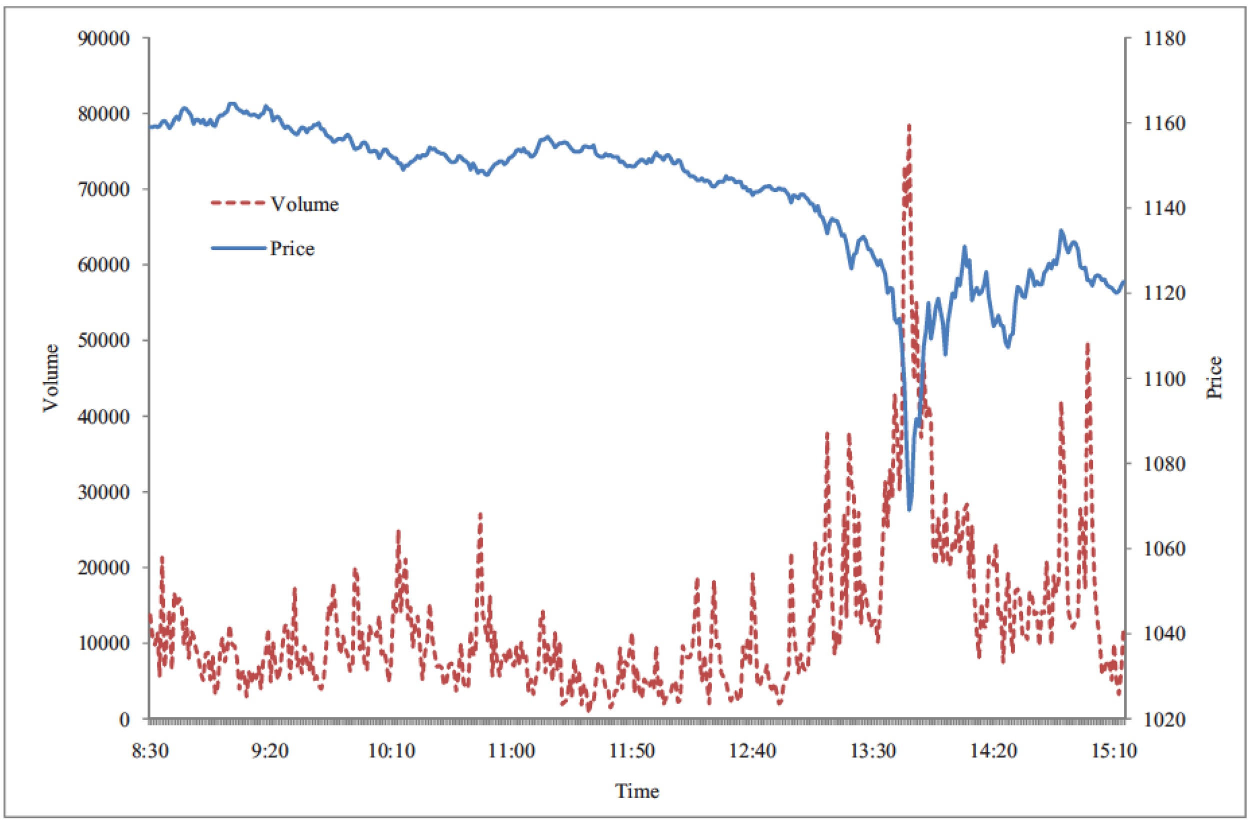


We note that the E-mini S&P 500, which naturally follows the trend of the DJIA and the S&P 500, bottoms at 1056.00 (Kirilenko, Kyle, Samadi, & Tuzun, 2011). The DJIA and the S&P 500 bottomed at 9872.57 and 1065.79 respectively. In a mere 13 minutes June futures contracts in the E-mini S&P 500 declined by 5.1%. Within another second of 13:45:27, the E-mini S&P 500 market dropped another 1.3% due to cascading orders. It is in the next immediate transaction that the CME Globex Stop Logic Functionality was triggered at 13:45:28 because the market would be operating out of its predefined bounds.

CME Globex has a Stop Logic Functionality (SLF) safety feature, which is, as indicated in the United States Commodity Futures Trading Commission's website (2015), "designed to prevent excessive price movements caused by cascading stop orders" in the CME futures market. The SLF safety function temporarily pauses the execution of transactions for about 5 seconds (known as the Reserve State) to theoretically increase market liquidity by allowing additional bids/offers to enter. The market is still open during the Reserve State, where order functionality remains normal.

Immediately after the Reserve State concluded, prices in the E-mini S&P 500 quickly rebounded, recording an increase in 6.4% from the minima from 13:45:38 until 14:06 (Kirilenko, Kyle, Samadi, & Tuzun, 2011). The market was said to have recovered, showing a price of 1123.75, which is close to where it was at 13:32:00 before the rapid futures sell-offs. One-minute interval trading volume and prices for May 6, 2010 are summarized in the E-Mini S&P 500 Stock Index Futures Contract time series in Figure 8.

Figure 8



The joint SEC and CTFC investigation led to the following statement (2010):

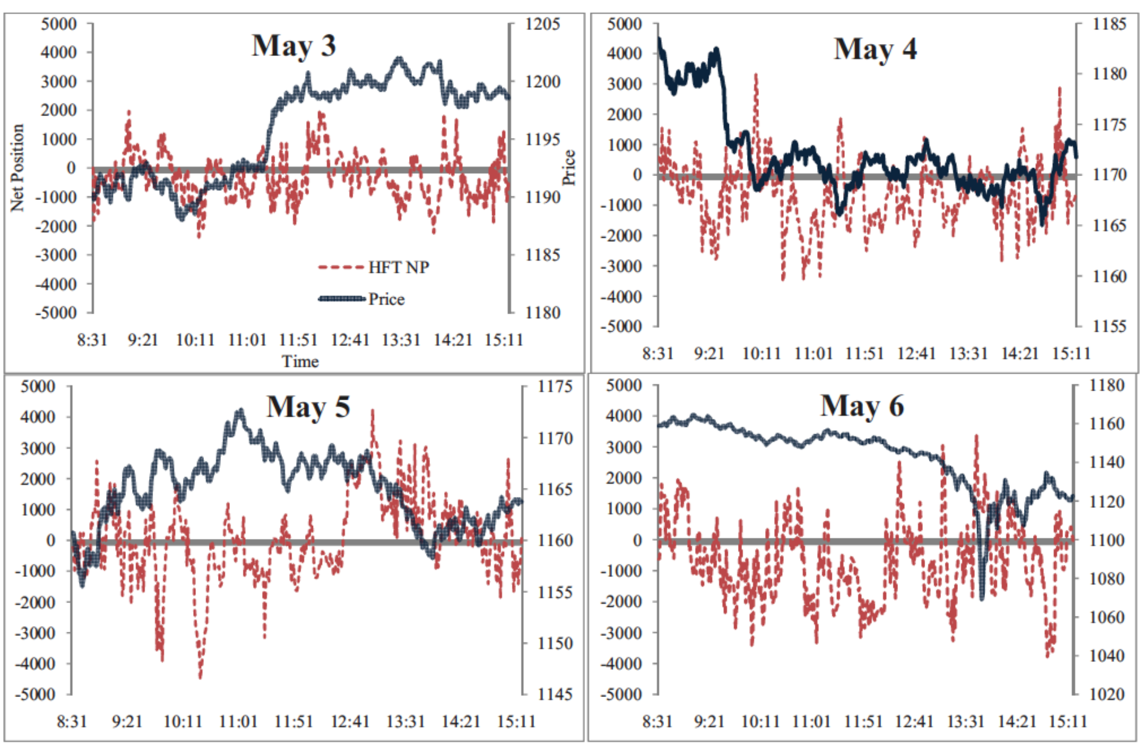
> At 2:32 p.m., against this backdrop of unusually high volatility and thinning liquidity, a large fundamental trader (a mutual fund complex) initiated a sell program to sell a total of 75,000 E-Mini contracts (valued at approximately $4.1 billion) as a hedge to an existing equity position.
>
> This large fundamental trader chose to execute this sell program via an automated execution algorithm (Sell Algorithm) that was programmed to feed orders into the June 2010 E-Mini market to target an execution rate set to 9% of the trading volume calculated over the previous minute.

