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## High Frequency Trading and the Stock Market: A Look at the Effects of Trade Volume on Stock Price Changes

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## High Frequency Trading and the Stock Market: A Look at the Effects of Trade Volume on Stock Price Changes

### Abstract

The effects of high frequency trading span far beyond what many are able to comprehend. There is, however, a great deal of evidence regarding the affects that trade volumes have on stock prices. As previously mentioned, computers now conduct over 70% of all trades made every day. Just four years ago the market was 30% computer based (CBS News, 2010). It is evident, then, that the numbers of shares traded each day (volume) have increased with the rise in the trades made each day (frequency). For example, the average volume of trades made weekly on the Dow Jones Industrial Average from 2000-2005 leapt over 180% from 2005-2010 (Yahoo! Finance, 2010). So, since high frequency trading can be linked to the large increase in trade volumes, it is appropriate to look at the relationship between volatility of the stock market and the volume of trades made.

By using time series analysis, it is hoped to find whether or not high frequency trading (looked at in terms of trade volume) is positively or negatively affecting the stock market. It is hypothesized that the higher the volume of trades made, the more volatile the stock prices will be. If this is the case, there may be policy implications regarding restrictions placed on the firms using high frequency trading.

# High Frequency Trading and the Stock Market: A Look at the Effects of Trade Volume on Stock Price Changes

Kyle Portnoy

## I. Introduction

It is no surprise that there have been extreme advances in technology over the past two decades. Information is now being processed at speeds that were once believed to be impossible and people are staying connected from farther away every day. Opinions on this rapid change are mixed, but there is no hiding the benefits that computers are producing. Virtually every aspect of life has been affected by the technology boom and the stock market is no exception.

For over 100 years, the New York Stock Exchange (NYSE) acted as the global hub of all investing. Brokers and investors alike once flocked to this financial Mecca with aspirations of profiting from the trades they would make. Now, though, the NYSE no longer has this huge presence of human investors on the floor. Rather, it is almost exclusively computers. Roughly 70% of all trades in the stock market are now done through computers using high frequency trading (CBS News, 2010). This strategy uses computers to apply complex algorithms created to scan different exchanges, trying to anticipate which direction individual stocks are likely to move in the next fraction of a second based on current market conditions and statistical analysis of past performance. But the computers have no real understanding of what these companies are and what they do. Because of this lack of “investing knowledge”, the world of high frequency trading has come under much scrutiny of late.

Those in favor of high frequency trading believe that the rapid trades provide liquidity in the market. This means that investors are able to buy and sell stocks right away at a fair price. Without high frequency trading, there is not as much liquidity and thus less stability. Those opposed to high frequency trading, however, think that it is manipulating the market. These computers are able to react to different triggers within milliseconds, much faster than any human investor. Because of this, the computers are able to sniff out potential booms and busts before anyone else and capitalize on their moves to the tune of billions of dollars in profit. The large profits (rarely offset by dramatic losses) are causing policy makers to question the justness of high frequency trading. Is it fair for large firms to make huge gains at the hand of the average investor? This is the question that has been storming through Wall Street (CBS News, 2010).

The effects of high frequency trading span far beyond what many are able to comprehend. There is, however, a great deal

of evidence regarding the affects that trade volumes have on stock prices. As previously mentioned, computers now conduct over 70% of all trades made every day. Just four years ago the market was 30% computer based (CBS News, 2010). It is evident, then, that the numbers of shares traded each day (volume) have increased with the rise in the trades made each day (frequency). For example, the average volume of trades made weekly on the Dow Jones Industrial Average from 2000-2005 leapt over 180% from 2005-2010 (Yahoo! Finance, 2010). So, since high frequency trading can be linked to the large increase in trade volumes, it is appropriate to look at the relationship between volatility of the stock market and the volume of trades made.

By using time series analysis, it is hoped to find whether or not high frequency trading (looked at in terms of trade volume) is positively or negatively affecting the stock market. It is hypothesized that the higher the volume of trades made, the more volatile the stock prices will be. If this is the case, there may be policy implications regarding restrictions placed on the firms using high frequency trading.

