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## **The Effects of High Frequency Trading**

High Frequency Trading is the term used to describe several different types of computerized algorithmic trading systems that are employed with the intention of buying and selling securities quickly. It is characterized by a very short holding period intended to minimize exposure to risk. High frequency traders generally complete each transaction within a few minutes to less than a second. High Frequency Trading, or HFT, is often synonymous with algorithmic trading, or black box trading. These forms of trading rely on high-speed computers to analyze and interpret stock data and place orders based on this data with little or no human interaction. Over the past decade, algorithmic trading has advanced from being relatively unknown to being responsible for as much as 73% of trading volume in the United States<sup>1</sup>. New methods of computing and analyzing stock data have been developed over the years. Up until this point, the effect of these new developments has been unclear. This paper seeks to answer the question: What is the effect of High Frequency Trading on the stock market? I will begin with a background of High Frequency Trading, and then explore the different strategies employed by HFT firms. I will then examine stock data to explore how widespread use of HFT can affect the stock market as a whole. This section will be concerned with the effects of HFT on market liquidity as seen in recent events, such as the flash crash of May 6, 2010. Historical

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<sup>1</sup> R. Iati. The real story of trading software espionage. TABB Group Perspective, 10/07/09.

stock data will be used to analyze HFT's effects on volume, stock spreads, and liquidity on the market. Specifically, I will test to see if this HFT provides liquidity or removes liquidity. I will provide an overview from the Securities and Exchange Commission (SEC) and other expert economists as to the role of HFT in market volatility.

### **Why is High Frequency Trading Important?**

High Frequency Trading is a new development in the ever-changing world of finance. Over the past 10 years, the way people do business in the stock market has been completely redefined. A recent Reuters<sup>2</sup> poll asked the following questions:

Does the growth of high frequency trading present a threat to the stability of financial markets? The most common answer was: "It is certainly possible" which garnered 40% of the responses

In the same poll Reuters asked: Do regulators have a clear understanding of high frequency trading and its effects? To this, the discouraging response was: "They are completely behind the curve"

It is evident from the news media and from researchers that there is a lot of unanswered questions pertaining to High Frequency Trading and computer algorithmic trading. To get a good idea of what is going on, we can look at the historical changes that have taken place in the last decade, and put quantifiable analysis in the face of uncertainty.

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<sup>2</sup> "Thomson Reuters – High Frequency Trading."

## Overview

It is necessary to explain how the stock market has worked historically to understand the changes that are taking place. The stock market was created to allow publicly traded companies to generate capital. The initial sale of a company's stock generates income for a company, which can in turn be used to fund new projects, or purchase new equipment that will generate revenue in the future. The company will also pay out cash, called dividends, usually on a fixed schedule, for every share of stock outstanding. It is these dividend payments, which ultimately give value to a share of stock. We can imagine a simplified scenario in which a company will pay a fixed dividend payment of \$1.00 every year. We will also assume that this company will exist in perpetuity. We could simply add these payments up and decide that the stock is worth an infinite amount of dollars, but this is an incorrect way to think about the situation because the money is not received immediately but rather distributed over time. Just as interest is paid on a bank loan, one would pay more money in the future to have money now. The percentage increase that would be paid in one year for a dollar right now is called the yearly discount rate. If we assume a discount rate of five percent (5%), a simplistic equation to evaluate the value of a stock is shown by the following:

$$\begin{aligned}
 \sum_{i=1}^{\infty} \$1 * .95^i &= \$1 * .95^1 + \$1 * .95^2 + \$1 * .95^3 + \$1 * .95^4 + \dots + \$1 * .95^{\infty} \\
 &= \$ .95 + \$ .90 + \$ .8573 + \$ .8145 + \dots + 0 \\
 &= \$ 20^3
 \end{aligned}$$

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<sup>3</sup> This infinite sum is also known as the harmonic series. It can be calculated with the equation

Here we evaluated the stock to be \$20. This is a simplification because our calculation makes several assumptions. Specifically, it assumes that the company will last forever, that the dividend payment is constant, and that the discount rate is the same for all people. In practice investors often do not assume they will hold a stock forever, but rather intend to sell it after some period of time, called the investors ‘time horizon’<sup>4</sup>. However, even if an investor intends to sell the security, the price at which they can sell it depends on the same infinite sum, and thus the calculation is still true as if the investor were to hold onto the stock forever. As stated before, investors do not assume that a dividend will stay constant. Most investors assume that while a company is in operation, it will grow, and increase the dividend payment, which has the effect of raising the price of the security. This is the most basic method of evaluating a stock, but many investors have developed layers of abstraction. In reality, an investor primarily cares about the risk and the rate of return of a stock. The rate of return can come in the form of dividend payments or increases in the price of the stock when it is sold. An increase in the value of stock when it is sold is known as a capital gain. The risk component is a measurement of how likely a security will actually achieve its expected rate of return. Most investors are risk averse, meaning when all things are equal, they would prefer a secure rate of return rather than a varied one, and they will pay a premium for it. This is the base of the risk-reward trade off.

When long-term investors evaluate a security, they may look at a company’s long-term growth potential. Looking at factors that relate to a company’s profits, losses, new investments, management, and growth potential is called fundamental analysis. The flip side to this is technical analysis. Technical analysis relies on historical prices to determine future prices.

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$\sum_{i=1}^{\infty} n^i = \frac{1}{1-n}$  when  $n < 1$   
<sup>4</sup> Clifford, Christopher P.

Technical analysis does not take into account factors that are related to how the underlying business is managed; it only looks at past price changes in a security or group of securities and identifies patterns that can be used to predict the future price changes. High Frequency Traders are concerned with technical analysis and almost never get involved in how the underlying asset is managed. This is one of the key distinctions between HFT's and long-term investors.

### **Players in the Market**

There are three different players: the investor, the broker and the exchange. When an individual wants to buy or sell a stock, the first step is to contact a broker to create an order. The broker communicates with the exchange, which will have either a specialist or a Market Maker<sup>5</sup>, who acts as a conduit between a bank and the broker. There are two types of trading in America today: floor based and screen based. The exchange is a centralized institution, regulated by the federal government, that is designed to match buyers and sellers for the securities that are listed on that exchange. On a floor exchange, brokers can buy and sell shares of stock the entire time the exchange is open. By looking at the price at which the public is buying and selling shares of stock, we can see what the price of the stock is at any second of the day. The New York Stock Exchange (NYSE) is known as a floor based exchange because traders gather on a physical floor to buy and sell shares on behalf of their clients. In earlier times investors would call their brokers who would in turn contact their representative on the floor who would make transactions using physical slips of paper. On a floor exchange a specialist sets the price, and guarantees that market orders will get the best prices available. In modern times floor brokers use computers but still physically move to the point of sale in order to represent their clients. A specialist working

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<sup>5</sup> Connor, Gregory

on the NYSE is responsible for posting the best bid and offer price including after-hours events. The specialist will also cover large market imbalances by buying and selling with his or her own reserve of cash. The NASDAQ, on the other hand, is a screen-traded exchange. It operates entirely through electronic transactions. Instead of a specialist, the NASDAQ has market makers, but they fulfill the same role. The market maker is required to have a firm bid and offer price for any security with which they operate. Multiple Market Makers operate on the same security in competition with each other. It is this competition that guarantees individual or institutional investors will get the best bid and offer price available.

### **Overview of HFT**

High Frequency traders can be individuals, firms, or Market Makers. They operate exclusively by using electronic signals, which can be employed on the NASDAQ as well as the NYSE. They use a variety of strategies to make a profit using the most up to date technology. This includes lightning fast computers that perform millions of actions per second<sup>6</sup>. Latency is a term used to describe the delay between a computer signal and the actual transaction. Low latency or super low latency refers to the high speeds with which HFT firms can react to changes in the stock market. Low latency not only refers to the computing power necessary to process complex algorithms, but also the speed with which firms can receive data from stock market exchanges, and can submit orders to those exchanges. It has been referred to as a technological arms race, in which firms compete against each other to get bigger computers and faster connections. The latest weaponry in this sort of warfare has been provided by the exchanges themselves.

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<sup>6</sup> Hendershott, Terrence, Jones, Charles M. and Menkveld, Albert J.