> The execution of this sell program resulted in the largest net change in daily position of any trader in the E-Mini since the beginning of the year (from January 1, 2010 through May 6, 2010). Only two single-day sell programs of equal or larger size, one of which was by the same large fundamental trader, were executed in the E-Mini in the 12 months prior to May 6.
>
> When executing the previous sell program, this large fundamental trader utilized a combination of manual trading entered over the course of a day and several automated execution algorithms, which took into account price, time, and volume. On that occasion it took more than 5 hours for this large trader to execute the first 75,000 contracts of a large sell program.

Interestingly enough, on Tuesday, April 21, 2015, British authorities arrested Navinder Singh Sarao on charges of fraud, manipulation, and spoofing, among a lengthy list of other charges (Brush, Schoenberg, & Ring, 2015). In the U.S. he is charged with 22 criminal accounts for his actions that are believed to have played a significant role in creating the liquidity imbalance observed during the 2010 Flash Crash. Sarao's illegal algorithmic trading strategies were recorded in the derivatives market and stock markets. To put the gravity of his actions into perspective, Sarao made approximately $200 million worth of orders betting the market would fall (Viswanatha & Hope, 2015). At the time, the trade represented 20-29% of market orders. 19,000 modifications ensued before the orders were cancelled. Trader strategies will be discussed in Section III. Sarao is accredited with making $40 million in profits between 2010 and 2014.

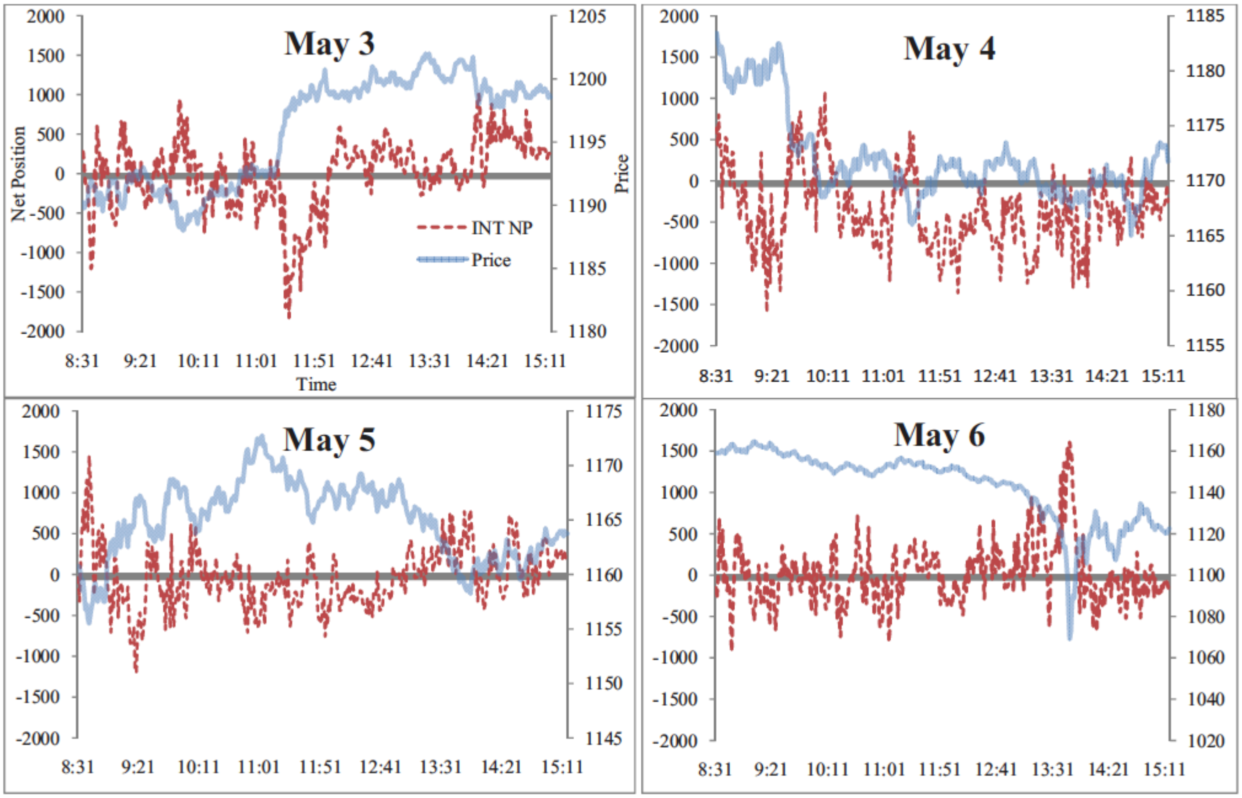
Furthermore, we analyze net holdings positions of High Frequency Traders and Intermediaries. A time series of net position of high frequency traders is shown in Figure 9 while net position of intermediaries is shown in Figure 10 (Kirilenko, Kyle, Samadi, & Tuzun, 2011).

Figure 9: Net Position of High Frequency Traders



From May 3-6 we conclude that High Frequency Traders' net position fluctuates between +/- 3,000 contracts and maintains a mean close to zero.

Figure 10: Net Position of Intermediaries



From May 3-6 we observe that Intermediaries do not accumulate a significant position, and even though they behave like High Frequency Traders during the same day interval, their mean seems to be below zero with a smaller range of net position.

From the plots in Figures 9 and 10 it is evident that HFTs maintained the same behavior over the four-day period. When prices initially fell on May 6, HFTs were able to sell their long inventory since they had accumulated a positive net long position before prices fell at a faster rate (Kirilenko, Kyle, Samadi, & Tuzun, 2011). Conversely, the Intermediaries held their net long positions longer than HFTs before they eventually sold them. High Frequency Traders increase price volatility when seeking liquidity in the market. Market imbalances occur as a result of a lack of long-term liquidity suppliers and Intermediaries that do not want to temporarily hold large buy or sell orders from large traders.

In conclusion to this section, the 2010 Flash Crash is arguably the most important event to date regarding the role of High Frequency Traders. It puts into perspective the fragility of the financial ecosystem and the immense volatility the future potentially holds.