## II. Literature Review

The relationship between volume and price change has been looked at many times in the past. Understanding this relation provides insight into the structure of financial markets as well as implications for research in futures markets (Karpoff, 1987). What is interesting, though, is how the relationship has transformed over time. Karpoff's survey was done in 1987 and included studies dating back to the 1960's. Clearly, high frequency trading did not exist then. Therefore, it could be inferred that the positive relationship between trading volume and stock price changes found in those studies is even more important now that volume is higher than it has ever been.

More recent studies have looked at a vast array of topics related to the one in this paper. Chakravarty (2001) examined the phenomenon of stealth trading in the stock market. He hypothesized that medium-sized trades are associated with a disproportionately large cumulative stock price change relative to their proportion of all trades and volume. His findings are consistent with the hypothesis and prove that trades initiated by institutions have an incredible amount of influence on changes in stock prices. This suggests that high frequency trading firms do influence the market immensely. If these firms are found to be making medium-sized trades at high frequencies,

their actions could drive price changes through the roof. It also could be argued that medium sized trades could trigger additional trades in the same direction (i.e., buy or sell) through algorithmic trades that are triggered by the original stock price changes. Thus there could be a multiplier effect that is triggered by algorithms with the multiplier growing as this type of trading increases in popularity.

With increased influence coming from institutions comes a phenomenon known as the bandwagon effect. The bandwagon effect occurs when a consensus view develops that anticipates a severe change in future spot prices, resulting in an overwhelming move to buy or sell (Raines et al. 2007). If average, human investors are acting upon anticipations based on previous shifts in demand for a certain stock, the price of that stock could rise or fall dramatically. Depending on whether or not that change is detected and corrected could alter the profits of many investors not using algorithmic trading. According to Paul Davidson, it is the bandwagon effect that causes problems in financial markets and that the solution for this must involve the creation of a market maker prepared to “lean into the wind” when markets show signs of departing from fundamentals (Davidson, 1998). Perhaps restrictions on high frequency trading are what the market needs.

These restrictions are already being looked at overseas. The European Union is considering regulating the world of high frequency trading because of its imposed risk on individual investors. The United States is also looking into imposing parameters for high frequency trading firms in order to benefit individual investors (Moshinsky, 2010). For instance, New York’s Trillium Brokerage Services, through nine proprietary traders, sent non-bona fide orders into the markets to create false volume, thereby attracting buying or selling interest. The “shenanigans” give regulators more reason to consider putting restrictions on high frequency trading firms (Moyer, 2010). The reason there aren’t more moves being made, though, is that individual investors are not investing for the same reasons as high frequency trading firms. High frequency trading firms turn their investments to profits in virtually no time at all. Average investors, however, hold on to stocks for long periods of time. Even if they hold onto a stock for minutes, that is considered long term in the world of high frequency trading. Because of this difference, though, it seems as if high frequency trading isn’t doing anything negative to the market because it is so different from traditional trading (CBS News, 2010).

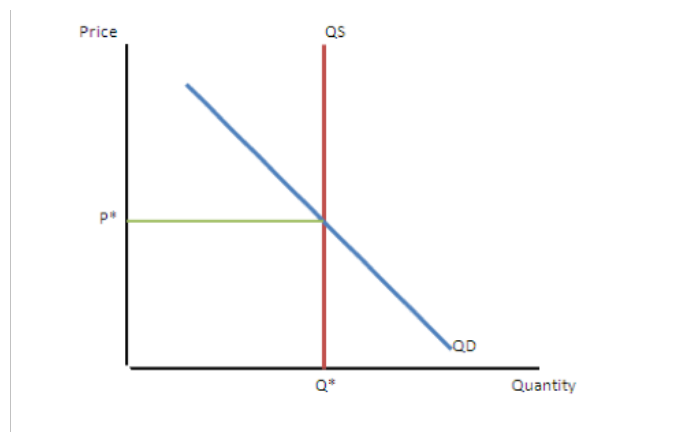
On the other hand, some investors believe that restrictions on high frequency trading would actually hurt the market. Stuart Kaswell, general counsel of the Managed Funds Association, wrote to the Securities and Exchange Commission and Commodity Futures Trading Commission, “Changes not supported by empirical data and directed at preventing rare market dislocations, could further harm investors.” This is in reference to the idea that some have suggested that high-frequency traders made May 6’s market plunge (when the Dow Jones Industrial Average fell 600 points only to recover those losses within minutes) worse by pulling out of the markets (FINalternatives, 2010).

