An Empirical Analysis of the Efficient Market Hypothesis and the Quantifiable Impact of Financial Metrics on Abnormal Returns

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INTRODUCTION

The Efficient Market Hypothesis (EMH) is the notion that all publicly available information is reflected in the price of the stock leading to returns not greater than the market (Mishkin). This theory has been the foundation of multiple doubts regarding the financial market. The efficiency of the financial market is a crucial property since it establishes the approach investors should take when investing in equity markets. For instance, believers of the EMH often invest in index funds aiming to replicate the returns of major stock indices such as, S&P 500, DJIA, and NASDAQ. Furthermore, the EMH is essential to evaluate the funds allocated to information gathering. Investment intermediaries, such as mutual and hedge funds, assign millions of dollars to information gathering, thereby raising queries on whether these funds are being utilized efficiently, since this information should already be priced in. This paper adds to the existing literature by quantifying the impact of increments in financial metrics, relative to the consensus, on abnormal returns, as well as conducting analysis on the most recent set of data, the daily stock prices from the beginning of 2015 to the end of 2019. The secondary portion of the paper is vital to assessing the influence of the independent variables for investors looking to generate positive alphas, since it highlights the importance that must be given to each financial metric when considering investment strategy.

In this paper, I will be initially testing the weak form of the EMH. This form articulates there exists no serial correlation between past and future price movements (Bodie). Weak form of the EMH discredits technical analysis, a technique related to finding appropriate support and resistance levels for stock prices, under the belief that technical indicators are already reflected in the price of the stock. For instance, at the end of each year, the market expects a rally in stock prices due to a general increase in the demand for stocks [usually attributed to end of year bonuses, the exit of individuals expecting the stock prices to fall and the entrance of individuals expecting an appreciation in the stock prices, transactions undertaken to generate losses to offset taxes, et cetera]. Thus, an individual can easily profit from purchasing shares in a S&P 500 ETF and holding till the end of year. However, if the market does not rally, absent of any negative news, the market is said to be weak form efficient since this rally was already reflected in the market prices. Secondly, I will be assessing the strength of semi-strong form of the EMH. This form states all publicly available information, less any information available to corporate insiders alone, should be reflected in the price of a given stock (Bodie). This form goes as far to conclude the failure of both fundamental and technical analysis to generate substantial gains to beat the market. Fundamental analysis is the use of forecasts of earnings, dividends, interest rates, and general market conditions to assess the purchase of a stock (Bodie). Given semi-strong form of the EMH holds true, all information used in fundamental analysis should be reflected in the stock price and the only information absent should be information available to corporate insiders alone, thereby reducing the ability of fundamental analysis to beat the market. Finally, I shall be evaluating the impact of essential financial metrics on abnormal returns to deduce the importance of each financial metric.

To ensure accuracy of the research paper, I will be following the methods outlined in *Testing Weak Form Efficiency for Indian Stock Markets* for testing the weak form, however applied to a different data set with a different time frame. This article explores the weak form in the Indian stock market and concludes the Indian stock market is weak form inefficient. It conducts statistical analysis of its own through multiple unit root tests, out of which only two will be utilized in the writing of my research paper, the ADF and PP. Thus, this paper proves to be of great importance since it follows the similar procedure applied to the US market. The article explores the importance of each test providing a detailed explanation of methodology along with a clear interpretation of the results. Furthermore, it also conducts a non-parametric test, a runs test, which I shall be incorporating in my research paper.

Furthermore, to obtain a firmer understanding of the workings of the market and reasoning behind the EMH, I shall be using *Is the Stock Market Efficient* by Burton Malkiel. Although not handling any data itself, the paper debates the empirical analysis conducted by others, thereby laying the foundation of few of the arguments presented in my research paper. The article expounds historical findings exploring the weak form, providing arguments which reason with and against the evidence.

Finally, to better understand the ADF test, the textbook, *Introductory Econometrics,* shall also be used. This textbook is a great introduction to working with time series data and conducting serial correlation tests. The mathematical notation in this text is limited relative to articles addressing similar topics, thereby making it easier to understand. The serial correlation is focussed on autoregressive models of order one, which my research paper focusses on. The focus will be on Chapters 11 and 18. Chapter 11 introduces the subject of random walks, providing mathematical background whereas Chapter 18 dives into unit root tests to identify random walks and detecting serial correlation in my time series analysis of the S&P 500.