The first in this arsenal is a technique called “collocation.” Collocation occurs when a firm pays an exchange a premium to place their computers physically close to the exchange itself<sup>7</sup>. This method has been institutionalized by major exchanges such as the NASDAQ and the NYSE. These exchanges have created “data centers” where firms can rent computing space for tens of thousands of dollars a month. These data centers allow a trading firm’s super computers to access raw data from the exchange almost instantaneously. This allows traders to act fast, seeing orders faster and placing orders faster than other smaller investors. These technological tools may lower a trader’s latency by mere fractions of a second, but this may be enough to give them an advantage worth millions or even billions of dollars, by some reports.

The next tool in the HFT wars is called the flash order. In a flash order, an exchange such as the NASDAQ offers premium members the ability to see incoming orders before the general public. This boost may only be a 50-millisecond peek, but this is enough to give a huge competitive advantage. The precedent of this sort of behavior harkens back to the early days of trading on the floor of an exchange. At that time, when an order came in a specialist would receive the order via phone. The specialist would then yell out the order to the floor, and then enter the order into the computer. This gave floor traders an advantage in that they learned of the order a few seconds before the public, thereby gaining the ability to satisfy the order before the general public if they could react fast enough. Critics have accused flash orders as being an unfair advantage, and describe it as a form of “front running.”<sup>8</sup> Front running is the illegal practice that occurs when a broker uses the knowledge of his client’s orders to make a profit for himself. This might occur if the broker is directed to make a large sell order in a particular stock for his client and that sell order will inevitably result in lowering the price of the stock. An

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<sup>7</sup> "Data Center Knowledge."

<sup>8</sup> R. Iati.

unscrupulous broker might sell his own shares of the stock first, in expectation of the price movement before selling the shares of his client. Flash orders do bear a resemblance to this practice, in that a small group of investors use their advanced knowledge of orders to make a profit. In 2009, the SEC debated a rule, which would ban the practice of flash orders<sup>9</sup>. This proposal was never adopted because many exchanges voluntarily ceased the practice.

The final piece of the weaponry is the algorithms that firms actually employ. These are generally kept secret since a competitor could predict every trade a firm would make by using the firm's algorithm. This competitor could then use this knowledge to profit by anticipating these trades, and making preemptive trades that reduce the firm's profits and increases the competitor's profits. Also, portfolio managers tweak these algorithms constantly in order to maximize profit. In this sense, algorithms may be a tool to increase the efficiency of portfolio managers.

Who employs HFT strategies? I have compiled a list of 46 HFT firms in Appendix A. At the top of this list are the two major firms: Goldman Sachs and Merrill Lynch. The smaller firms often offer their services to investors much like any other hedge fund. They provide the algorithms and computational firepower for investors to participate in HFT strategies.

## **Strategies**

The following is a description of the main strategies employed using algorithms and high frequency trading:

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<sup>9</sup> Thomson Reuters



Market Making: In this form of high frequency trading, an investor makes a profit based on the bid-offer spread. In general there is a small difference between the bid-price, or the highest price investors are willing to pay for a security, and the offer-price, or the lowest price that investors are willing to sell a security. Generally, the spread is a few pennies for highly traded stocks, while it might be much more for stocks that are only traded infrequently. In general, it is said that when investors input a limit order, an order to sell for no less than a particular price or to buy for no greater than a particular price, they are providing liquidity to the market. Limit orders are executed only if they are the lowest or highest respectively on the exchange at a particular time, and thus they reduce the bid-offer spread. When investors buy and sell with a market order, they take the price of the best limit order available, and they are said to reduce market liquidity. This is because by fulfilling the limit order, the next limit order available becomes the new bid/offer, and thus they increase the bid-offer spread. When a small investor puts a market order to sell for a particular price, a high frequency trading may be on the other side of the trade with a limit order at the bid price. They will then hold this stock until an investor comes along to buy stock at the offer price. Each transaction nets the HFT a small profit due to the spread but it also entails a risk. Stock prices might fluctuate before the HFT has a chance to unload the stock. The exchanges themselves promote this liquidity by providing what is called a liquidity rebate, which awards the HFT with a fraction of a penny per share for the liquidity they provide. In this way HFTs may make a profit even if there is a net loss due to their transactions.

Flash Orders: In this strategy, an HFT employs the instruments of flash orders and collocation as described above. This application is the most dependent on low latency than any

other strategy described here, with events happening in microseconds. In this strategy, a firm will wait for an institutional investor, such as a pension fund or investment bank, to make a large order; for example, we will envision a buy order. A few milliseconds after the order is placed on the exchange, it is sent out as a flash order to those members of the exchange who pay a premium to receive these. HFT see the number of shares that the institutional investor wishes to buy, but they do not see the limit price. Before anyone in the general market even sees the order, the HFT starts to “ping” prices. They put out a sell order in penny increments. These sell orders are what is called “immediate or cancel.” When they put the order on the market, it is sold immediately if it is below any limit orders, and is canceled if there are no takers. With this method they almost instantaneously travel up the scale of prices. Each one is gobbled up by the large institutional investor’s buy order, until it goes above the limit price. At this point the order from the HFT automatically cancels. An HFT can see exactly which order was canceled and pinpoint the limit price of the institutional investor. They use this method to “sniff out” prices. This is also a key point in the technological arms race. If one HFT firm can send out “immediate or cancel” orders faster than another, even by a few milliseconds, they have a competitive advantage that can reap large profits. Once the limit price is known, they can go to the general market and buy up all the shares that are below the institutional investor’s limit price. They can complete all this in a mere 40 milliseconds after the initial order was placed. Because the HFT firms are collocated and pay a premium, they are able to put their orders into the general market while the institutional investor’s order is still in the “flash order” stage where it lingers for up to 50 milliseconds before being released to the general exchange. As soon as this happens, the HFT has acquired all the available shares. They turn around and sell these shares to the institutional investor right at its limit price. The HFT may only make pennies for every share that it sells, but

they can do this all day every day, monitoring hundreds of stocks and make huge profits. It has been argued by a NASDAQ representative on the television show 60 Minutes<sup>10</sup> that large investors do not care about pennies because they are generally looking for long-term profits. The legality of this practice is still under debate, but for now, it remains legal.

Algorithmic Analysis: This method is very similar to the ‘Flash Order’ method described above. This strategy is predicated not from special access to an exchange, but rather from institutional investors who have adopted algorithmic programs of their own. These institutional investors have realized that a large buy or sell order may swing the market before their transaction is complete, thus losing potential gains. These market movers have employed trading algorithms that fracture a large order into many smaller orders. These smaller orders are released electronically by computer algorithms designed to minimize their impact on that market and maximize profits. HFT firms have developed software of their own that looks for patterns in buy and sell orders characteristic of these algorithms. HFT firms, once they find one of these patterns, can assume that an institutional investor is making a large trade; only it has been fractured into smaller units. HFT firms can even predict the next time the institutional investor algorithm is likely to make a trade. Armed with knowledge the firms can use the same ‘immediate or cancel’ method to pinpoint the limit price of the institutional investor, purchase stock, and sell it back for a higher price. Although this method can entail more risk, since an HFT firm does not know what volume of stock the institutional investor wishes to purchase, the HFT firms can buy and sell shares so quickly that they drastically reduce their exposure to risk. As with flash orders, they may only make pennies per share of stock, but can reap huge profits over time.

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<sup>10</sup> R. Iati

Statistical Arbitrage: The efficient market hypothesis claims that all investors cannot receive greater than market returns for less than market risk. This is due to the fact that any such opportunities would be snatched up so fast that a typical investor would not be able to react in time to take advantage of it. There is even a joke among economists: If an economist is walking down the street and sees a \$20 bill on the ground, he will not pick it up. The simple logic is that if the \$20 were really there, someone else would have gotten to it first. HFTs are the people who take the \$20 before you get to. These opportunities are called arbitrage. HFT firms employ parity formulas that relate the price of one financial commodity to the price of another. One example is the Forward Contracts parity. This equation states that the current price of a financial good must be equal to the agreed price of a forward contract adjusted by the interest free rate. If the current price is too low, but the futures price remains high, an arbitrageur can purchase the financial commodity and enter into a forward contract to sell it at a specified date that guarantees a risk free profit for greater than the risk free rate of return. HFT use the fastest computers and the fastest algorithm to scan for these arbitrage opportunities. This technique is also called “mean reversal,” because it often depends on two commodities that should be in parity, such as a call option on a stock and a put option on a stock. These two prices are related to each other through the call-put parity equation. If they diverge enough to be statistically significant, an HFT will buy one and sell short the other. It is unclear if one or both prices will move to restore parity, but by making offsetting transactions, as long as prices return to parity, the HFT will make a profit.