The arguments have gone both ways for a while now and will probably continue for some time. No matter what side one

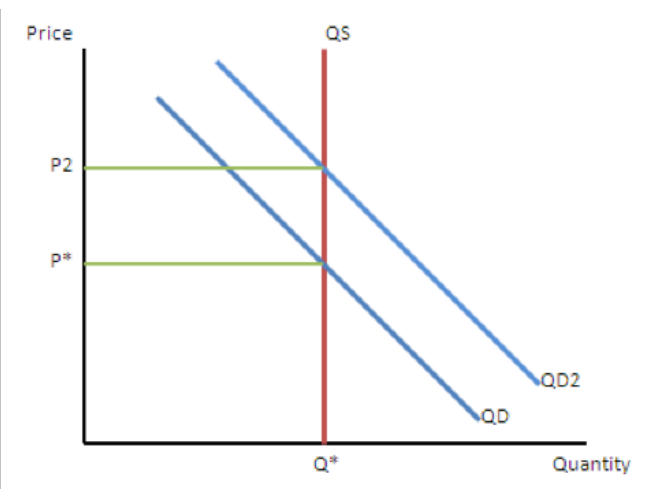
argues for, it is still clear that high frequency trading is affecting the stock market in one way or another. It could be causing commotion or it could be keeping everything stable. Either way, there must be an answer so that policymakers can take steps in the right direction.

### III. Theoretical Model

The model used in this paper will be the simple supply and demand model. As stocks are issued, there is an inelastic, or fixed, supply. Demand is set for the stock based on different factors including intrinsic value, fundamental analysis, and expectations.



When volume increases, the demand for that stock will shift right (more buyer initiated trades) or left (more seller initiated trades). When the demand curve shifts, the price of the stock will also shift. What is seen here is that informed investors, high frequency firms for the sake of this study, will initially shift the demand causing an increase in bandwagon investing. Bandwagon investing occurs when investors see a trend in a certain stock and trade based on that trend. Oddly enough, high frequency trading firms also contribute to bandwagon investing, but their roles are limited considering they will get in and out of a stock in a matter of seconds, perhaps correcting any shifts they may have caused. Bandwagon investors, though, drive the demand even further in whichever direction the informed investors originally pushed it.



So, shifts in demand are caused by an increase in the volume of trading. The problem here is that computers are responsible for most of the volume, but none of the computers know anything about the companies they are trading. Therefore, it

is possible that there is artificial inflation/deflation occurring, pushing prices higher/lower when in reality the company's value is much different.

#### IV. Empirical Model

In order to test the hypothesis, data from the stock market were extracted. Weekly quotes from the Dow Jones Industrial Average (DJIA) over the last decade (January 1, 2000-December 31, 2009) were pulled from Yahoo! Finance. The DJIA was used because of the fact that it is an index of 30 blue-chip, or well-established and financially sound companies which means its prices will not only be less volatile, but it should portray the condition of the market as a whole fairly well. In looking at the data, five variables were recorded: open price, close price, high price, low price, and volume. The open and close prices are the prices that the DJIA opened at on Monday and closed at on Friday of the given week, the high and low prices are the highest and lowest prices the DJIA traded at during the given week, and the volume is the average trading volume for each day during the given week. From this given data, two more variables were derived: the absolute value of the difference between the open and close price (POC) and the absolute value of the difference in the high and low price (PHL). These derived variables come into play once testing begins. Before knowing the testing methods, though, it is important to understand where the methods come from.