DATA

The data observed is collected daily. Unless specified, all data is taken from Yahoo Finance and applies to the US stock market alone. There are a total of 1,257 observations dating from 1st January 2015 to 30th December 2019 for completeness, uniqueness and to determine the strength of the EMH on the most recent data set. For assessing the weak form, I have taken a time series of the close prices for the S&P 500 index due to its wide acceptance as the market based index. Due to the nature of tests involved, no additional data is required.

To analyze the semi-strong form, from the S&P 500 index, a panel data set of the largest ten firms, by market capitalization, have been chosen. The independent variable of interest is trading volume, which has been standardized for both simplicity and the elimination of the units, measured in thousands. Instead of conducting the analysis on the entire index, individual firms have been chosen to best reflect the infusion of new information peculiar to the respective firm. The Capital Asset Pricing Model (CAPM) will be used to calculate predicted returns. The employment of the model will be studied in more detail during the analysis although an introduction will be made to it. The CAPM can be summarized by Equation 1. The individual subscript is ignored for simplicity.

$$r_p = r_f + \beta(r_m - r_f) \qquad \text{Equation 1}$$

r_p corresponds to the predicted return calculated from this model. r_f and r_m are the risk free rate and the market return respectively. β in the model corresponds the extent to which individual firm returns vary along with the market returns represented by S&P 500 returns. The calculation of β will be explored further during the analysis. Thus, in addition to the S&P 500 close prices, the risk free rate also will be observed on a daily basis as the 10 year treasury rate taken from Macrotrends due to it being a key component in the model. Upon calculation of the predicted returns, they will be subtracted from the realized returns to observe the abnormal returns.

To complete the paper and quantify the impact of financial metrics on abnormal returns, since all earning reports are published on a quarterly basis, keeping the time frame fixed, I shall continue using daily data, however, report the same values of financial metrics for a quarter, incorporating new variables such as earnings per share (EPS), return on equity (ROE), current ratio [defined as the ratio of current assets to current liabilities], and debt to equity ratio. All such data is recorded from MacroTrends due to its ease of accessibility (The Long Term Perspective on Markets). I shall also be using the daily values of CBOE Volatility Index, VIX, to act as a control in the regression equation. This data is taken from Yahoo Finance over the same time period.

EMPIRICAL STRATEGY

To test the weak form, I shall be employing the runs test, Augmented Dicky Fuller (ADF) test, and the Philips Perron (PP) test, to determine whether the S&P 500 close prices follow a random walk and ensure there exists none or limited correlation between the data and its lagged values. The runs test, due to being a nonparametric test, can be used when the distribution of the underlying data is unknown (Wang). A single run is identified by a consecutive series of identical symbols within an ordered data set consisting of two symbols (Wang). A series with too few runs implies a data set with runs that are long, whereas a series with too many runs implies a data set with runs that are short, thereby concerning us with the number of runs involved. The expected value and variance of the runs test is given by Equation 2 and Equation 3 (Khan).

$$\mu = \frac{2n_1 n_2}{n_1 + n_2} + 1 \qquad \text{Equation 2}$$

$$\sigma^2 = \frac{2n_1 n_2(2n_1 n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)} \qquad \text{Equation 3}$$

n_1 corresponds to the number of observations which are greater than the average of the entire data set whereas n_2 corresponds to the number of observations which are smaller than the average of the entire data set. To fail to reject the null hypothesis of the data being independently and identically distributed, the number of runs that should be observed should be approximately μ. The z-statistic is obtained through standardizing the runs as shown in Equation 4 where R is the total number of runs observed in the data.

$$z = \frac{R - \mu}{\sigma} \qquad \text{Equation 4}$$

The ADF test is similar to the DF test, in the sense it is used to test for unit roots, however allowing for higher order serial correlation when required (Wooldridge, Jeffrey M). Equation 5 and Equation 6 show the models that will be used for the ADF test (Khan).