## **Recent History**

Many of the practices that high frequency traders use have been developed only recently.

The following is an outline of major event in Algorithmic trading:

1998            The Securities and Exchange Commission adopts Regulation ATS, which stands for Alternative Trading Systems. This allowed for electronic exchanges (ECNs) to be linked to the NASDAQ exchange and paves the way for completely automated trading.

2000            The NYSE adopts decimal pricing quotes rather than fractional quotes. This effectively allows traders to make profits on a difference of pennies rather than the previous minimum of 1/8 or 1/16 of a dollar.

2005            The Securities Exchange commission adopts Regulation NMS, or National Market System. This ties together different national trading systems to promote competition. It creates a standardized method of describing securities information and allows for easier price comparison across exchanges. This opens up new opportunities for cross-exchange statistical arbitrage.

2009            Sergey Aleynikov, a programmer for Goldman Sachs, is arrested for corporate espionage when he steals 32 Megabytes of proprietary algorithmic trading code. The court case brings Algorithmic trading to the attention of the media.

2010            The Flash crash of May 6<sup>th</sup> happens. The Dow Jones Industrial Average Plunges 998.5 points, only to rebound minutes later. Algorithmic traders share some of the blame in the official SEC reported.

2010            NYSE opens the Mahweh data center offering collocation server support of low latency algorithmic operations with an advertised 100 gigabit per second connectivity.

### **Flash Crash**

One of the major events that cast a dark shadow on HFT was the flash crash of May 6<sup>th</sup>, 2010. On this day the Dow Jones lost a trillion dollars in value only to rebound moments later. The SEC released a 100-page report detailing the events that led up to the crash and made recommendation for future preventative measures.

The crash was initially triggered by a large investor that initiated a sell order of a particular electronic financial commodity known as an E-Mini S&P, which is a commodities that mirrors the returns of S&P 500 futures contract at approximately 1/5 the price. The total sell had a value of 4.1 billion dollars, but it was broken up into smaller pieces by a computer algorithm so as not to subject the market price to fluctuations. The algorithm itself was tied to the total market trading volume of E-mini's, and sought to maintain a sell rate of 7% of market total volume. In the past brokers have used volume as a measure for liquidity, but in this case it snowballed into a catastrophe. High frequency traders began to buy up E-Mini contracts as they started to enter the market. As more contracts came in, Algorithmic programs started to activate which caused a large volume of buying and selling among high frequency traders. This increased volume cause the initial sale to speed up. As more E-mini's flooded the market, the

price drop and cross market arbitragers started to perform offsetting transactions throughout the market. The algorithmic traders acted as a floodgate that continued to buy shares of stock as the price sank lower. Eventually, the price dropped to the point that HFTs started to sell their shares to avoid further exposure to risk. Since all the algorithmic traders acted more or less simultaneously there was an enormous flood of downward pressure on the price of e-mini's as well as all underlying assets related to the S&P 500. The SEC reports that market depth was not adequate to offset such a fast price change. Market depth is the queue of offer and bid prices that activate when the price reaches specific levels. The price dropped so fast that all the bid prices in line were activated and there was not time for market makers to activate further bid prices before the price tumbled to extreme lows. The market makers themselves were concerned that there was some sort of national calamity at play and withdrew their remaining bid and offer prices. The market makers are legally obligated to retain a bid and offer at all time, so prices for some securities were set to extreme levels such as a bid price of \$.01 and an offer price of \$100,000, that was never meant to be activated. Incredibly, during the frantic market environment, some investors submitted immediate buy and sell orders only to find that they had purchased or sold their stock for these extreme values.

Ultimately, a circuit breaker like even shut down the E-trade mini servers for 5 seconds at exactly 2:45:28. This was enough time for bid orders to build up and quickly rebound the price of E-mini's. Soon after the price of the Dow Jones also rebounded. In the days following, the SEC ruled that many of the trades made that day should be retroactively nullified, under a "clearly mistaken" rule that exists for erroneous trades.

It seems from the report that HFT did play a role in this crash, and much of their practices have not changed meaning they might do it again in the future. According to the report, HFT

provided stability up until a point. After that point they actually caused an influx of instability and risk. This seems like an especially insidious effect of HFTs since long run historical analysis might show that a particular stock is low risk, due to the stability provided by algorithmic traders. This stability might dissipate without warning if price fluctuations go beyond a certain level, and traditional investors may be left holding the losses. We start the following analysis by looking at how HFT might affect liquidity, especially the bid-offer spread.

## **Analysis**

In this paper I will focus on the effects of HFT on market quality. Specifically for this portion I will look at how HFT affects market liquidity. To a certain extent, arbitrage and market making, both entail risk and return and are within the Efficient Market Hypothesis. Some of the more exotic uses of HFT seem to guarantee higher returns with low risk. If this is true then why do not more firms engage in high frequency trading to seek out maximized profit? They answer to that many do. This begs the question; how does this affect the traditional investor? I will look at its effects on market liquidity through historical analysis of stock data. I will use the following equation to measure spread:

$$\text{spread} = (\text{ofr} - \text{bid}) / \text{price}$$

ofr = the lowest price for which any market maker is willing to sell an asset

bid = the highest price for which any market maker is willing to buy an asset

price = the price of the most recent trade of an asset, this turns the bid offer spread into a percentage of price and makes it more consistent when compared across time or to other securities.



This equation measures the difference between the best bid and the best offer as a percentage of price. It is important to note that if markets are in equilibrium, this value will always be a positive number. If the best offer price was ever equal to or lower than the best bid price, it would imply that someone is willing to buy and someone else is willing to sell at the same price. They should immediately transact with each other until one or both parties no longer want to buy/sell at that price. This principle guarantees that there will always be a bid offer spread, but the more efficient the market, the lower this spread is. A narrow bid offer spread allows from slightly less risk in trading. The spread is a cost that will immediately be forfeit if you attempt to sell back a stock soon after you buy it, because you will have bought it for the higher offer price and will sell it for the lower bid price. Most of the stocks that I will look at have a narrow bid ask spread, falling between \$.01 and \$.25 cents, 95% of the time.

Our previous understanding of HFT's makes several predictions. The first is the HFT will be present when we see a lot of orders. Orders are different then trade in the stock data. A trade takes place when a buyer and seller exchange shares of a stock for the agreed open price. An order takes place anytime a buy or seller sends a request to the exchange to purchase or sell stock at a particular price. Orders may or may not result in a trade. When someone submits an order to buy a stock at a particular price, even if it is the highest order price, it will only be fulfilled if a seller is willing to sell for that price. Since one of the tactics that HFT's use is to submit Immediate or Cancel orders at lightning speed in order to gauge the limit price of other market participants, we can expect to see an increase in the actual number of orders submitted, even if we do not see an increase in the number of trades, or an increase in trading volume. This is a sign that computer algorithmic trading is a work in a particular stock.

The second prediction we can make is the HFT will likely trade in stocks that are already highly traded. Highly traded stocks tend have higher liquidity, and there will always be market participants ready to buy or sell. Since algorithmic trading is entirely based on short-term immediate gains, the ability to buy and sell quickly is paramount. We would not expect to see a high amount of HFT activity on an obscure stock that has a lower trading volume. If a stock is poised to make long-term gains, it is more likely that savvy portfolio managers that depend on some sort of fundamental analysis, rather than the technical analysis that characterizes Algorithmic traders, would picking this up.

Proponents of algorithmic trading have argued that the increased activity and the increased number of orders both serve to improve liquidity, and lower the bid ask spread. But we also know that Algorithms are scooping up shares every time a price is better than normal. With advanced technology and advanced analysis they will find these opportunities faster than non-HFT's. They make a profit when they reverse their position scooping up pennies every time. This may have the effect of lowering liquidity and increase the bid ask spread.