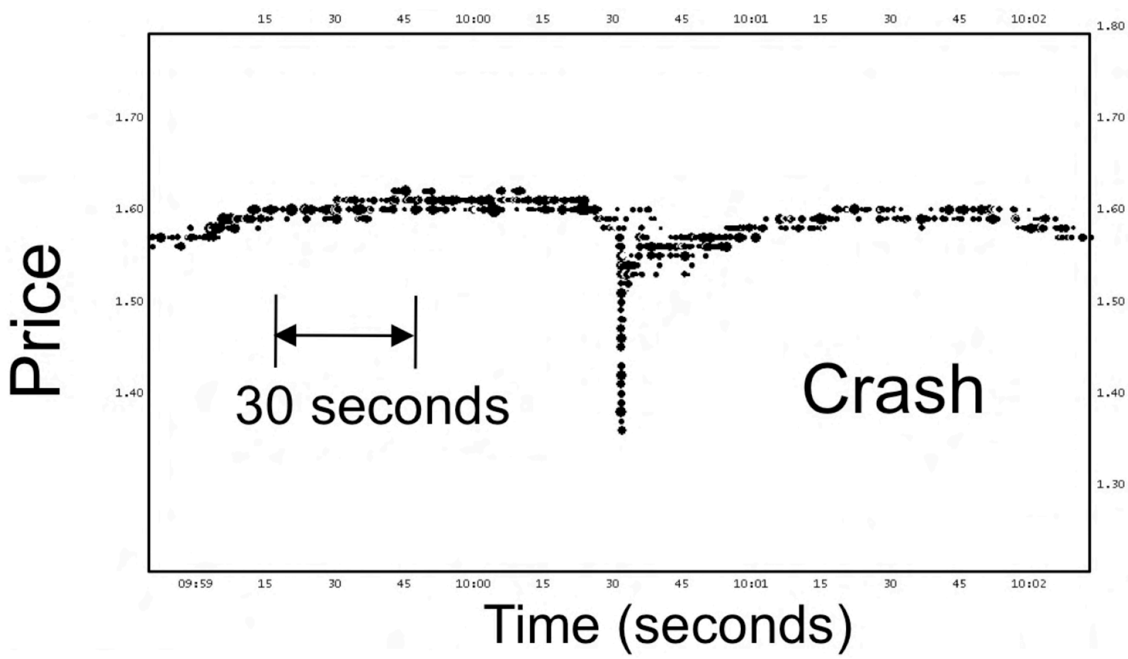
Black Swans in an Ever-Changing Financial Landscape

A report by Johnson et al. uncovered 18,520 ultrafast black swan events in stock-price movements in the 2006-2011 timeframe. The implementation of extremely fast socio-technical systems has demonstrated the increased frequency of surprising extreme events that have major effects, yet inaccurate, immediate explanations. The Flash Crash of 2010 is one such example, where it has taken experts years to grasp a thorough understanding of the root causes triggering the event.

Black Swan events are difficult to foresee and manage in the transition from a mixed human-machine phase to an all-machine phase. Humans are typically able to identify and react to a troubling situation in approximately 1 second, or 1000 milliseconds (Johnson, et al., 2012). In order to analyze ultrafast black swan events, both stock price drops and rises must be recorded. Their respective definitions are as follows, as presented by Johnson et al.:

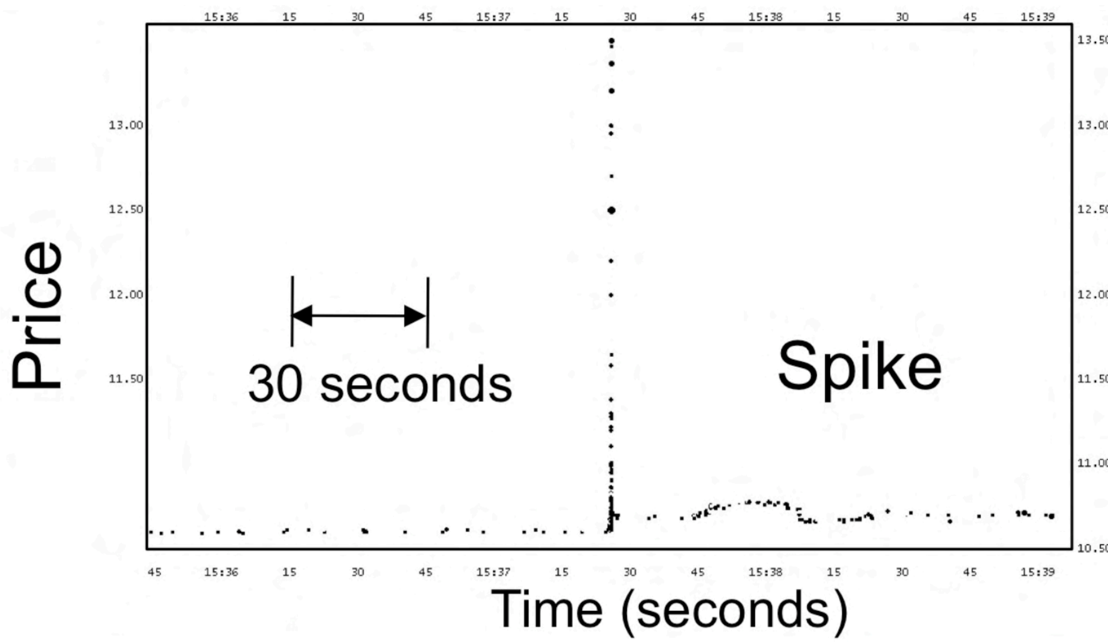
- "For a large price **drop** to qualify as an extreme event (i.e. black swan crash) the stock price had to tick **down** at least ten times before ticking up and the price change had to exceed 0.8%" (refer to Figure 11).

Figure 11



- "For a large price **rise** to qualify as an extreme event (i.e. black swan spike) the stock had to tick **up** at least ten times before ticking down and the price change had to exceed 0.8%" (refer to Figure 12).

Figure 12



On average, approximately one black swan event occurred per trading day (Johnson, et al., 2012). In the findings, researchers concluded that automatically triggered exchange responses or predatory algorithms likely cause the market to quickly recover after the black swan event occurred. For example, in the 2010 Flash Crash, the Stop Logic Function was triggered, leading the market recovery. As part of the 2008 Financial Crisis was attributed to subprime lending from large financial institutions, it comes as no surprise that financial institutions accounted for the top ten stocks with the highest incidences of ultrafast black swan events from 2006-2011.

Black swan events are analogously related to micro-fractures in mechanical structures; as micro-fractures can cause a certain area to weaken, or even break off, these financial micro-fractures can lead to catastrophic financial downturns, or crises. Furthermore, small time scales of 100-200ms contained ten times more fractures than fractures recorded from 900-1000ms (Johnson, et al., 2012).

Johnson et al. develop a mathematical model that describes the scale of price fluctuations in specific phases given a certain number of agents participating. This model explains the reasoning for an increase in black swan events during shorter durations. Ultimately, black swans are constantly increasing in worldwide markets, demonstrating the fragility of such a complicated system. It is suggested that policy is at a subpar level to effectively regulate the technical intervention of the financial markets within the past decade. Formulating efficient policy is hindered by the immense complexity of a multitude of variables lacking clear understanding among humans.

Furthermore, operating on an inconceivable time scale to humans, although has many benefits, increases the chance for human error to cause financial meltdowns. Although immediate recovery seems to be ensured, as demonstrated with previous black swan type events, the evolving financial ecosystem may become more fragile with impending technological advancements. It seems therefore paramount to adequately control and understand what has currently been implemented before moving forth.

Flash Orders

Flash orders remain as one of the most controversial topics discussed in high frequency trading. Flash trades use ultra fast technology that "allows traders to view orders from other market participants fractions of a second before others in the market place because an exchange or market center is not quoting the best price or cannot fill that order in its entirety" (Harris & Namvar, 2011).