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + u_t \qquad \text{Equation 5}$$

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 t + \sum_{i=1}^{p} \gamma_i \Delta y_{t-i} + u_t \qquad \text{Equation 6}$$

Both equations include a constant term also known as a drift term, however Equation 6 includes a time trend term to control for the observed trend. p represents the number of optimal additional lags chosen by minimizing Akaike Information Criteria (AIC), otherwise by choosing lags until there exists no serial correlation in the residuals. Assuming $p = 0$ so there exists no need for additional lags Equation 5 can easily be derived.

$$y_t = \beta_0 + \alpha_1 y_{t-1} + u_t \qquad \text{Equation 7}$$

$$y_t - y_{t-1} = \Delta y_t = \beta_0 + (\alpha_1 - 1) y_{t-1} + u_t \qquad \text{Equation 8}$$

A unit root is identified in Equation 7 upon the failure to reject the null hypothesis of $\alpha_1 = 1$ (Wooldridge, Jeffrey M) which can be simplified by subtracting y_{t-1} on both sides in Equation 7 and setting $\beta_1 = \alpha_1 - 1$ in Equation 8 as done in Equation 5. Instead of testing the null hypothesis for the coefficient, α_1, being equal to one, the test is now done for the coefficient, β_1, being equal to zero. Now assuming the existence of a unit root, the importance of a drift term can be demonstrated in the presence of a time trend as observed in Figure 1. In Figure 1, a clear upward time trend can be observed.

$$y_t = \beta_0 + y_{t-1} + u_t \qquad \text{Equation 9}$$

$$y_t = 2\beta_0 + y_{t-2} + u_t + u_{t-1} = \cdots = t\beta_0 + y_0 + \sum_{i=1}^{t} u_i \qquad \text{Equation 10}$$

$$E(y_t) = t\beta_0 + y_0 \qquad \text{Equation 11}$$

Thus, from substitution, the general value of y_t can be determined, as shown in Equation 10, from which the expected value of y_t can be calculated, as shown in Equation 11. From the conditional mean zero assumption, $E(u_i) = 0, \forall i$ whereas β_0 and y_0 are known constants, so Equation 11 holds. Without the presence of the drift term, $t\beta_0$ would be eliminated from Equation 11, thereby representing a movement around a constant term y_0, rather than a time trend.

For the S&P 500 time series to resemble a random walk, a unit root must be observed in Equation 5 and Equation 6. When a unit root is observed, the data is said to be non-stationary (Wooldridge, Jeffrey M) due to the mean and variance being functions of time. Under the model presented in Equation 5, the mean is clearly a function of time, t. A similar approach can be taken for calculating variance shown by Equation 12.

$$\sigma_y^{\ 2} = t\sigma_u^{\ 2} \qquad \text{Equation 12}$$

Through backward substitution, we obtain Equation 10. By taking the variance on both sides, the result is Equation 12. Since β_0 and y_0 are both known constants, their respective variances are zero and from the independent error terms assumption from linear regression, the variance of the sum of the error terms is simply the sum of their variances. Clearly, both mean and variance are a function of time and thus non-constant. A similar approach can be taken for the model presented in Equation 6.

The PP test augments the ADF test just described. It corrects for any unnoticed or unobserved heteroskedasticity as well as serial correlation in the error terms (Unit Root Tests). The test statistics for the PP test can be viewed as heteroskedastic-robust test statistics of the ADF test. Therefore, the PP test essentially reinforces the ADF test by being free of any parametric errors (Khan).