Volume, as previously mentioned, has been greatly affected by the introduction of high frequency trading. In looking at the data, it is evident that there is a considerable upward trend in trade volume during the last ten years. This upward trend in volume could explain some of the upward trend also found in POC and PHL but not all of it. The reason for this is the presence of unit roots. Unit roots state that current data is affected by the data from the previous time period and an error term. Therefore, in the case of this data, the unit root would explain current POC and PHL by looking at previous POC and PHL plus an error term. In order to test this, an ordinary least squares (OLS) regression must be run. This method minimizes the sum of squared distances between the observed responses in the dataset and the responses predicted by the linear approximation. The resulting estimator can be expressed by a simple formula, especially in the case of a single regressor on the right-hand side (Statistics.com).

The regression to be run in this test will be between volume and price. For this reason, the general regression equation will look like this:

$$\Delta\text{Price} = c + \beta\Delta\text{Volume}$$

In order to run this regression, however, some steps must be taken. First, the value of the volumes must be transformed into growth rates. By using growth rates, the focus will be on how much the volume grows relative to itself rather than just as a number. When using volumes in the billions of trades, a change of two million may seem large, but in reality could be as small as .005%.

The next step is to test that these newly derived growth rates are stationary. A stationary series has a constant mean and variance. This focuses on the consistency of the series over time. In order to test for stationarity, two unit root tests are

employed. The Augmented Dickey Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests will be used in order to do this. If these tests show that the data has unit roots, it may also be said that the series are stationary.

If, and only if, the series are stationary, regressions may be run in order to test the hypothesis. If the series are not stationary, they must be transformed so that they are stationary. The general regression equation will be altered in order to examine volume and volatility. The first alteration will make PHL the dependent variable while leaving volume as the independent variable:

$$\text{PHL} = c + \beta\Delta\text{Volume}$$

This equation will explain the impact that the change in volume has on the change between the high and low prices of a given week. The next alteration will leave the change in volume as the independent variable and replace PHL with POC as the dependent variable:

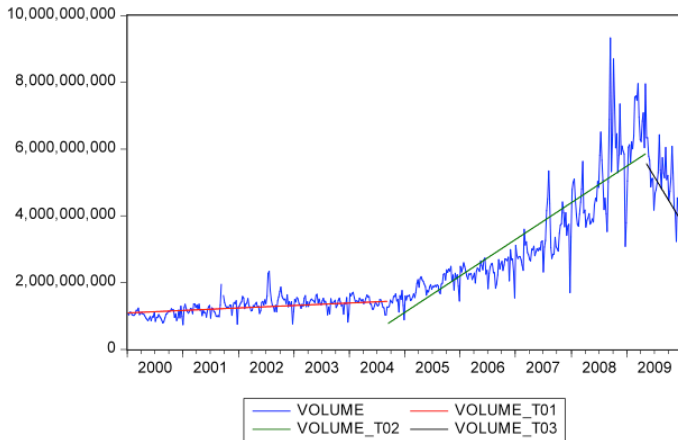
$$\text{POC} = c + \beta\Delta\text{Volume}$$

This equation will explain the impact that the change in volume has on the change between the open and close prices of a given week. When looking at both of these equations together, it will be possible to determine if changes in volume lead to more volatility in prices in terms of weekly data.

#### V. Results

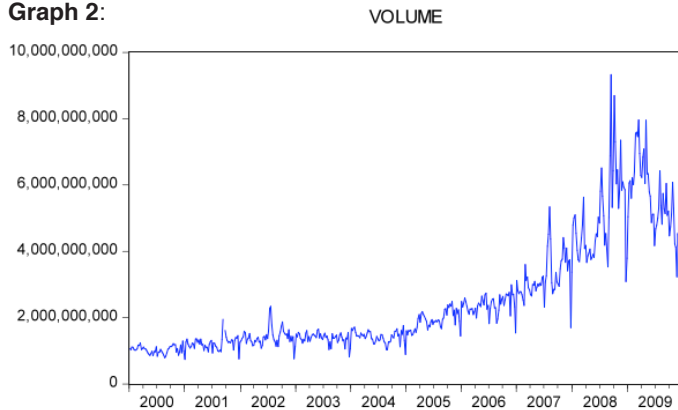
As shown in Graph 1, the trends associated with trading volume have been in a state of change over the last decade. From 2000-2004, there was a slight increase in the average weekly trade volume. From 2004-2009, however, there was exponential growth in trading volume. This tremendous escalation just so happened to coincide with the emergence of high frequency trading. Technology allowed traders to make larger and larger trades at faster and faster speeds, so it is no surprise that this "volume boom" occurred. From the middle of 2009 through the end of the year, though, growth turned into decay and the average volume of trades per week began to fall. Because this decay was relatively insignificant compared to the growth from 2004-2009, it would be accurate to assume a great presence of high frequency trading firms remaining in the market while more individual traders backed out due to both the losses they suffered during the recession and their lack of confidence in the economy.