A recent economic analysis (Harris & Namvar, 2011) describes the involvement of three potential traders labeled as "submitter," "responder," and "maker" to explore how flash trades work. Submitters are traders who send orders to the exchange and Responders are traders who use the exchange's flash facility to respond to incoming orders; the Maker trader makes the best market at a different exchange.

Flash orders have the ability to be attractive to Submitters over intermarket order routing for several reasons. One primary reason is that flash facilities provide greater liquidity and lower fees as compared to make-or-take exchanges (Harris & Namvar, 2011). Furthermore, Submitters are able to cancel or modify their orders if a flash trade is not advantageous. Responders are able to fill the order during the flash period or otherwise be rerouted using intermarket routing where Makers are selling at the best price. Flash orders do carry some risk, however, as Responders can use a technique called front-running, which is considered illegal. Front-running occurs when Responders fail to immediately execute the Submitter's exposed order. As Responders are able to take liquidity from other markets during the flash period that Submitters would have obtained by intermarket routing, the Responders can return and fulfill the original Submitter's order at an inferior price. The Responders are therefore able to make a profit bearing negligible risk.

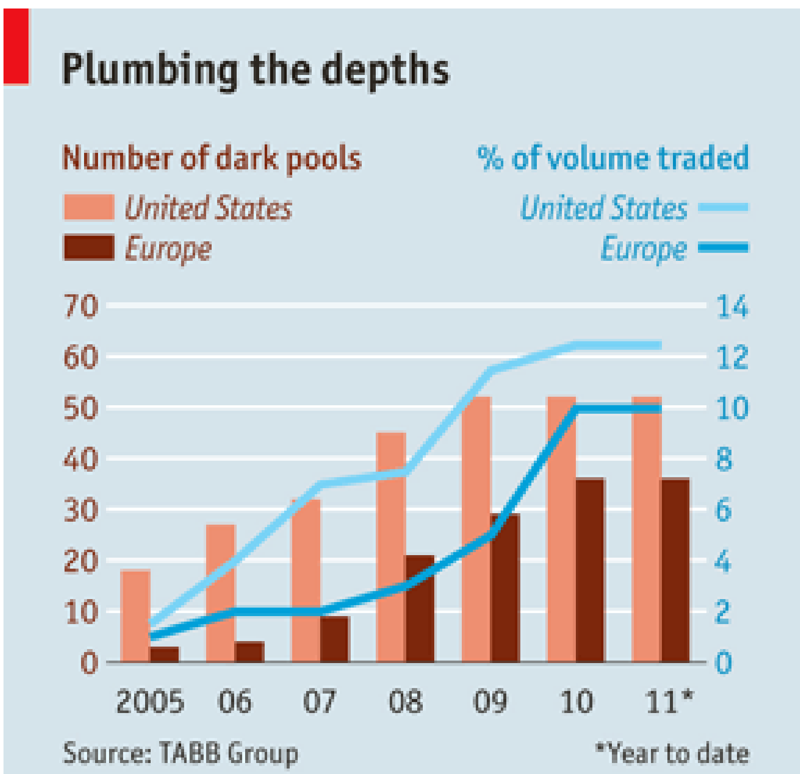
Flash orders are considered by many to be unfair because handpicked Responders receive order information before other market participants are exposed to the same information (Harris & Namvar, 2011). The handpicked Responders typically have to pay for the privilege or fulfill other market-making responsibilities. High frequency trading systems allow Responders to easily front-run Submitters. Contrary to this unfair belief, many flash order advocates draw parallels between flash orders and traditional, U.S. floor-based equity exchange trading. Floor trading had an analogous "flash period" where floor traders were exposed to order information before the rest of the competing buyers and sellers in the market connected electronically. In this argument, "the notion of seeking additional liquidity from other participants in the exchange is essentially the same."

Exchanges prematurely "flash" critical market information about buy and sell orders to preferred traders who pay the exchange a fee. The market information has not been made publicly available at the time of the "flash." This clearly gives specific traders a sustainable competitive advantage to ultimately outperform the traders without the market information.

Dark Pools

Dark liquidity trading pools, or Alternative Trading Systems (ATS), or most commonly referred to as "dark pools", have emerged as one of the murkiest trading platforms and resulted in much debate and controversy surrounding high frequency trading (Tuttle, 2013). Dark pools are similar to central trading exchanges in that they allow buyers and sellers to enter the market to purchase or sell volume. Access to dark pools for the general public is prohibited (2012); dark pools are created to facilitate traders who routinely place large orders. Most commonly, dark pools are owned by brokers and independent companies. As Dr. Haoxiang Zhu from MIT's Sloan School of Management defines them as "equity trading systems that do not publicly display orders" (2013). Figure 13 (2011) shows the emergence of dark pools in the United States and Europe from 2005-2011.

Figure 13



We note from Figure 13 (2011) that the number of dark pools in both the United States and Europe skyrocketed between 2005 and 2011. By 2009, the United States had just over 50 dark pools, while Europe had 30. The percent of volume traded in dark pools also increased substantially in the United States and Europe. Although the United States and Europe only executed about one percent of trades in dark pools in 2005, 2008 through 2010 data showed an increase of about seven percent in trade volumes in dark pools. By 2011, just over 12 percent of volume was traded in dark pools in the United States, while that number for Europe was about 10 percent.

Most notably, the Goldman Sachs dark pool known as "Sigma X" and the Credit Suisse dark pool known as "Crossfinder" infamously competed to be Wall Street's biggest private stock exchange (Lewis, Flash Boys: A Wall Street Revolt, 2014). As Michael Lewis reveals in *Flash*

Boys, "transparency was big Wall Street Banks' enemy." Exchanges run by brokers were not required to reveal the transactions within their respective dark pools to the public; only these brokers knew exactly what would occur. Because there was sufficient delay in trade reports, knowing what occurred in the broader market at the time of an initial trade was impossible. Each dark pool is able to have its own set of rules and subscribers. The costs of running a dark pool are offset, primarily because a lot of people were willing to pay a lot of money to be in the pool, most notably high frequency traders.

Although dark pools are used for potential price improvements (Zhu, 2013) they remain unattractive for uninformed traders because, as Brad Katsuyama, a trader at RBC at the time, commented, "you could front-run an order in a dark pool on a bicycle." High frequency traders, specifically, had this advantage and could exploit the market and get away with it while making huge profits.

The following excerpt illustrates the actions of a high frequency trader in a dark pool (Lewis, Flash Boys: A Wall Street Revolt, 2014):

> "The pension fund trying to buy 100,000 shares of Microsoft could, of course, specify that the wall street bank not take its orders to the public exchanges at all but simply rest it, hidden, inside the dark pool. But an order hidden inside a dark pool wasn't very well hidden. Any decent HFT who had paid for a special connection to the pool would ping the pool with tiny buy and sell orders in every listed stock, searching for activity. Once they'd discovered the buyer of Microsoft, they'd simply wait for the moment when Microsoft ticked lower on the public exchanges and sell it to the pension fund in the dark pool at the stale, higher 'best' price."