For assessing semi strong, multiple regressions would be run. To calculate predicted returns, as stated before, the CAPM will be utilized. An essential component of the model is a stock's beta, mathematically defined by Equation 13 (Perold) and calculated from the regression run in Equation 14.

$$\beta_i = \frac{COV(R_i, R_M)}{VAR(R_M)} \qquad \text{Equation 13}$$

$$R_{it} = \alpha_{it} + \beta_i R_{mt} + u_{it} \qquad \text{Equation 14}$$

R_{it} and R_{mt} correspond to the return of the i^{th} firm at time t and the market return at time t respectively both above the risk free rate at time t. Afterwards, the abnormal return is calculated as outlined by Equation 15.

$$r_{a_{it}} = r_{it} - [r_{f_t} + \beta_i \left(r_{m_t} - r_{f_t}\right)] \qquad \text{Equation 15}$$

$r_{a_{it}}$ corresponds to the abnormal return for firm i at time t. r_{it}, r_{m_t}, and r_{f_t} correspond to the realized return for firm i, the market return, and the risk free rate respectively all at time t. β_i corresponds to the coefficient value for firm i from Equation 14. The final regression is shown in Equation 16.

$$r_{a_{it}} = \beta_0 + \beta_1 \widetilde{V_{it}} + u_t$$

Equation 16

Here, $\widetilde{V_{it}}$ corresponds to the standardized trading volume for firm i at time t. The notion behind using abnormal returns and standardized trading volume is of importance. Abnormal returns represent the realized returns out of the ordinary due to events not captured by the CAPM, and therefore is a variable of interest when measuring the extent to which publicly available information is reflected in the price of the stock. The use of standardized trading volume simplifies the interpretation of the regression coefficients and eliminates the units. Moreover, the standardized trading volume reflects any impacts of new information decisive enough to incentivize investors to act upon it, thereby increasing trading volume and thus, standardized trading volume.

To prevent changes to trading volume due to liquidity issues, insider trading, or any other factor not a representation of the latest information, $\widetilde{V_{it}}$ is constrained to be larger than x_i such that a large fraction of random noise is eliminated. Due to the non-randomness of the independent variable, I shall be using the fitted values obtained from the regression truncated from below in Equation 17 where $\widetilde{V_{it}}$ takes on the values shown by Equation 18 and $\widetilde{V_{it}}^*$ is the observed standardized trading volume.

$$\widetilde{V_{it}} = \beta_0 + \beta_2 VIX + u_t$$ Equation 17

$$\widetilde{V_{it}} \begin{cases} \widetilde{V_{it}}^* if\ \widetilde{V_{it}}^* > x_i \\ -\ otherwise \end{cases}$$ Equation 18

In Equation 17, VIX corresponds to the CBOE Volatility Index and is a measure for uncertainty in the market. By using VIX, fitted standardized transaction volume values can be calculated. VIX is often a very strong indicator of transaction volume. When volatility in the market is high and investors are uncertain, they often switch their investments into risk free assets such as bonds, reducing the demand for stocks and thus standardized transaction volume. By using the fitted values from the regression, random sampling, which was violated initially, now holds and therefore OLS can be used. For semi-strong form to hold, the coefficient, β_1, in Equation 16 must be negative and statistically significant at the 5-10% significance level. As the standardized trading volume increases, thereby reflecting the infusion of newer and more information into the market, it should become considerably harder to obtain abnormal returns. Additionally, lack of information should allow abnormal returns to be made easily since information gathered by individual investors will easily beat the quantity and quality of information being produced by the market.

Choosing the value of x_i requires a logical approach. Figure 2 displays the standardized trading volume of AAPL over time. The line $y = 0$ is able to capture the spikes in volume whilst eliminating random noise to a considerable extent. The values of x_i for other firms are chosen in a similar manner with the line $y = x_i$ defining the truncation limit in the regression equation, Equation 17 and Equation 18. For instance, Figure 3 shows the standardized trading volume as a function of time for Amazon. Taking $y = 0.25$ eliminates a substantial amount of random noise and incorporates sudden spikes in the standardized trading volume representing the admission of additional information into equity markets. Due to the approach taken, a small amount of random noise is allowed, however it is not considerable enough to skew the results.