**Graph 1:**



In order to perform a precise regression, the data had to be transformed into growth rates. To do that, unit root tests had to be performed making it possible to detect stationarity. This is done by taking the log (Graph 3) of the original data (Graph 2). The tests were first performed in levels and then, if a data set were not stationary, in first order differences. Table 1 contains the relevant statistics from each of these tests.

**Graph 2:**

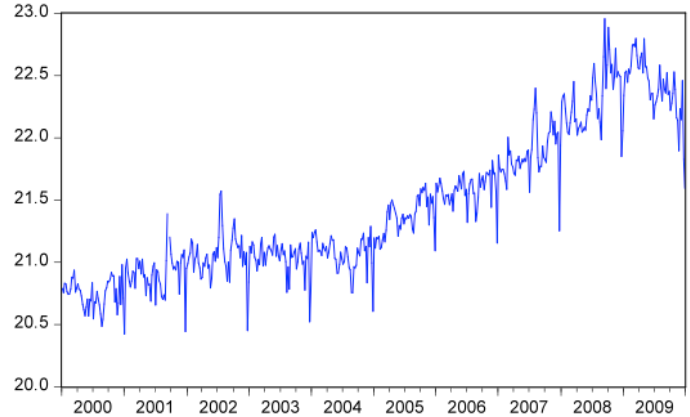


The numbers in Table 1 help justify whether or not the null hypothesis for each test can be rejected. For the ADF test, if the test statistic is larger than the critical values we do not reject the null hypothesis of a unit root in levels. This is important because if there is a unit root, it is likely that the data is not stationary. Stationarity tests still need to be done, though, to make sure the data is stationary. The stationarity test used in this study was the KPSS test. For this test, if the test statistic is larger than the critical values, we do reject the null hypothesis of stationarity in levels.

In the case of the growth rates for volume, when tested in levels, the test statistic was larger than the values at each confidence interval, thus we do not reject the null hypothesis of a unit root in levels. The KPSS test confirms the inference from the ADF test. Because the test statistic is larger than the critical values at every confidence interval, we reject the null hypothesis that volume is stationary in levels. Graph 3 provides a visual for the lack of stationarity in levels.