This elementary example is fascinating, because, as previously discussed, the high frequency trader uses predatory algorithms and front-running to ultimately reap profits. One of the reasons Wall Street banks felt that the dark pools were beneficial was because investors could reveal large market orders without fearing that the orders would be exploited. By mid 2011, public exchanges noticed a decrease in orders by 30% (Lewis, Flash Boys: A Wall Street Revolt, 2014). Zhu deduces that price discovery is improved when dark pools are added to normal market exchanges (2013). As a result, reduced exchange liquidity enhances price discovery, demonstrating a more efficient market.

All of a sudden there was a rush for each Wall Street bank or broker to glorify their dark pool (Lewis, Flash Boys: A Wall Street Revolt, 2014). It seemed as though all Wall Street banks published reports ranking their dark pools number one across an array of categories. Furthermore, a significant amount of data about specific dark pools was obviously self-generated for glorification purposes. Dark pools had become a source of income for banks among competing high frequency traders. Clearly big banks as well as high frequency traders were making profits at the expense of traditional traders and investors. Illicit activity could easily be covered up. The primary reasons institutional clients prefer dark pools are because of high liquidity, improved order pricing, and low transaction costs. We seem to have an arms race.

Section III: Algorithmic Trading Strategies

Algorithmic Techniques

We discussed the fact that high frequency trading is a subset of algorithmic trading. High Frequency Trading can be divided into two kinds of groups:

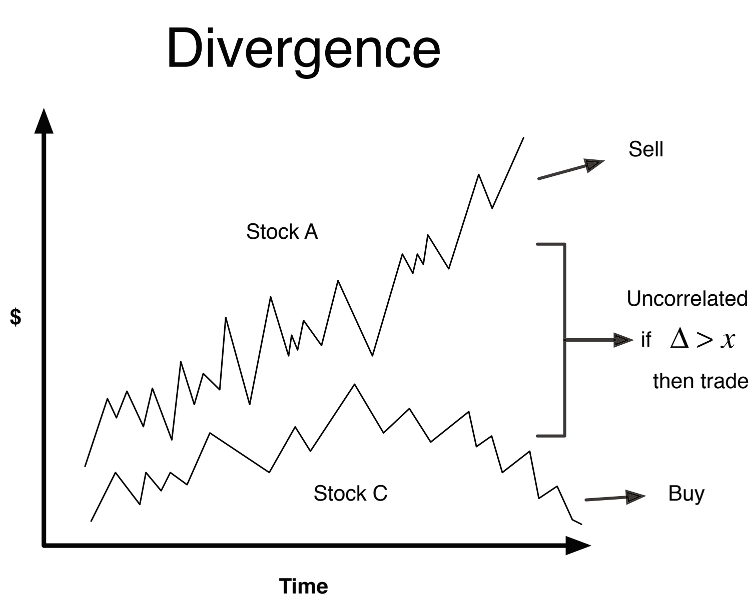
1. Market Makers
2. Statistical Arbitrage

As statistical arbitrage aids in determining what will happen to the market in the future, a number of common algorithm techniques fall into this category. While there is a plethora of trading strategies, this section analyzes the main strategies pertinent to high frequency traders. A key distinction between the two categories of trading strategies is that those associated with high frequency trading typically carry very little risk. Traditional trading strategies common to typical traders carry significantly more risk than those of high frequency traders.

Pairs Trading

A pairs trade is one of the classic examples of a statistical arbitrage trade. It works by transforming a time series of a single stock into a binary signal of zeros and ones. The algorithm proceeds to extract the time series from all other stocks in the market and again is able to convert those time series into binary, hoping to find a correlation. If the algorithm finds another stock in the market that is highly correlated with the original stock, it tracks the two together. The key is to find when the two originally correlated stocks diverge, as demonstrated in Figure 14 (Gourley, 2013).

Figure 14

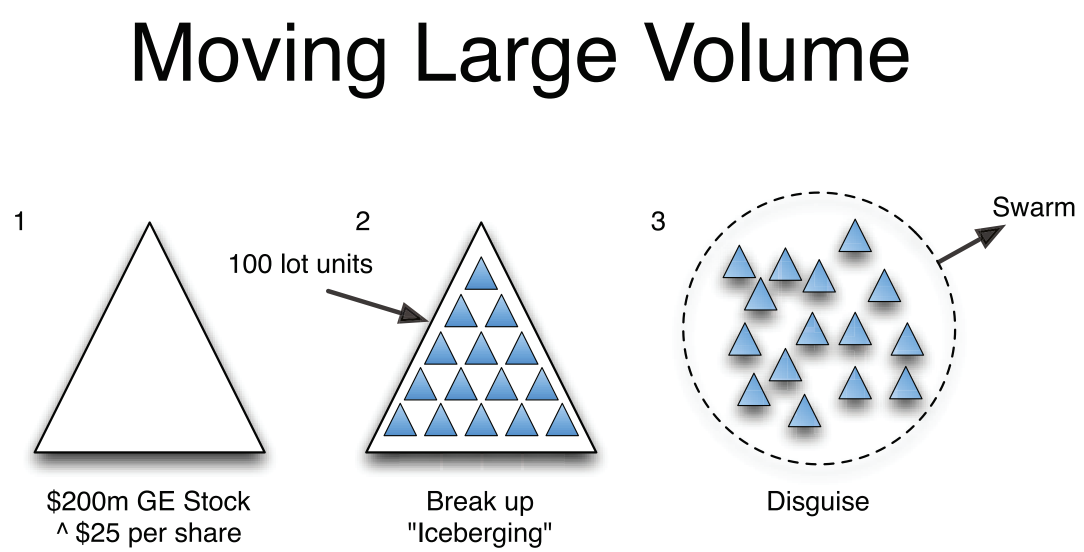


If the delta value between the two prices reaches a predetermined value, *x*, the algorithm makes the trade (Gourley, 2013). Timing is critical, because if the algorithm is the first to respond and make the trade, the trader makes a profit. If the algorithm is too slow and is not able to make the trade in time, the trader has effectively lost to other competition in the market. In this case the algorithm will buy C and sell A at the same time. Given C's price, A is overvalued, but given A's price, C is undervalued. The belief is that the divergence was a mere fluctuation in the market, and that the ratio between A and C will be restored. As long as the ratio has been restored, money has been made off the trade. The only risk is whether the convergence actually occurs.

Moving Large Volume and Predatory Algorithms (Sharks)

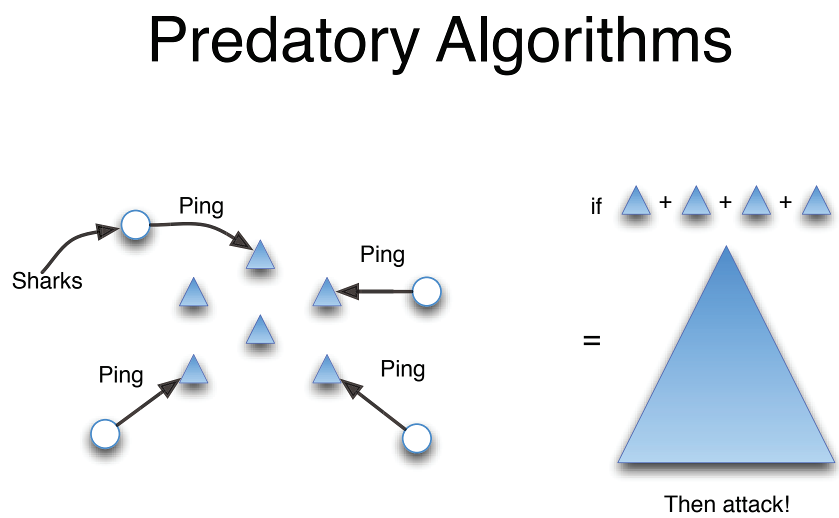
Another example of a strategy used in high frequency trading is when a trader wants to move a large amount of volume through the market. In Figure 15 (Gourley, 2013), the large volume is $200 million of General Electric (GE) stock. The algorithm takes this $200 million chunk and breaks it up into blocks, effectively disguising it. Failure to disguise the large volume will result in obvious market saturation, causing the stock to lose value. The swarm is then able to effectively move through the market, retaining the original market value determined in step one.