To assess the impact of financial metrics on abnormal returns, a multivariate regression is conducted of abnormal returns on the essential financial metrics, EPS, ROE, current ratio, debt to equity ratio, and VIX. The regression equation is identified by Equation 19. By using VIX, I am implicitly controlling for multiple variables, such as risk free rate and the health of the economy which are confounders. During times of falling rates and a healthy economy, VIX tends to be low as investors are more certain about the future economic outcomes, whereas during times of rising rates usually implemented to curb inflationary pressures, VIX tends to be high as investors are more uncertain about the state of the economy in near future. This equation will define the importance of each financial metric on beating the market and assess the effectiveness of an investment strategy utilizing such variables.

$$r_{a_{it}} = \pi_{0i} + \pi_{1i}EPS + \pi_{2i}ROE + \pi_{3i}Curr + \pi_{4i}DeEq + \pi_{5i}VIX + \tau \quad \text{Equation 19}$$

RESULTS

The null hypothesis of the runs test is that the observed data is a random variable which is identically and independently distributed. From conducting the runs test on the S&P 500 market close prices, the total number of runs obtained is 14 whereas the mean number calculated from Equation 2 is 629 rounded to the nearest integer and the variance calculated from Equation 3 is 313 rounded to the nearest integers. A p-value of 0 is obtained, thereby rejecting the null at the 5% significance hypothesis, implying the data shows strong serial correlation. However, due to the simplicity of this test, this result should be taken with a grain of salt. It is important to establish the data taken between 2015 and 2019 is during a bull market [a market within which prices are rising such that prices do not fall by more than 20% over a span of two months] (The Economic Times). Thus, it is very unlikely to experience multiple runs where the prices continuously fall and rise, a possible reason for observing only 14 runs.

The ADF test is of much more interest relative to the runs test due to its application in detecting unit roots. As previously mentioned, two models have been implemented with the number of lags chosen to minimize the AIC value. Table 1 shows AIC is minimized for a lag of a single period. Thus, a lag of a single period will be implemented in both models displayed by Equation 7 and Equation 8.

The results for the first model in Equation 5 is displayed by Table 2. With a p-value of 0.4244 we fail to reject the null hypothesis of $\alpha_1 = 1$ in Equation 7 at the 5% significance level, thereby concluding the existence of a unit root. The existence of a unit root implies the data for the S&P 500 close market prices follows a random walk and thus the market, in general, is weak form efficient.

From Figure 1, a clear upward trend can be seen and thus an additional time variable must be added to control for this time trend. This gives rise to the second model presented in Equation 8. Table 3 displays the results of this model. When controlling for the time trend, the p-value drastically falls to 0.0970. Thus, at the 5% significance level the market is just weak form efficient.

A similar interpretation of results can be drawn from Table 4 and Table 5 which display the PP test results. In both cases the p-value is greater than 0.05 but falls drastically after controlling for the time trend. Thus, the market remains weak form efficient from the unit root tests. It is important to state that the reported p-values in the regression tables can be ignored and the p-values being referred to are the p-values for $Z(t)$. This difference arises due to the differences in the null hypothesis. In the unit root tests, the null hypothesis is the existence of a unit root.

Table 6 to Table 15 show the results of Equation 16 for top 10 firms by market capitalization. From the results, it can be inferred that only JPM and PG are semi-strong efficient. Thus, a standard deviation increase in transaction volume reduces abnormal returns by 0.126% approximately. Given that JPM is a bank and functions in the financial sector, this result is in line with logical reasoning. The financial sector of the economy is the most regulated sector (Mishkin, Frederic S). As a result, there is more efficient information gathering and a larger volume of information being gathered. It becomes exceptionally difficult to beat the market since a large amount of credible information is being absorbed by the stock and investors often lack information that exceeds in quantity and quality relative to the information being absorbed. Thus, it is plausible for JPM to be semi-strong efficient.

Despite having a p-value of greater than 0.05, PG's p-value of 0.125 is evidence of some semi-strong efficiency. PG operates in Household and Personal Products industry providing personal hygiene and baby products (Yahoo Finance). Due to the nature of its products, it is likely to be under scrutiny and thus have a larger volume of information being released into the market. Following a similar reasoning as JPM, it is reasonable for PG to show some degree of semi-strong efficiency. A standard deviation increase in transaction volume reduces abnormal returns by approximately 0.09%. However, this questions the validity of results for JNJ which operates in a similar industry providing similar products but has a p-value of 0.793, much larger than 0.05 and showing very strong evidence against efficiency.