### **Data Analysis:**

Let's look at some stocks. Here we have chosen several stocks to represent a broad swath of investment opportunities. These are the stats for twenty-one randomly selected stocks:

NAME	TICKER	MCAP (thous.)	Price	%Indst	avg day vol	Beta
APPLE COMPUTER	AAPL	\$237,000,000	\$259.95	70.50%	22100000	1.18
ALLIANCE FINANCIAL	ALNC	\$135,832	\$29.14	29.50%	10992	0.59
AMGEN INC	AMGN	\$53,600,000	\$55.72	80.30%	6836124	0.41
BANK OF MARIN	BMRC	\$172,605	\$32.88	40.10%	13769	0.97
COSTCO WHOLESALE	COST	\$26,600,000	\$60.75	78.70%	3964225	0.77
DELL INC	DELL	\$27,000,000	\$13.84	70.40%	25800000	1.35
ELECTRO SENSORS	ELSE	\$13,415	\$3.97	56.02%	2706	0.95
FIRST COMMUNITY	FCBC	\$246,857	\$13.87	45.50%	53277	1.17
GILEAD SCIENCES	GILD	\$34,100,000	\$39.30	90.80%	11700000	0.39
GS FINANCIAL	GSLA	\$15,039	\$11.97	9.80%	1478	0.28
HF FINANCIAL	HFFC	\$71,313	\$10.27	43.90%	4913	0.5
INTEL CORP	INTC	\$115,000,000	\$20.75	64.30%	66900000	1.04
LSI INDUSTRIES	LYTS	\$161,816	\$6.73	66.70%	93482	1.6
MICROSOFT	MSFT	\$235,000,000	\$27.01	64.70%	63700000	0.95
ORCL	ORCL	\$128,000,000	\$25.46	61.60%	31700000	1.05
PACIFIC CONTINENTAL	PCBK	\$179,434	\$9.75	59.70%	41350	0.51
PRESIDENTIAL LIFE	PLFE	\$292,286	\$9.88	48.10%	79575	1.64
QUALCOMM INC	QCOM	\$67,700,000	\$41.46	79.80%	20800000	1.06

RF INDUSTRIES	RFIL	\$15,636	\$5.48	13.30%	6718	0.71
S MISSOURI BANCORP	SMBC	\$31,237	\$14.96	1.30%	1271	0.39
WSI INDUSTRIES	WSCI	\$9,658	\$3.35	4.20%	14070	1.88

- This table was created by averaging all the daily values of 2008.

NAME: The common name of the underlying company

TICKER: The symbol used to represent the company on the exchange

MCAP (thous.): Market Capitalization, this is the total value of all the shares outstanding, in 1,000s

PRICE: the price of one share of stock, as taken from the average price during 2008

% INDST: The percentage of the stock held by institutions, rather than individuals

AVE DAY VOL: The average number of shares of stock traded in one day

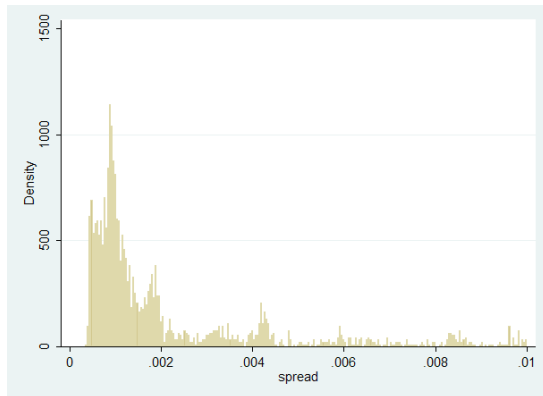
BETA: This is a measure of a stock's non-diversifiable "risk." It is risk that is related to the market as a whole. A

higher beta implies a higher expected return during market growth and higher losses during a market decline

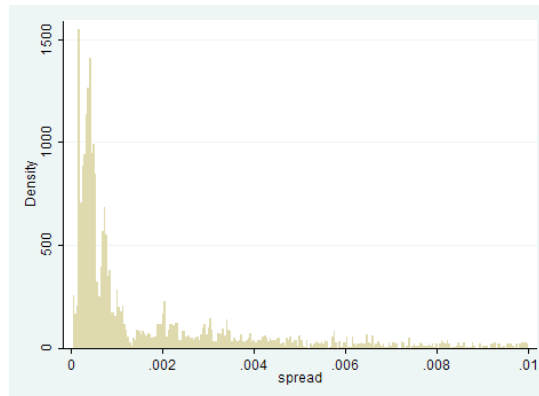
All the values in the above table provide a snapshot of the stock market in 2008. The large market capitalization stocks, or Large-Cap stock, with an MCAP of greater than \$10 billion, were chosen at random from the S&P 500 listing. All other stocks were chosen at random from the NYSE listing, to provide a representative example of investment options. We research historical data for eight years of the above stocks, spanning from January 2000 to January 2008 to give a wide range of results.

We can easily see some broad patterns by looking at the changes over time. The first questions are what are happening to the bid-offer spread? The following histogram shows a snapshot in 2000 and in 2008:

**Figure 1: Year 2000**



**Figure 2: Year 2008**



This histogram was created from the twenty-one random stocks listed above. It is somewhat multimodal because it was created from an amalgam of securities, but it does produce an overall trend; we can see that we have a higher density of narrow spreads when we compare 2008 to 2000. This is evidence that the market is more efficient than it has been in the past, and more liquid. This may be due to better technology, and more ease in trading. As the systems we use advance, we can create a more efficient trading space, but that does not necessarily guarantee that HFTs are responsible, only that the market is more efficient than it was eight years ago. To judge the real effect of HFT's we will look at the results of the changes in the number of orders per day.

The first result is that HFT is indeed changing the landscape of investing. For example, take a random stock such as ELSE also known as Electro-Sensors Inc. In 2000, their average

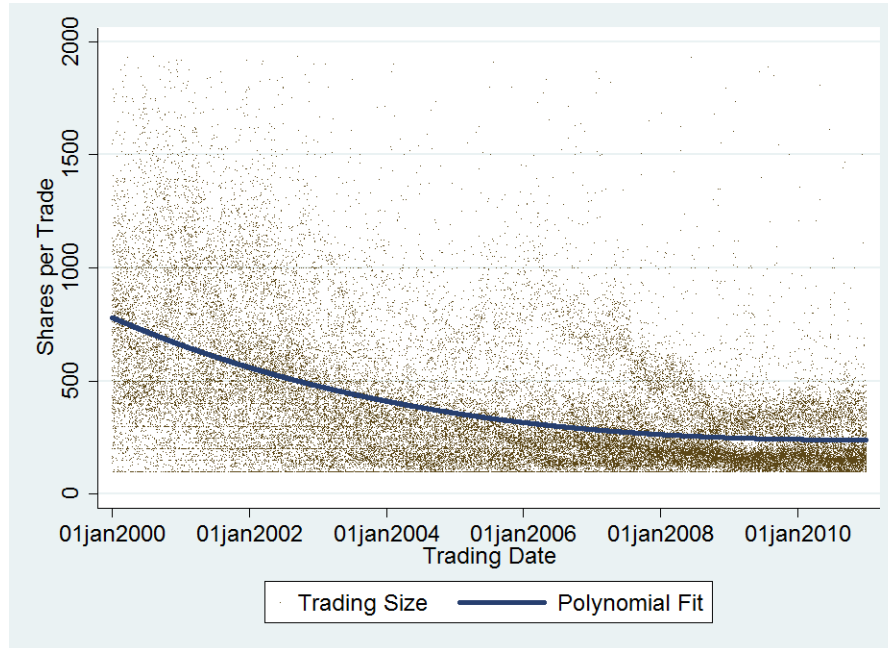
daily trading volume was 3,000 shares from an average of four trades per day. In 2008 the volume increased to 6,000 shares, but the number of trades jumped to 30 per day. Each trade went from 750 to only 200 shares per trade. This is the number of actual trades but note the order volume. The orders went from an average of 8.5 per day to a whopping 4,200 per day. This is a 500 times increase when the volume only increased by a factor of 2. This lopsided increase in orders per day vs. volume is evidence of the changing nature of trading due to High Frequency Traders. The following table provides summary statistics of the 21 stocks in January 2000 vs. January 2008:

Ticker	2000 avg day volume	2000 avg day trades	2000 avg day orders	2008 avg day volume	2008 avg day trades	2008 avg day orders
AAPL	5703053	11212	6890	56800000	302855	1594597
ALNC	2391	7.5	8	5754	17	3329
AMGN	12600000	3503985	5968	12600000	55018	31850
BMRC	982	3.3	2.5	11069	16	3641
COST	3506795	4248	2291	2207102	10639	293257
DELL	40000000	34716	8925	8774826	19917	570426
ELSE	3172	4	8.5	4161	18	4191
FCBC	8540	26	*	38295	273	12080
GILD	1298578	1483	1291	11200000	53834	371608
GSLA	4462	10	18	845	6.5	121

HFFC	9043	7.5	13	2436	6	710
INTC	35400000	38455	14583	113000000	194353	952810
LYTS	20211	37.5	44	354103	2051	29375
MSFT	32000000	37013	13507	93900000	189545	972459
ORCL	24100000	33854	12147	10900000	27418	551585
PCBK	3790	6	*	10810	47	5556
PLFE	65364	56	48	84101	571	27730
QCOM	26500000	46764	15609	26700000	105668	594103
RFIL	38487	45	60	5975	24	3894
SMBC	5307	3.6	6.5	813	3	1025
WSCI	6240	6.75	11	108737	281	16497

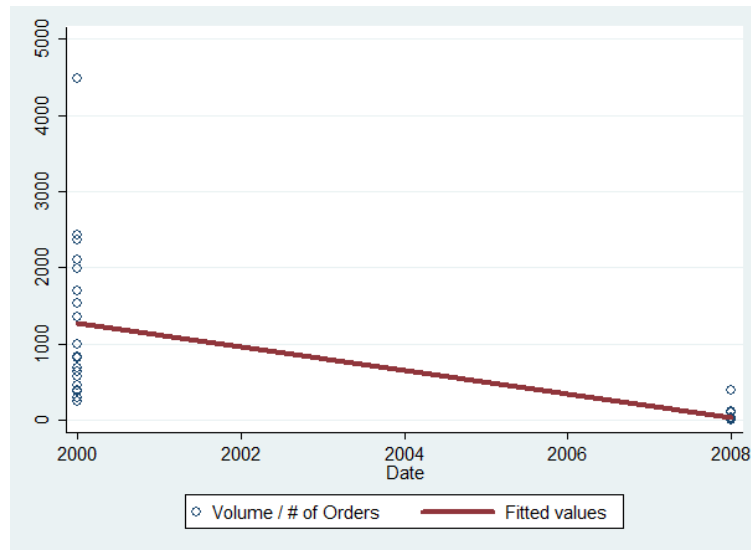
\* No values reported for this year

As you can see from the table, investors are placing more orders with fewer shares per order.



The graph above represents the average order size over time. Each tiny speck represents the average size of all the trades for a single day. The x-axis is the date of the trade and the y-axis is the size of the trade in shares. As you can see from the blue regression line, the average trade in 2000 was around 800 shares. By 2010 the average trade was only 200 shares, the lower limit is 100 shares because this is the smallest order size currently allowed on the exchange (individual investors may make smaller orders with their brokers, but the broker must group multiple order into blocks of 100 or more to participate on the exchange.) The effect of HFT is even more dramatic when we compare volume to number of orders.





In order to calculate the number of orders per day the program scanned every single inter-day orders then created data sets of several million observations. Due to computational limitations, we are only able to graph the values for the years 2000 and 2008. As you can see, in the year 2000 the blue circles center around the mean and there was approximately only one order for every 1,278 shares traded, but by 2008 that number had dropped to one order every 38 shares traded.

This is clear evidence that the way the stock market is working is changing, and now we ask ourselves what is the effect on the bid-ask spread? Many proponents of HFTs have claimed that the increased orders have provided more market liquidity and have lowered the bid-ask spread. When we performed the regression we have found this to not be the case on average.

In the year 2000, out of twenty-one securities, eight were statistically significantly correlated with a lower spread, nine were statistically significantly correlated with a higher spread, and two had no significant correlation. This implies that, in 2000, more orders in the market had an uneven effect on the spread of a particular stock. A positive coefficient implies

that the more orders there are on average, the larger the bid-offer spread, which is generally considered an undesirable quality in the market.

Ticker	2000 Coef.	2000 t-stat	2008 Coef.	2008 t-stat
AAPL	-4.63 e -08	-220	6.95 e -11	439
ALNC	-7.2 e -04	-5	6.01 e -.07	56
AMGN	1.09 e -08	27	5.21 e -10	287
BMRC	-.044 e -03	-5	3.86 e -07	31
COST	6.4 e -07	157	1.39 e -09	561
DELL	-2.39 e -08	-174	1.68 e -10	410
ELSE	.0055	6	-1.61 e -06	-60
FCBC	*	*	2.58 e -07	230
GILD	9.94 e -08	9	4.51 e -10	185
GSLA	-.000164	-1.8	-1.01 e -04	-9
HFFC	.0014211	12	-8.18 e -06	-30
INTC	.11 e -08	-240	2.02 e -10	683
LYTS	.0000433	4.27	9.29 e -08	111
MSFT	6.63 e -06	71	2.07 e -10	673
ORCL	3.83 e -09	-546	2.27 e -10	507
PCBK	*	*	1.08 e -07	14.25
PLFE	-.000027	-3.34	6.89 e -08	74

QCOM	2.5 e -09	58	6.10 e -10	465
RFIL	.0003027	10	-4.11 e -07	-8
SMBC	-1.2 e -03	-2.14	3.65 e -07	.81
WSCI	-2 e -05	-.05	-3.66 e -08	-22

By 2008, fifteen of twenty-one stocks had a spread that was larger when there was a high amount of orders. More surprising is the fact that all the large cap securities (securities with market capitalization over \$10 billion) show the correlation with wider spread. This large cap securities result is consistent with the hypothesis that High Frequency Traders will be most active in large cap securities. These securities have the highest volumes, and they are most likely to have a larger bid-offer correlated with this large number of orders. So how much does this result in profit for market makers? If institutional market makers are indeed the most common high frequency traders, then we can put an upper bound on the profits that they are generating due to the increased spread.

Take the example of Apple. Every time someone sells a share of Apple, it is sold to the market maker at the offer price. A few moments later the market maker will sell back that share to another investor for the bid price. The market maker will pocket the difference between the bid-offer spread. Since the correlation between the number of offers and the spread is negative, the more offers that exist. The greater the spread means a greater the profit to the Market Makers.

We can calculate what the effect is on market maker profits by making some assumptions. The volume of Apple share that are traded per day increased by a factor of ten between 2000 and 2008. If we assume that there was no high frequency trading, then we could

imagine that the number of orders per day also increased by a factor of ten (instead of the actual increase by a factor of 231). We estimate the new spread, given the smaller number of orders using the regression that we derived for 2008:

$$\text{Spread} = (b_0 + b_1 * \text{orders}) * \text{price}$$

Spread	The daily average difference between the bid price and the offer price
Orders	The daily average number of orders that are submitted 68,900 <sup>1</sup>
Price	Average price of 2008 160.8813
$b_0$	.0002183
$b_1$	6.95 E - 11

<sup>1</sup>This is 10 times the 2000 amount

The resulting Spread = \$.035694, this is lower than the actual spread in 2008 of \$.05262648, which leaves a profit of \$.01693 every time the market maker covers the bid-ask spread. If every trade goes through a market maker, they will cover the bid ask spread every two trades, one to buy and one to sell, giving them a bonus of:

$$\begin{aligned} .01693 * \text{volume}/2 &= .01693 * 56800000/2 \\ &= \$480,812 \end{aligned}$$

So the market maker can stand to gain an approximate extra half million dollars per day and this is only for Apple. There are several hundred large cap stocks with similar properties to Apple that could stand to profit in a similar manner due to the larger bid-ask spread. Bid-ask spreads

are normally kept low due to competition among market makers, but the increased orders of high frequency trading seems to correlate with higher bid-ask spread, thus higher profits for the market makers. So this market makers that employ HFT tactics may have found a way to circumvent the natural forces of competition.

**Conclusion:**

High frequency trading will remain a significant part of the investing landscape for years to come. We have seen that market has become more dynamic and more efficient as measured by a lower bid offer spread in the past years. We have also seen events in the past that would lead us to believe that the same technological advancements that make us all more efficient may favor some over others. Those that take advantage of these opportunities while reap large rewards while others will see their portfolios dwindle. We have shown that there is a general negative correlation between more High Frequency Trading and lowering the bid ask spread. It remains to be seen if the Securities and Exchange commission will create further legislature that will slow down some of the fastest algorithm, or if it will continue to allow companies to pay for collocation and other “flash order” like benefits in the face of legal questions and accusation of front running. There is a lot of uncertainty, but also a lot of potential to expand market participation, to give investors the information they need to make astute investment decision and yet keep all market participants on an equal playing field.