Figure 15



As the trader moving large volume is able to make a lot of money in these selling transactions at $25 per share, other traders will use algorithms to identify suspicious or notable market activity. The competing algorithms, otherwise known as predatory algorithms, or sharks, effectively aim to reverse engineer the disguise as depicted in Figure 16 (Gourley, 2013).

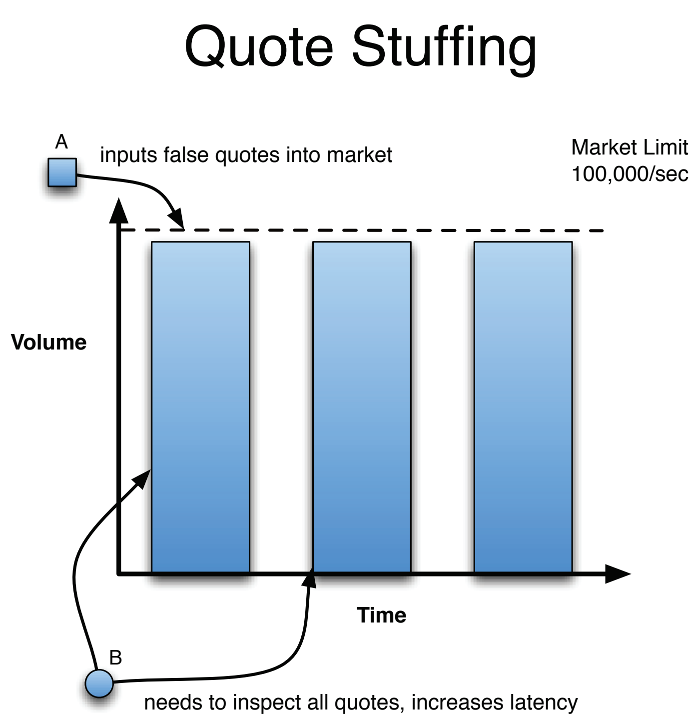
Figure 16



The sharks wait and constantly "ping" the market until they find a competitive price, for example at $24.50 (Gourley, 2013). Once the sharks receive a "hit," they will continue to "ping" the market, changing their desired price and volume specifications. The methodology aims to reveal the disguise fabricated by the original, "stealth algorithm" trying to move the swarm without detection. The sharks then attack the GE stocks if they receive enough hits, and ultimately end up making a profit through this process. This is because the predatory algorithm knows another trader is willing to the buy the shares at a slightly higher price. A typical trader places a market order for a certain amount of shares at what they believe will be a certain price. Because the nature of their order, this is not a set price. This predatory algorithm has the ability to buy all those shares in the market, beating the regular trader to the shares, and increasing the price by a small amount, and sell them back to the trader.

Quote Stuffing

Figure 17

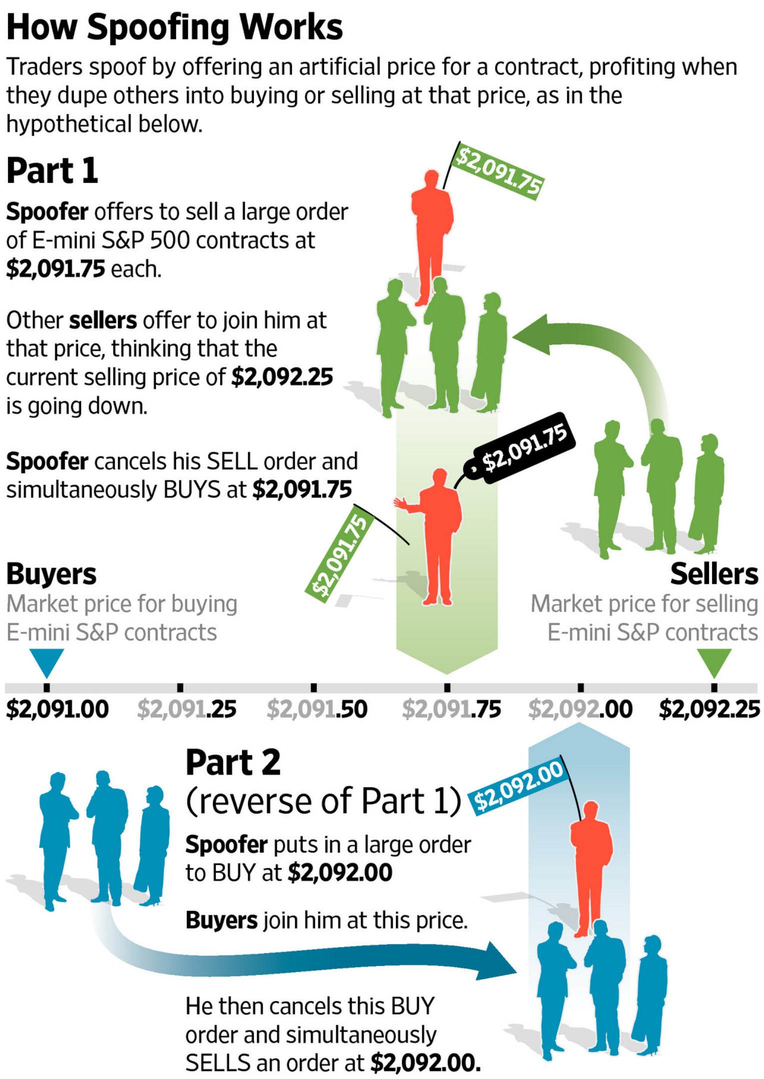


Another common algorithm is called quote stuffing and can be classified as illegal, depending on the trader's intent. The tactic is shown in Figure 17 (Gourley, 2013). The ideology behind this is that algorithms can make significant "noise" quicker than they can interpret large volumes of market information. Therefore, the quote-stuffing algorithm will "stuff" false quotes into the market, forcing competitors with other algorithms to sort through and interpret these false quotes. This process of interpretation adds significant time where microseconds are significant.

Spoofing

Although closely related to quote stuffing, spoofing is highly illegal and punishable. Spoofing was one of the strategies observed during the 2010 Flash Crash and aided Navinder Singh Sarao in amassing exorbitant profits. A recent Wall Street Journal article effectively describes a fundamental spoofing operation as shown in Figure 18 (Viswanatha & Hope, 2015).

Figure 18



A trader using the spoofing technique can either be a buyer or a seller. If the spoofer is initially a seller, the spoofing algorithm floods the market with false quotes and deceives other sellers. If the spoofer is initially a buyer, the spoofing algorithm deceives other buyers. Spoofers effectively fake the market in one of two ways:

1. They temporarily lower the price of a contract, making other sellers believe the market price is falling.

2. They submit an artificial order to buy a contract with the preconceived intention of cancelling the order.

We note that in Part 2 of Figure 13, the spoofer had originally bought the contract for $2,091.75. So, when the other buyers change their prices to meet the spoofer at his price, the spoofer cancels his buy order and sells at the new market price of $2091.75. He therefore makes a profit of $0.25 on each contract. The HFT spoofer will obviously sell as much as he can to increase his profits. Sometimes the profit on a contract is only a penny or two, however when selling thousands of contracts, the pennies can easily amount to large net profits.