The remaining stocks are semi-strong inefficient due to their p-values being much larger than 0.05. A plausible explanation could be due to the CAPM being used to predict returns and calculate abnormal returns. To retain simplicity in predicting returns and easy interpretation of results it was necessary to use a simplified model. The weakness of CAPM has been shown previously and a better model which could have been implemented would be the Black's version of CAPM which has been shown to be empirically more powerful (Fama). A secondary reasoning could be due to stock buybacks and the bull market. Both events contribute to appreciation in stock prices (Dobbs Richard), especially technological firms such as FB, AAPL, AMZN, GOOGL, and MSFT. Such appreciation in prices allow investors to make returns which easily beat the CAPM returns thereby violating the semi-strong form of market efficiency which states investors should not be able to do so. This reasoning is exemplified by the p-values of these stocks, 0.922, 0.972, 0.515, 0.599, and 0.956 respectively.

A similar explanation holds when comparing the results of PG and JNJ. From 2015-2019, PG has done stock buybacks ranging from $0.01 to $3.504 billion (Procter & Gamble Stock Buybacks). whereas JNJ has done stock buybacks ranging from $0.145 to $3.808 billion (Johnson & Johnson Stock Buybacks). As JNJ has done stock buybacks that exceed in value relative to PG, JNJ's ROE for 3 months prior to 30/12/2019 to 30/12/2019 was 39.27% (Johnson & Johnson ROE 2006-2019) compared with PG's ROE, for the same time period, of 27.14% (Procter & Gamble ROE 2006-2019). Since both firms have similar business operations, they must face similar market risk and thus have ROEs that are close to each other. Since JNJ did more stock buybacks than PG, its ROE was higher and attained returns greater than those dictated by CAPM. As a result, JNJ displayed semi-strong inefficiency whereas PG displayed semi-strong efficiency.

When assessing the impact of financial metrics on abnormal returns, JPM and PG have been dropped due to both stocks showing a degree of semi-strong efficiency. The financial metrics would be priced in and are unlikely to contribute to abnormal returns. Table 16 displays the results of Equation 19 for AAPL. From the table it can be seen that only EPS is statistically significant. The coefficient implies that a dollar change in EPS will lead to a 0.116% change in the abnormal returns for AAPL. It can be concluded that when investing into AAPL and trying to beat the market, importance must be placed on EPS instead of other financial metrics which are priced in. This conclusion from the results is reinforced from conducting a F-test. A F-test on ROE, current ratio, and debt to equity ratio gives a p-value of 0.1720. Thus, we fail to reject the null hypothesis which implies that ROE, current ratio, and debt to equity ratio jointly do not impact abnormal returns. When including EPS in the F-test the p-value is 0.0478, implying rejection of the null hypothesis. This shows the importance of EPS in achieving abnormal returns since including EPS in the F-test changes the p-value substantially enough such that the null hypothesis is rejected at the 5% significance level. VIX is not included in both F-tests since it serves as a control to obtain unbiased estimates of the coefficients.

Table 17 displays the results of Equation 19 for AMZN. Although each financial metric itself is not statistically independent, conducting a F-test on EPS, ROE, current ratio, and debt to equity ratio yields a p-value of 0.0022. This p-value is strong evidence for a statistically significant joint impact of financial metrics on abnormal returns for AMZN. AMZN's results of Equation 19 are weaker than AAPL's as not a single financial metric is statistically independent by itself. This resonates with the semi-strong results since the p-value for AAPL was 0.972 whereas the p-value for AMZN was 0.515. AAPL shows stronger evidence against semi-strong efficiency relative to AMZN therefore implying weaker absorption of information. Thus, it is easier to obtain statistically significant abnormal returns from AAPL from a single financial metric relative to AMZN.

Table 18 displays the results of Equation 19 for BRK-B. From the table it can be inferred that an investment strategy utilizing the same financial metrics should place importance on EPS due to its positive coefficient and statistical significance. For the chosen timeframe, BRK-B had no debt thereby yielding a coefficient of 0. Once again, the obtained results are consistent with the semi-strong efficiency analysis conducted previously. BRK-B in Table 8 had a p-value of 0.860, reflecting poor absorption of information. Thus, it should be feasible to obtain statistically significant abnormal returns from a single financial metric. The p-value of a F-test conducted on ROE, current ratio, and debt to equity ratio is 0.4782. When including EPS in the F-test, the p-value falls drastically to 0.0103. This is evidence of the importance of EPS in beating the market when investing in BRK-B. The results for BRK-B are similar to AAPL since the p-values for both stocks are large indicating strong evidence against semi-strong efficiency.