**Appendix A1 – HFT Firms**

(collected from the High Frequency Trading World Conference brochure)

Goldman Sachs	Infinium Capital Management
Bank of America - Merrill Lynch	DynamicFX Consulting
Hyde Park Global Investments	Olympian Capital Management L.L.C.
Lightspeed Financial	Tunnelbrook Capital
Cerebellum Capital, Inc	Hagin Investment Management
PensonGHCO	Tradeworx, Inc.
Nobilis Capital	Telesis Capital L.L.C.
SMB Capital	Momentum Trading Partners
Investment Company Institute - ICI	M3 Capital
Commodity Futures Trading Commission	NYSE Technologies
Deutsche Bank Securities	Dunecrest Asset Management, LLC
New Orleans Employees Retirement System	SunGard's Trading Business
Glenmede Investment Management, LP	Golden Archer Investments
Evnine & Associates	Themis Trading L.L.C.
Madison Square Investors	Woodbine Associates, L.L.C.
MSF Capital Advisors	TABB Group
Oklahoma Firefighters Pension & Retirement System	Quantlab Financial, L.L.C.
Rosenblatt Securites	Third Wave Global Investors, L.L.C.
T3 Capital Management	Robust Methods L.L.C.
Attis Capital	Lakeview Capital Market Services GmbH
Alchemy Ventures	Fenimore Asset Management, Inc.
Systematic Strategies L.L.C.	Aite Group
Courant Institute of Mathematical Sciences	Teza Technologies, LLC
	Renaissance Technologies

**Appendix B1 – 2000 Regression of Spread (aliq) determined by Orders Per Day (dayfreq)**

-> symbol = AAPL

Source	SS	df	MS	Number of obs =
Model	.000675333	1	.000675333	110540
Residual	.001543109110538		1.3960e-08	F( 1,110538) =48376.36
Total	.002218442110539	2.0069e-08		Prob > F = 0.0000
				R-squared = 0.3044
				Adj R-squared = 0.3044
				Root MSE = .00012

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-4.63e-08	2.11e-10	-219.95	0.000	-4.67e-08 -4.59e-08
_cons	.0014971	1.49e-06	1001.95	0.000	.0014941 .0015

-> symbol = ALNC

Source	SS	df	MS	Number of obs =
Model	.000859302	1	.000859302	86
Residual	.003454911	84	.00004113	F( 1, 84) = 20.89
Total	.004314214	85	.000050755	Prob > F = 0.0000
				R-squared = 0.1992
				Adj R-squared = 0.1896
				Root MSE = .00641

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-.0007253	.0001587	-4.57	0.000	-.0010409 -.0004098
_cons	.0331775	.0014327	23.16	0.000	.0303283 .0360266

-> symbol = AMGN

Source	SS	df	MS	Number of obs =
Model	5.6422e-06	1	5.6422e-06	100075
Residual	.000759239100073		7.5868e-09	F( 1,100073) = 743.68
Total	.000764881100074	7.6432e-09		Prob > F = 0.0000
				R-squared = 0.0074
				Adj R-squared = 0.0074
				Root MSE = 8.7e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	1.09e-08	4.00e-10	27.27	0.000	1.01e-08 1.17e-08
_cons	.0011583	2.40e-06	482.50	0.000	.0011536 .001163

-> symbol = BMRC

Source	SS	df	MS	Number of obs =
Model	.000389481	1	.000389481	19
Residual	.000284783	17	.000016752	F( 1, 17) = 23.25
Total	.000674264	18	.000037459	Prob > F = 0.0002
				R-squared = 0.5776
				Adj R-squared = 0.5528
				Root MSE = .00409

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-.0043672	.0009057	-4.82	0.000	-.0062781 -.0024563
_cons	.0419353	.0023416	17.91	0.000	.0369949 .0468757

-> symbol = COST

Source	SS	df	MS	Number of obs =	40689
Model	.003058972	1	.003058972	F( 1, 40687) =	24610.01
Residual	.005057308	40687	1.2430e-07	Prob > F =	0.0000
				R-squared =	0.3769
				Adj R-squared =	0.3769
Total	.00811628	40688	1.9948e-07	Root MSE =	.00035

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	6.40e-07	4.08e-09	156.88	0.000	6.32e-07	6.48e-07
_cons	.0003759	9.51e-06	39.55	0.000	.0003573	.0003945

-> symbol = DELL

Source	SS	df	MS	Number of obs =	139678
Model	.000301677	1	.000301677	F( 1,139676) =	30436.40
Residual	.001384429139676	9.9117e-09		Prob > F =	0.0000
				R-squared =	0.1789
				Adj R-squared =	0.1789
Total	.001686105139677	1.2071e-08		Root MSE =	1.0e-04

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	-2.39e-08	1.37e-10	-174.46	0.000	-2.42e-08	-2.36e-08
_cons	.0017227	1.25e-06	1376.87	0.000	.0017202	.0017251

-> symbol = ELSE

Source	SS	df	MS	Number of obs =	70
Model	.070993602	1	.070993602	F( 1, 68) =	35.03
Residual	.137807262	68	.002026577	Prob > F =	0.0000
				R-squared =	0.3400
				Adj R-squared =	0.3303
Total	.208800864	69	.003026099	Root MSE =	.04502

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	.0055837	.0009434	5.92	0.000	.0037012	.0074662
_cons	.138801	.0098027	14.16	0.000	.11924	.158362

-> symbol = GILD

Source	SS	df	MS	Number of obs =	21432
Model	.000037172	1	.000037172	F( 1, 21430) =	83.60
Residual	.009528719	21430	4.4464e-07	Prob > F =	0.0000
				R-squared =	0.0039
				Adj R-squared =	0.0038
Total	.009565891	21431	4.4636e-07	Root MSE =	.00067

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	9.94e-08	1.09e-08	9.14	0.000	7.81e-08	1.21e-07
_cons	.0030875	.0000148	209.26	0.000	.0030586	.0031164

-> symbol = GSLA



Source	SS	df	MS	Number of obs =	143
Model	.000717764	1	.000717764	F( 1, 141) =	3.23
Residual	.031381131	141	.000222561	Prob > F =	0.0747
Total	.032098895	142	.000226049	R-squared =	0.0224
				Adj R-squared =	0.0154
				Root MSE =	.01492

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-.0001642	.0000914	-1.80	0.075	-.0003449 .0000166
_cons	.0352972	.002036	17.34	0.000	.0312722 .0393221

-> symbol = HFFC

Source	SS	df	MS	Number of obs =	135
Model	.014606154	1	.014606154	F( 1, 133) =	145.60
Residual	.013342287	133	.000100318	Prob > F =	0.0000
Total	.027948441	134	.00020857	R-squared =	0.5226
				Adj R-squared =	0.5190
				Root MSE =	.01002

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	.0014211	.0001178	12.07	0.000	.0011882 .0016541
_cons	.0076832	.0017983	4.27	0.000	.0041263 .01124

-> symbol = INTC

Source	SS	df	MS	Number of obs =	206874
Model	.000202425	1	.000202425	F( 1,206872) =	57619.37
Residual	.000726771206872	3.5131e-09		Prob > F =	0.0000
Total	.000929196206873	4.4916e-09		R-squared =	0.2178
				Adj R-squared =	0.2178
				Root MSE =	5.9e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-1.10e-08	4.59e-11	-240.04	0.000	-1.11e-08 -1.09e-08
_cons	.0009078	6.82e-07	1331.16	0.000	.0009064 .0009091

-> symbol = LYTS

Source	SS	df	MS	Number of obs =	616
Model	.00052967	1	.00052967	F( 1, 614) =	18.24
Residual	.017829525	614	.000029038	Prob > F =	0.0000
Total	.018359195	615	.000029852	R-squared =	0.0289
				Adj R-squared =	0.0273
				Root MSE =	.00539

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	.0000433	.0000101	4.27	0.000	.0000234 .0000633
_cons	.0132989	.0004967	26.78	0.000	.0123235 .0142742