It is important to make a clear distinction between quote stuffing and spoofing. Spoofing is directed at non-HFT traders and doesn't necessarily slow anyone down to the same degree quote stuffing does. Quote stuffing, however, is intended to slow other competing HFT algorithms so that the spoofer gains a time advantage over the other traders. The spoofer is subsequently able to react to favorable market conditions before others and execute the necessary transaction to yield a profit. Algorithms competing with spoofers aim to quickly sort false quotes, or "noise," that have flooded the market.

In summary, algorithms are top secret among the HFT shops competing for profits. It could be stated that HFT shops persistently try to be first to develop a new strategy and implement it in the market. If the strategy is successful in yielding profits, it typically does not take a long time for competitors to pick up on the strategy and create a modified algorithm to exploit a particular weakness. As strategies and subsequently algorithms are becoming more complex, the financial services landscape has changed immensely over the last several years. The danger of these constantly adapting strategies and algorithms is that the effects on the market when they intersect are, for the most part, unknown.

Section IV: Elementary Policy Analysis

Understanding Existing Market Structure and Policy

(Johnson, et al., 2012) argue that effective regulation is paramount to the financial industry until scientists develop a theory for human-machine ecology on inconceivable timescales.

As quoted from IEX (2015), on the most basic level, stock markets exist for two reasons:

- "For companies to raise capital through the issuance of stock to investors."
- "To allow investors to buy and sell shares with each other in a fair and efficient way."

The Securities Exchange Act of 1934 envisioned a market ecosystem with four primary responsibilities:

1. "Uphold just and equitable principles of trade
2. Remove impediments to a free and open market
3. Protect the investors and public interest
4. Facilitate an opportunity for investor orders to meet directly"

The current market place is arguably incredibly convoluted, complex, and deviates from the ideals formally introduced in 1934. Since 1934, a number of laws have been implemented to effectively govern the securities industry (2015). A few examples include the Investment Company and Investment Advisers Acts or 1940, and more recently Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.

There exist 13 registered exchanges that are regulated and approved by the Securities and Exchange Commission (SEC) (2015). Furthermore, over 40 dark pools exist. The sum of over 50 markets has made it difficult for investors to interact with each other. Furthermore, since high frequency traders have entered the market, informed, traditional investors have lost confidence in executing once normal transactions that could not be taken advantage of. Traditional investors desire highly liquid markets where predatory trading is forbidden. Brokers and exchanges have been trying to solve the complexity problem by adding dark pools. The addition of new exchanges only increases the complexity of the existing market system.

One seemingly obvious resolution to the complexity problem is to create a single market where all investors and brokers can interact with each other in real time. This would likely limit liquidity, though.

The inception of IEX has been pinpointed as a type of solution. Contrary to dark pools, IEX is owned by mutual funds, family offices, hedge funds, and individuals, or natural investors (2015). Creating unfair market advantages for IEX subscribers violates the company's vision and code.

IEX was launched on October 25, 2013 and effectively eliminates the conditions that allow HFTs to gain unfair market advantages (2015). For example, IEX does not give preferential treatment or access to high paying investors, only allows market, limit, and Mid-Point Peg orders, equally charges buy and sell sides of trades, and openly publishes its rules. IEX is not an ordinary dark pool in that it allows transparency and eliminates the possibility of HFT strategies (e.g. predatory trading, front-running) to diminish investor confidence (2015).

At first, many of the large institutions running suspicious ATSs despised its efforts for a simplified, fair market approach (2015). Although it initially struggled to capture investors, the average daily volume skyrocketed from 18,178,617 in January 2014 to 133,363,420 a year later.

Independent Policy Analysis of Five Proposed Options

In Q4 2012, EU lawmakers created a policy that strived to limit extreme market volatility. A minimum half-second delay would be attached to all market orders (Norman & Froymovich, 2012). The Wall Street Journal article emphasized that this rule was enforced, "to create a regulated trading environment for over-the-counter derivatives and other financial products to bring transparency to 'dark pools,' where financial instruments are traded away from public exchanges."

The goal of the policy side of the thesis is to outline five major policy options, analyze them, and provide a final recommendation to enhance market regulation. This policy analysis hinges on the ideal of "fairness," which can take different meanings; eliminating competitive advantages for specific market participants may be one view, while reducing overall liquidity leading to fewer profits may be another view. This distinction becomes critical.

The framework used to analyze policy stems from a graduate class (19-656) at Carnegie Mellon University's H. John Heinz III College cotaught by Dr. Deanna Matthews and Dr. Deborah Stine.

The analysis is evaluated on the following categories:

- **"Effectiveness**: Is the policy or program going to meet the goals?
- **Efficiency**: Is the cost of a policy or policy proposal minimum relative to its expected benefits to society?
- **Equity**: Is the policy option fair or equitable?
- **Ease of Implementation**: How will government officials and other policy actors appraise the acceptability of the proposal?"

As shown in Table 4, each policy option is rated on a scale from 1 (poor) to 5 (excellent) on the four equally weighted criteria: effectiveness, efficiency, equity, and political feasibility. Scores are individually assigned and then explained.

Table 4

1 = Poor	2 = Bad	3 = Neutral	4 = Good	5 = Excellent

We will chronologically discuss the five policy options below:

1. The first proposed policy option is to leave the status quo intact. This means leaving the current regulatory system as is.

2. The second policy option is to ban high frequency trading.

3. The third policy option is to ban flash orders.

4. The fourth policy option is to enforce a minimum half-second delay on executing orders.

5. The fifth policy option is to implement fee structures.

It should be noted that when identifying policy options, it is standard practice to begin with the status quo scenario and then analyze the extreme policy intervention. These theoretically provide a benchmark for comparing among policy options.

Furthermore, the proposed policy options are reasonable government interventions. Creating a single exchange such as the IEX for the entire international market, for example, is both non-sensible and completely unrealistic. A single global market would reduce and limit liquidity.

<u>Policy Option 1: Status Quo</u>

Effectiveness received a "poor" score primarily due to the fact that the current financial system evidently allows high frequency traders to gain unfair advantages in the market. Many of these topics (i.e. front-running, predatory algorithms) were comprehensively discussed in Sections II and III. This rating therefore reflects the Status Quo's inability to create a level playing field among market participants.

Efficiency received a "neutral" score. Evidence suggests that high frequency trading increases market liquidity, but the cost to society is not exactly known. Increasing volume can artificially manipulate market prices and increase volatility. Seemingly equal pros and cons surface, justifying the score.

A "good" score was assigned to equity. Although concerns surrounding predatory algorithms and dark pools arise, the benefits to investors (e.g. increased liquidity) outweigh the costs. As the policy is definitely fair among HFTs, because investors are better off with high frequency trading, it would be unfair to them to remove it. There is room, however, for increased fairness.

Ease of implementation received an "excellent" score. No additional measures would need to be implemented.

The results are summarized in Table 5.