Table 19 displays the results of Equation 19 for FB. From the table, it is conclusive that no financial metric has a statistically significant impact on abnormal returns alone. Conducting a F-test on EPS, ROE, current ratio, and debt to equity ratio yields a p-value of 0.7274 implying that the financial metrics jointly do not impact abnormal returns. However, from Table 9, the p-value for FB was 0.922 showing very strong evidence against semi-strong efficiency. As explained previously, FB's semi-strong inefficiency can be attributed to stock buybacks which FB has participated aggressively in (Facebook Stock Buybacks). Continuous stock buybacks causes appreciation in the stock price which in turn allows investors to obtain returns that beat the returns dictated by CAPM. Since the p-value for the F-test implies abnormal returns are not impacted by financial metrics, they must be impacted by stock buybacks to explain the inefficiency observed.

Table 20 displays the results of Equation 19 for GOOGL. The results for GOOGL are similar to that of AMZN and FB in the sense that no financial metric is statistically significant by itself. However, when conducting a F-test on EPS, ROE, current ratio, and debt to equity ratio, GOOGL shows similar results as FB with a p-value of 0.3663. From the p-value it can be concluded that the chosen financial metrics jointly do not impact abnormal returns. Following a similar line of reasoning as FB, GOOGL's semi-strong inefficiency can be attributed to stock buybacks. GOOGL, just like FB, has purchased a substantial amount of stock (Alphabet Stock Buybacks) which has been responsible for its stock price appreciation being greater than what is dictated by CAPM.

Table 21 displays the results of Equation 19 for JNJ. Similar to AAPL and BRK-B, there exists a financial metric, ROE, which is statistically significant. The coefficient implies that a percent point change in ROE causes a 0.007 percent point change in abnormal returns. Notice when testing semi-strong efficiency, the p-values of AAPL, BRK-B, and JNJ are all extremely large which is strong evidence against efficiency. Therefore, it is reasonable to obtain a single financial metric which is statistically significant by itself. When conducing a F-test on EPS, current ratio, and debt to equity ratio the p-value is 0.3069. When including ROE in the F-test, the p-value decreases to 0.0083. This shows the importance of ROE in an investment strategy which uses similar financial metrics to beat the market and obtain abnormal returns.

Table 22 displays the results of Equation 19 for MSFT. From the table, it is evident only debt to equity ratio is statistically significant. Thus, if the debt to equity ratio increases by 0.1, abnormal returns will increase by 0.0308%. Notice here instead of increasing debt to equity ratio by 1 I gave the interpretation of the coefficient in terms of an increase by a tenth of that. The notion behind this is as 1 is a very large change in debt to equity ratio as firms desire to hold stable units for debt. MSFT was one of the stocks which showed very strong evidence against semi-strong efficiency with a p-value of 0.956 in Table 13. Thus, it should be reasonable to be able to obtain statistically significant abnormal returns from a single financial metric. The strength of debt to equity ratio in obtaining statistically significant abnormal returns can be double checked by a F-test. The p-value of a F-test on EPS, ROE, and current ratio is 0.4709. But when adding debt to equity ratio in the F-test, the p-value falls to 0.0487 leading to a rejection of the null hypothesis at the 5% significance level.

Table 23 displays the results of Equation 19 for V. From the table, not a single financial metric is statistically significant. Conducting a F-test on EPS, ROE, current ratio, and debt to equity ratio yields a p-value of 0.5630. Thus, even jointly, the financial metrics do not impact abnormal returns. However, from Table 15, V showed extremely strong evidence against semi-strong efficiency with a p-value of 0.835. This inefficiency is instead explained by stock buybacks. Just like FB, V has also participated in aggressive stock buybacks (Visa Stock Buybacks). Following a similar line of reasoning as FB, V’s inefficiency can be explained by its stock buybacks.