-> symbol = MSFT

Source	SS	df	MS	Number of obs =	200048
				F( 1,200046) =	4994.18

Model		6.6305e-06	1	6.6305e-06	Prob > F	=	0.0000
Residual		.000265589200046	1.3276e-09		R-squared	=	0.0244
-----							
Total		.000272219200047	1.3608e-09		Adj R-squared	=	0.0244
					Root MSE	=	3.6e-05

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		3.83e-09	5.41e-11	70.67	0.000	3.72e-09 3.93e-09
_cons		.0006165	7.36e-07	837.82	0.000	.0006151 .000618

-> symbol = ORCL

Source		SS	df	MS	Number of obs	=	174232
Model		.006916635	1	.006916635	F( 1,174230)	=	.
Residual		.004047075174230	2.3228e-08		Prob > F	=	0.0000
-----							
Total		.010963709174231	6.2926e-08		R-squared	=	0.6309
					Adj R-squared	=	0.6309
					Root MSE	=	.00015

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		-6.50e-08	1.19e-10	-545.68	0.000	-6.53e-08 -6.48e-08
_cons		.001742	1.49e-06	1166.86	0.000	.001739 .0017449

-> symbol = PLFE

Source		SS	df	MS	Number of obs	=	790
Model		.000222628	1	.000222628	F( 1, 788)	=	11.15
Residual		.015738431	788	.000019973	Prob > F	=	0.0009
-----							
Total		.015961058	789	.000020229	R-squared	=	0.0139
					Adj R-squared	=	0.0127
					Root MSE	=	.00447

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		-.0000274	8.22e-06	-3.34	0.001	-.0000436 -.0000113
_cons		.012237	.000429	28.52	0.000	.0113949 .0130792

-> symbol = QCOM

Source		SS	df	MS	Number of obs	=	215652
Model		.000015057	1	.000015057	F( 1,215650)	=	3351.56
Residual		.000968836215650	4.4926e-09		Prob > F	=	0.0000
-----							
Total		.000983894215651	4.5624e-09		R-squared	=	0.0153
					Adj R-squared	=	0.0153
					Root MSE	=	6.7e-05

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		2.50e-09	4.33e-11	57.89	0.000	2.42e-09 2.59e-09
_cons		.0006542	6.90e-07	947.58	0.000	.0006529 .0006556

-> symbol = RFIL

Source		SS	df	MS	Number of obs	=	507
Model		.042855883	1	.042855883	F( 1, 505)	=	98.01
Residual		.220821628	505	.000437271	Prob > F	=	0.0000
-----							
					R-squared	=	0.1625
					Adj R-squared	=	0.1609

Total | .263677511 506 .000521102 Root MSE = .02091

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	.0003027	.0000306	9.90	0.000	.0002426	.0003628
_cons	.047981	.0020415	23.50	0.000	.0439702	.0519919

-> symbol = SMBC

Source	SS	df	MS	Number of obs =
Model	.000741733	1	.000741733	40
Residual	.005859638	38	.000154201	F( 1, 38) = 4.81
Total	.006601371	39	.000169266	Prob > F = 0.0345
				R-squared = 0.1124
				Adj R-squared = 0.0890
				Root MSE = .01242

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	-.0012142	.0005536	-2.19	0.034	-.002335	-.0000935
_cons	.0483505	.0040267	12.01	0.000	.040199	.056502

-> symbol = WSCI

Source	SS	df	MS	Number of obs =
Model	1.8851e-06	1	1.8851e-06	104
Residual	.086678078	102	.000849785	F( 1, 102) = 0.00
Total	.086679963	103	.000841553	Prob > F = 0.9625
				R-squared = 0.0000
				Adj R-squared = -0.0098
				Root MSE = .02915

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
dayfreq	-.0000196	.0004167	-0.05	0.963	-.0008462	.000807
_cons	.0761447	.0055185	13.80	0.000	.0651988	.0870906

**Appendix B2 – 2008 Regression of Spread (aliq) determined by Orders Per Day (dayfreq)**

-----  
 -> symbol = AAPL

Source	SS	df	MS	Number of obs =
Model	.000360329	1	.000360329	486398
Residual	.000911004486396	1.8730e-09		F( 1,486396) = .
Total	.001271333486397	2.6138e-09		Prob > F = 0.0000

R-squared = 0.2834
Adj R-squared = 0.2834
Root MSE = 4.3e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	6.95e-11	1.59e-13	438.62	0.000	6.92e-11 6.99e-11
_cons	.0002183	2.60e-07	838.43	0.000	.0002178 .0002188

-----  
 -> symbol = ALNC

Source	SS	df	MS	Number of obs =
Model	.052704267	1	.052704267	15888
Residual	.263248249	15886	.000016571	F( 1, 15886) = 3180.50
Total	.315952516	15887	.000019887	Prob > F = 0.0000

R-squared = 0.1668
Adj R-squared = 0.1668
Root MSE = .00407

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	6.01e-07	1.07e-08	56.40	0.000	5.80e-07 6.22e-07
_cons	.0232721	.000048	484.98	0.000	.023178 .0233661

-----  
 -> symbol = AMGN

Source	SS	df	MS	Number of obs =
Model	.000580478	1	.000580478	394040
Residual	.002784639394038	7.0669e-09		F( 1,394038) =82140.03
Total	.003365117394039	8.5401e-09		Prob > F = 0.0000

R-squared = 0.1725
Adj R-squared = 0.1725
Root MSE = 8.4e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	5.21e-10	1.82e-12	286.60	0.000	5.17e-10 5.24e-10
_cons	.0004588	5.94e-07	772.47	0.000	.0004577 .00046

-----  
 -> symbol = BMRC

Source	SS	df	MS	Number of obs =
Model	.014240958	1	.014240958	22494
Residual	.336363516	22492	.000014955	F( 1, 22492) = 952.27
Total	.350604474	22493	.000015587	Prob > F = 0.0000

R-squared = 0.0406
Adj R-squared = 0.0406
Root MSE = .00387

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	3.86e-07	1.25e-08	30.86	0.000	3.61e-07 4.10e-07
_cons	.0219192	.0000523	418.97	0.000	.0218167 .0220217

-> symbol = COST

Source	SS	df	MS	Number of obs =	410557
Model	.004187155	1	.004187155	F( 1,410555) =	.
Residual	.005461579410555	1.3303e-08		Prob > F =	0.0000
				R-squared =	0.4340
				Adj R-squared =	0.4340
Total	.009648734410556	2.3502e-08		Root MSE =	.00012

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	1.39e-09	2.48e-12	561.03	0.000	1.39e-09 1.40e-09
_cons	.0003236	7.49e-07	432.01	0.000	.0003221 .0003251

-> symbol = DELL

Source	SS	df	MS	Number of obs =	439954
Model	.000358041	1	.000358041	F( 1,439952) =	.
Residual	.000933907439952	2.1227e-09		Prob > F =	0.0000
				R-squared =	0.2771
				Adj R-squared =	0.2771
Total	.001291948439953	2.9366e-09		Root MSE =	4.6e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	1.68e-10	4.08e-13	410.69	0.000	1.67e-10 1.68e-10
_cons	.0006334	2.43e-07	2606.02	0.000	.0006329 .0006339

-> symbol = ELSE

Source	SS	df	MS	Number of obs =	20954
Model	.544029229	1	.544029229	F( 1, 20952) =	3659.27
Residual	3.11496714	20952	.000148672	Prob > F =	0.0000
				R-squared =	0.1487
				Adj R-squared =	0.1486
Total	3.65899637	20953	.000174629	Root MSE =	.01219

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-1.61e-06	2.66e-08	-60.49	0.000	-1.66e-06 -1.56e-06
_cons	.061173	.0001398	437.47	0.000	.0608989 .0614471

-> symbol = FCBC

Source	SS	df	MS	Number of obs =	64521
Model	.141701786	1	.141701786	F( 1, 64519) =	53161.38
Residual	.171975555	64519	2.6655e-06	Prob > F =	0.0000
				R-squared =	0.4517
				Adj R-squared =	0.4517
Total	.313677341	64520	4.8617e-06	Root MSE =	.00163

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	2.58e-07	1.12e-09	230.57	0.000	2.56e-07 2.60e-07
_cons	.0123986	.000015	828.25	0.000	.0123693 .012428