Table 5: Policy Option 1

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
U.S. Status Quo	1	3	4	5	13

Policy Option 2: Ban High Frequency Trading

In terms of effectiveness, an "excellent" score was assigned. High frequency traders would no longer have competitive advantages over traditional investors.

Efficiency received a "bad" score because the anticipated costs to society will far outweigh the benefits.

Equity was assigned a "poor" score because no market stakeholders would benefit from a permanent ban. For example, brokers owning dark pools would not receive subscription costs, HFTs would not be able to make profits, and markets would not be as liquid for traditional investors.

Ease of implementation was given a "bad" score, as it may take time to pass such an extreme recommendation through legislature. From a company or exchange perspective, it would be easy to ban HFT.

Results are illustrated in Table 6.

Table 6: Policy Option 2

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
Ban HFT	5	2	1	2	10

Policy Option 3: Ban Flash Orders

Effectiveness received a "bad" score. Predatory algorithms and other HFT strategies still exist in the markets where HFTs predominantly benefit. Banning flash orders only reduces a small subset of the problems that give HFTs unfair advantages. 2011 demonstrated that dark pools only compose approximately 10 percent of trading volume; since flash orders occur in dark pools, a minimal increase in effectiveness results.

Efficiency, equity, and ease of implementation mirror the respective scores and reasoning outlined in Policy Option 1. Briefly, efficiency received a "neutral" score due to market ambiguity and proportionate pros and cons. Equity received a "good" score because investors are deemed better off with HFTs. Ease of implementation was assigned an "excellent" score due to the relative ease of passing this through legislature and having each exchange eliminate flash orders. The results are summarized in Table 7.

Table 7: Policy Option 3

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
Ban Flash Orders	2	3	4	5	14

Policy Option 4: Enforce a minimum half-second delay on executing orders

Effectiveness takes an "excellent" score. The time delay eliminates the ways in which HFTs gain unfair advantages, like front-running. Furthermore, extreme market volatility will be tempered and dark pools will be transparent (Norman & Froymovich, 2012).

Efficiency received a "good" score because it eliminates the advantage for HFTs created by predatory algorithms and front-running. Logically, more investors will partake in meaningful trades due to increased confidence, which will result in increased liquidity.

Equity was allocated an "excellent" score because the time delay does not give advantages to specific market players. Cumulatively, no stakeholder would be worse off, yielding the highest possible score.

A "good" score was given to ease of implementation. It would theoretically be easy for exchanges to implement a delay in their systems and regulatory agencies to monitor this. HFTs, however, would obviously oppose this option, resulting in delays and potential difficulty in passing this.

The results are illustrated in Table 8.

Table 8: Policy Option 4

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
Time Delay (0.5 sec)	5	4	5	4	18

Policy Option 5: Implement Fee Structure

Effectiveness received an "excellent" score. Depending on the fee structure, the controversial aspects of HFT could be disincentivized to the degree that they are not used all together. This would result in a market where specific traders do not have an advantage over others.

Efficiency and equity both received "poor" scores. Analogous to a state tax, a fee structure penalizes all types of traders, especially high volume traders. This policy would primarily disincentivize HFTs from engaging in typical, high volume trading. Traditional, innocent investors with generally lower profits would unfairly be "taxed." As HFTs are mostly responsible for removing market integrity, it is irrational to "tax" a stakeholder that refrained from exploiting market loopholes. Reduced liquidity would also result as a result of less volume.

Ease of implementation received a "neutral" score due to heavy opposition from market participants but acceptance among policy leaders, as they might argue that generated revenue might benefit society somehow.

Results are shown in Table 9.

Table 9: Policy Option 5

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
Fee Structure	5	1	1	3	10

Policy Option Comparison and Framework Review

The results from the five analyses are summarized in Table 10.

Table 10

	Effectiveness	Efficiency	Equity	Ease of Implementation	Total
1. U.S. Status Quo	1	3	4	5	13
2. Ban HFT	5	2	1	2	10
3. Ban Flash Orders	2	3	4	5	14
4. Time Delay (0.5 sec)	5	4	5	4	18
5. Fee Structure	5	1	1	3	10

The previous analysis yields the following results, from best policy to worst: Option 4, Option 3, Option 1, Option 2 and Option 5 (tied).

Options 2 and 5 are clearly the worst. Although this analysis ranks them evenly, it could be argued that a fee structure is slightly worse than banning HFT. We previously identified advantages of HFT (i.e. increased market liquidity) with empirical evidence. Given the negative implications of the fee structure, the government would be the only entity to benefit. By completely banning HFT, it seems reasonable to hypothesize a larger negative effect on society. Clearly Options 2 and 5 are the worst at meeting our goal of market fairness.

In Option 1 and Option 3, efficiency, equity, and ease of implementation, share the same scores; effectiveness is the only difference. The ranking makes sense since Policy 1 is the base case and in Option 3, banning flash orders merely targets a narrow section of the overarching problem; therefore, overall effectiveness barely increases. We conclude that dark pools may be a feature of the past. With controversy surrounding them, it naturally follows that attention from all domains is attracted.

Option 4 prevails as the best solution to target the fairness problem.

The five policy options were evaluated without a proper mathematical model. Sections I, II, and III were essential for understanding the dynamics and implications of HFT so rational explanations could support individually allocated category scores.

Further research should be conducted to build an appropriate mathematical model where quantitative data can be derived to support the qualitative hypotheses. Given the time constraint on the thesis and the difficulty of this proposed task, this was not feasible.

Furthermore, quantitatively estimating benefits and costs to society is difficult. Assuming a mathematical model was implemented, sensitivity analysis could ensue by changing weights on categories and reevaluating the model's output scores. In theory, this would be the best policy evaluation.

Section V: Conclusion

The financial landscape of tomorrow will inevitably be heavily reliant on technology. As we sought to answer the effect of electronic transactions on the global economy, we conclude more short-term volatility seems unavoidable; this provides a justification for more frequent “Flash Crash” or ultrafast black swan type events as the norm. As (Kirilenko, Kyle, Samadi, & Tuzun, 2011) explain, “conflict is that HFTs believe they are providing liquidity, but just buying and selling assets can artificially manipulate market prices and not necessarily provide liquidity.” Large orders have the ability to exert an impact on price and create market disruptions. The industry has evolved in such a way where HFTs know exactly who and what they’re playing against. The implications point to issues of market power and anti-trust.

As technology evolves, the effects of more saturated markets with increased interactions among incredibly complex algorithms remain unknown. The evolution of technology has greatly benefited society. However, even though rigorous testing and automatic safe guards are instituted to “save the day” when turmoil occurs, the degree of human error in technological systems may fail to prevent a catastrophe. From technical troubles during the 1987 Market Crash to technical troubles with the Facebook IPO, technology has the ability to paralyze the markets, leading to worldwide panic. The following question emerges: will the government always be able to save the day when a market crash attributed to technology occurs? As Murphy’s Law states, “whatever can go wrong will go wrong” (Kirilenko & Lo, 2014), we draw a parallel with the housing bubble to ponder the possibility of an analogous, impending technology bubble.

The future undoubtedly rests on the interaction between humans and machines. It is therefore paramount to rebuild a well-understood financial system that disallows unfair advantages and fairly punishes those who try to game the system. Although the speed race seems to have dissipated, the world of trading, especially among HFTs, has remained competitive for the pursuit of money. The intersection of morals and evolving technology paired with human innovation has created an unhealthy, societal obsession with the nuances.

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