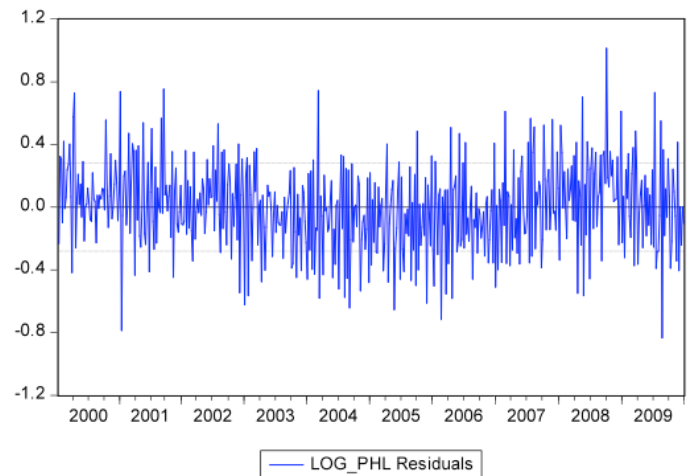
**Graph 3:**

LOG\_VOLUME



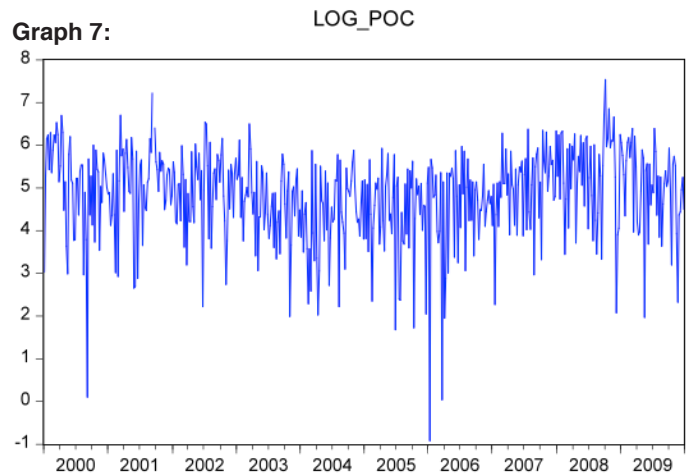
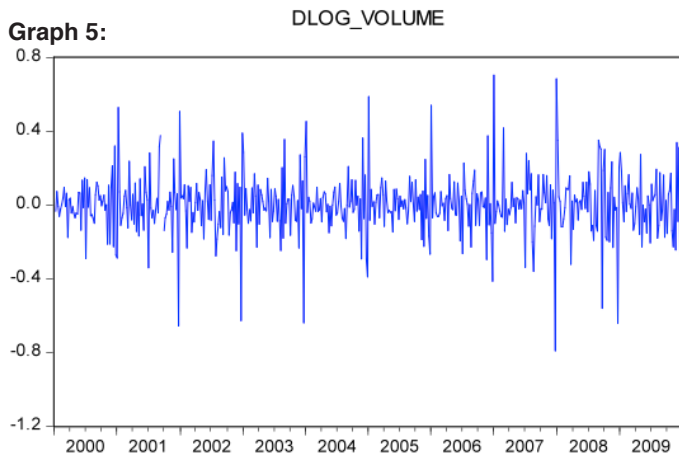
Because the data were not stationary, it was necessary to take the first order difference. When using first order differences, the ADF test statistic was much smaller than the critical values at every level, therefore we do reject the null hypothesis of a unit root in first order differences. The KPSS test again confirms the inference that the data is stationary. We do not reject the null hypothesis that the data is stationary because the test statistic is smaller than the critical values at each confidence interval. The stationarity can be seen in Graph 4.

**Graph 4:**



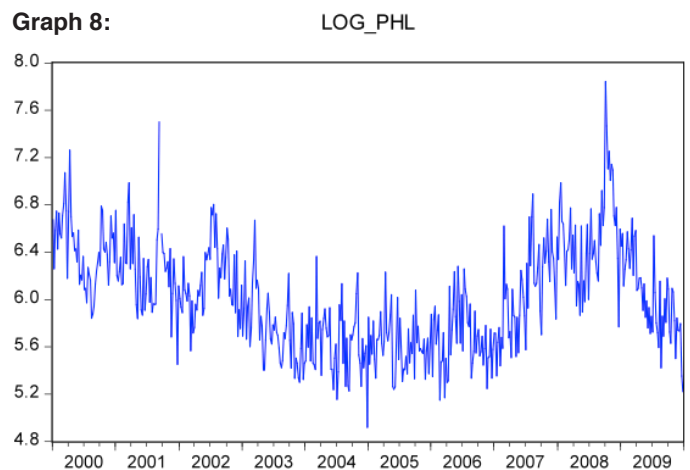
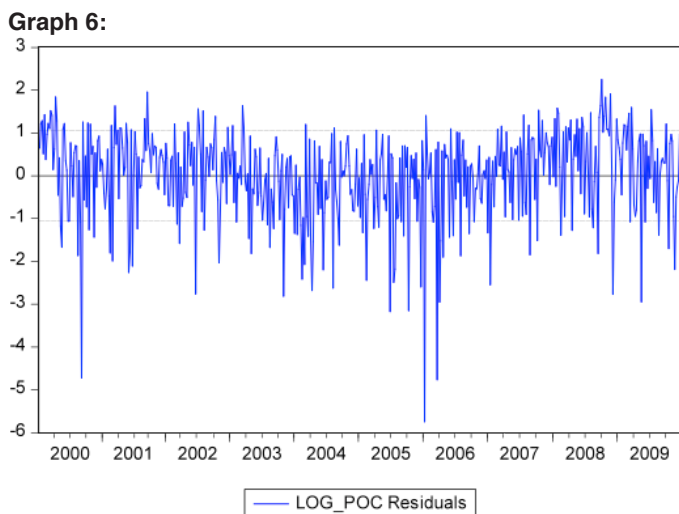
POC and PHL were both easier to handle due to the lack of a unit root and presence of stationarity in each. The ADF test statistic was smaller than the critical values at each confidence interval when testing POC and PHL. The KPSS test, though, had a bit of a difference. For POC, the KPSS test statistic was larger than the critical values at the 5% and 10% levels, but smaller than the critical value at the 1% level. This means that, with 99% confidence, we do not reject the null hypothesis of stationarity in levels. Graph 5 shows the stationarity of POC.