-> symbol = GILD

Source	SS	df	MS	Number of obs =
Model	.00051531	1	.00051531	424320
Residual	.006369951424318	1.5012e-08		F( 1,424318) =34326.04
Total	.006885261424319	1.6227e-08		Prob > F = 0.0000
				R-squared = 0.0748
				Adj R-squared = 0.0748
				Root MSE = .00012

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	4.51e-10	2.44e-12	185.27	0.000	4.47e-10 4.56e-10
_cons	.0005664	9.25e-07	612.55	0.000	.0005645 .0005682

-> symbol = GSLA

Source	SS	df	MS	Number of obs =
Model	.015500629	1	.015500629	364
Residual	.0704341	362	.000194569	F( 1, 362) = 79.67
Total	.085934728	363	.000236735	Prob > F = 0.0000
				R-squared = 0.1804
				Adj R-squared = 0.1781
				Root MSE = .01395

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-.0001093	.0000122	-8.93	0.000	-.0001334 -.0000852
_cons	.0509907	.0016572	30.77	0.000	.0477317 .0542496

-> symbol = HFFC

Source	SS	df	MS	Number of obs =
Model	.034012999	1	.034012999	3054
Residual	.112700467	3052	.000036927	F( 1, 3052) = 921.09
Total	.146713465	3053	.000048056	Prob > F = 0.0000
				R-squared = 0.2318
				Adj R-squared = 0.2316
				Root MSE = .00608

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	-8.18e-06	2.70e-07	-30.35	0.000	-8.71e-06 -7.65e-06
_cons	.0444659	.0002209	201.32	0.000	.0440328 .0448989

-> symbol = INTC

Source	SS	df	MS	Number of obs =
Model	.001547719	1	.001547719	476072
Residual	.00157709476070	3.3127e-09		F( 1,476070) = .
Total	.003124809476071	6.5637e-09		Prob > F = 0.0000
				R-squared = 0.4953
				Adj R-squared = 0.4953
				Root MSE = 5.8e-05

aliq	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq	2.02e-10	2.95e-13	683.52	0.000	2.01e-10 2.02e-10
_cons	.0005868	2.93e-07	2000.60	0.000	.0005862 .0005874

-> symbol = LYTS

Source	SS	df	MS	Number of obs =
Model	.105389735	1	.105389735	146739
				F( 1,146737) =12387.48
				Prob > F = 0.0000

Residual		1.24840333146737	8.5078e-06	R-squared	=	0.0778
-----						
Total		1.35379306146738	9.2259e-06	Adj R-squared	=	0.0778
-----						
				Root MSE	=	.00292

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		9.29e-08	8.35e-10	111.30	0.000	9.13e-08 9.45e-08
_cons		.0095954	.0000257	373.77	0.000	.0095451 .0096457

-> symbol = MSFT

Source		SS	df	MS	Number of obs	=	473715
-----							
Model		.00141986	1	.00141986	F( 1,473713)	=	.
Residual		.001486322473713	3.1376e-09		Prob > F	=	0.0000
-----							
Total		.002906182473714	6.1349e-09		R-squared	=	0.4886
-----							
					Adj R-squared	=	0.4886
					Root MSE	=	5.6e-05

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		2.07e-10	3.08e-13	672.70	0.000	2.06e-10 2.08e-10
_cons		.0005079	3.10e-07	1637.21	0.000	.0005072 .0005085

-> symbol = ORCL

Source		SS	df	MS	Number of obs	=	455954
-----							
Model		.000619293	1	.000619293	F( 1,455952)	=	.
Residual		.001098037455952	2.4082e-09		Prob > F	=	0.0000
-----							
Total		.00171733455953	3.7665e-09		R-squared	=	0.3606
-----							
					Adj R-squared	=	0.3606
					Root MSE	=	4.9e-05

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		2.27e-10	4.49e-13	507.11	0.000	2.27e-10 2.28e-10
_cons		.0005807	2.58e-07	2252.11	0.000	.0005802 .0005812

-> symbol = PCBK

Source		SS	df	MS	Number of obs	=	36508
-----							
Model		.005123464	1	.005123464	F( 1, 36506)	=	203.03
Residual		.921249226	36506	.000025236	Prob > F	=	0.0000
-----							
Total		.92637269	36507	.000025375	R-squared	=	0.0055
-----							
					Adj R-squared	=	0.0055
					Root MSE	=	.00502

aliq		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dayfreq		1.08e-07	7.55e-09	14.25	0.000	9.27e-08 1.22e-07
_cons		.0310118	.0000495	626.65	0.000	.0309148 .0311088

-> symbol = PLFE

Source		SS	df	MS	Number of obs	=	147492
-----							
Model		.018948424	1	.018948424	F( 1,147490)	=	5406.55
Residual		.516910731147490	3.5047e-06		Prob > F	=	0.0000
-----							
Total		.535859155147491	3.6332e-06		R-squared	=	0.0354
-----							
					Adj R-squared	=	0.0354
					Root MSE	=	.00187

```
-----
      aliq |      Coef.  Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
  dayfreq |  6.89e-08  9.37e-10   73.53  0.000   6.71e-08   7.07e-08
   _cons |  .0103501  .0000264   391.52  0.000   .0102983   .0104019
-----
```

-> symbol = QCOM

```
-----
      Source |      SS      df      MS                Number of obs = 451880
-----+-----+-----+-----+-----
      Model |  .002818819      1  .002818819          F( 1, 451878) = .
      Residual |  .005875156451878  1.3002e-08          Prob > F      = 0.0000
-----+-----+-----+-----+-----
      Total |  .008693975451879  1.9240e-08          R-squared     = 0.3242
                                          Adj R-squared = 0.3242
                                          Root MSE     = .00011
-----
```

```
-----
      aliq |      Coef.  Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
  dayfreq |  6.10e-10  1.31e-12   465.62  0.000   6.07e-10   6.12e-10
   _cons |  .0004198  7.96e-07   527.14  0.000   .0004183   .0004214
-----
```

-> symbol = RFIL

```
-----
      Source |      SS      df      MS                Number of obs = 22668
-----+-----+-----+-----+-----
      Model |  .038453887      1  .038453887          F( 1, 22666) = 56.74
      Residual |  15.3605569  22666  .000677692          Prob > F      = 0.0000
-----+-----+-----+-----+-----
      Total |  15.3990108  22667  .000679358          R-squared     = 0.0025
                                          Adj R-squared = 0.0025
                                          Root MSE     = .02603
-----
```

```
-----
      aliq |      Coef.  Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
  dayfreq | -4.11e-07  5.46e-08   -7.53  0.000  -5.18e-07  -3.04e-07
   _cons |  .0698526  .0002741   254.88  0.000   .0693154   .0703898
-----
```

-> symbol = SMBC

```
-----
      Source |      SS      df      MS                Number of obs = 1035
-----+-----+-----+-----+-----
      Model |  .000036494      1  .000036494          F( 1, 1033) = 0.65
      Residual |  .058032393  1033  .000056179          Prob > F      = 0.4204
-----+-----+-----+-----+-----
      Total |  .058068886  1034  .000056159          R-squared     = 0.0006
                                          Adj R-squared = -0.0003
                                          Root MSE     = .0075
-----
```

```
-----
      aliq |      Coef.  Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
  dayfreq |  3.65e-07  4.53e-07    0.81  0.420  -5.24e-07  1.26e-06
   _cons |  .0561762  .0005203   107.97  0.000   .0551552   .0571971
-----
```

-> symbol = WSCI

```
-----
      Source |      SS      df      MS                Number of obs = 70138
-----+-----+-----+-----+-----
      Model |  .014692516      1  .014692516          F( 1, 70136) = 510.70
      Residual |  2.0177506  70136  .000028769          Prob > F      = 0.0000
-----+-----+-----+-----+-----
      Total |  2.03244312  70137  .000028978          R-squared     = 0.0072
                                          Adj R-squared = 0.0072
                                          Root MSE     = .00536
-----
```

```
-----
      aliq |      Coef.  Std. Err.      t    P>|t|    [95% Conf. Interval]
-----+-----
```



dayfreq	-3.66e-08	1.62e-09	-22.60	0.000	-3.97e-08	-3.34e-08
_cons	.0307651	.0000335	918.39	0.000	.0306994	.0308307

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