When testing for PHL, the KPSS test statistic was smaller than the critical values at the 1% and 5% levels. Since the test statistic was only larger than the critical value at the 10% level, though, we do not reject the null hypothesis of stationarity in levels with 90% confidence. Graph 6 shows the stationarity of PHL.

The POC regression was not as helpful. The low R-squared signifies little correlation between the independent and dependent variables. Graph 8 shows how the residuals of this regression leak far outside the bands. Because of this lack of a constant variance we say that the regression is heteroskedastic and not a reliable indication of how volume affects POC.



With all of the variables stationary, it was possible for a regression to be run. The results for the two regressions can be found in Table 2. The first regression was run using PHL as the dependent variable and volume as the independent variable. The second regression kept volume as the independent variable but used POC as the dependent variable.

## VI. Conclusion

Because the R-squared for the regression was significant and because the independent variable explained the dependent variable with 99% confidence, the regression using PHL as the dependent variable has supported the hypothesis. What these numbers mean is that a 10% increase in trading volume results in a 7.77% increase in the PHL. Graph 7 shows the residuals, or error between volume and PHL, of the regression. Because the residuals stay inside of the bands, it is said that this regression is homoskedastic deeming the interpretation trustworthy.

Even though one of the two regressions did not say anything noteworthy about the impact of high frequency trading on stock price changes, there is still something to take away from this study. When considering that the PHL regression was significant, it can be said that the weekly volume of trades does have an effect on the changes in stock prices. Since the POC regression was not as significant, however, those changes that occur throughout the week may be corrected by the time the market closes for the weekend. Because of this, it seems as though high frequency trading does not have a direct impact on the stock market solely by the amount of trades made by firms using the technique. Rather, the impacts may affect the morale of the average investor. When an individual sees the fluctuation of stock prices during the week due to the volume of trades (as the PHL regression supports), their confidence may be boosted or dwindled depending on which way the fluctuations are going. By the end of the week, though, the market will correct itself and

change based not on volume, but on many other factors.

These findings could help support the proponents of high frequency trading. Their use of technology has been profitable, has provided liquidity to the market, and has not directly affected the market in terms of trade volume. Restrictions may still be imposed on these firms in order to curb other influences they may have on market activity, but there should not be any made to limit the trade volume.

This study could be extended in a number of ways. Changing the data frequency to daily or even minute-by-minute quotes could possibly bring microscopic changes to the attention of those conducting the study. It would also be interesting to see if different indices, stocks, or sectors feel the effects of trade volume more than another. Hopefully these extensions will be regarded in the future, but for now, as the data shows, there is no need to worry about how high frequency trading affects stock prices in the long run.

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**Table 1: Unit Root/Stationarity Tests**

Variable	ADF	KPSS
Volume	-1.312 (-12.831)***	2.714 (0.166)***
POC	-10.029***	0.484***
PHL	-4.339***	0.444*

\* Indicates 90% confidence

\*\* Indicates 95% confidence

\*\*\*Indicates 99% confidence

() Indicates first order differences

**Table 2: Regression Results**

Dependent Variable	R-squared	Coefficient	Probability
PHL	0.605	0.777	0.000
POC	0.029	0.897	0.001