CONCLUSION

In conclusion, although the market shows substantial evidence for weak form efficiency it fails to show enough evidence to conclude semi-strong efficiency. As stated in the above discussion of weak form results, the results of runs test, although not ignored, have been given a very small weight. The time period for the panel data set is during a bull market. Thus, it is highly unlikely to observe multiple runs with exception of December 2018 which was a particularly bad year for stocks evident from Figure 1. After controlling for the upwards time trend in Figure 1, the market was marginally weak form efficient with p-values just above 0.05. When conducting semi-strong analysis 80% of stocks showed semi-strong inefficiency, one stock showed strong evidence of efficiency, and one stock showed some degree of efficiency. Although, the bull market and stock buybacks heavily fueled this inefficient behavior the weak results are also explained by the weakness of CAPM in predicting returns. When assessing the impact of financial metrics on abnormal returns, stocks with a p-value of close to 0.80 in their semi-strong analysis had a single statistically significant financial metric. The only outlier to this was V, however this difference is explained by stock buybacks. Thus, it can be assumed that a p-value of 0.80 is indeed very strong evidence of semi-strong inefficiency implying poor absorption of information by the stock price allowing investors to make statistically significant returns from a single financial metric.

To make a final point, due to weak form efficiency it can be concluded that technical analysis could not beat the market from 2015-2019. All historical information about the market and statistical and technical indicators were effectively priced in. However, one can certainly use fundamental information about a firm to beat the market. This is evident by the net worth of Warren Buffet and the likes which have made their substantial gains through investing in underpriced firms. By using a firm’s fundamentals one can assess whether a firm is overpriced or underpriced relative to its fair market value. Thus, although information regarding technical analysis may not be useful in beating the market, information about a firm and its fundamentals are extremely important to generate a positive alpha.

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FIGURES AND TABLES

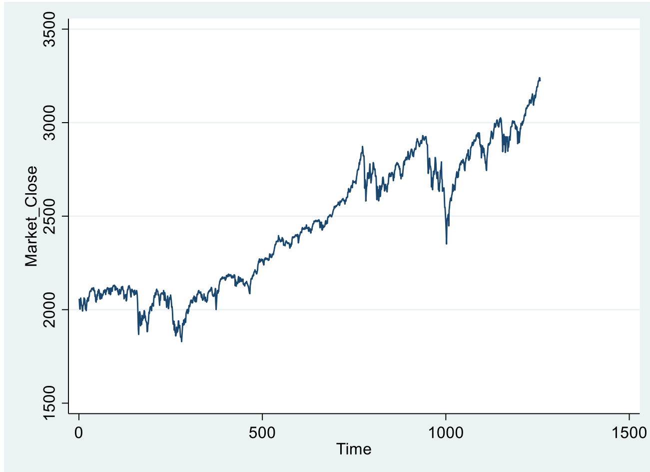

Figure 1 – Market Close vs Time

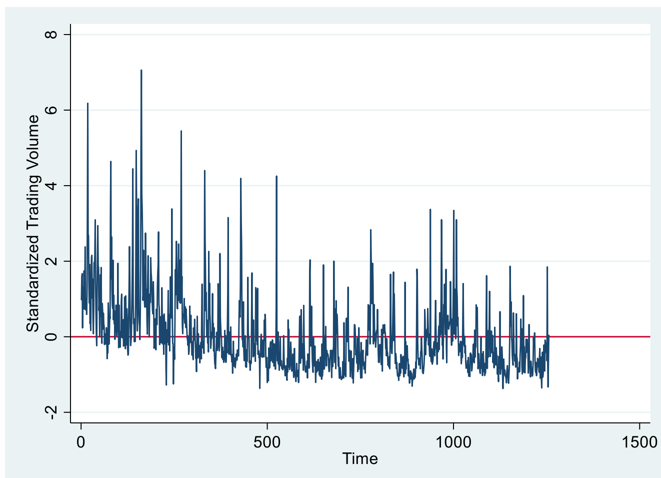

Figure 2 – AAPL Standardized Transaction Volume over Time, $y = 0$

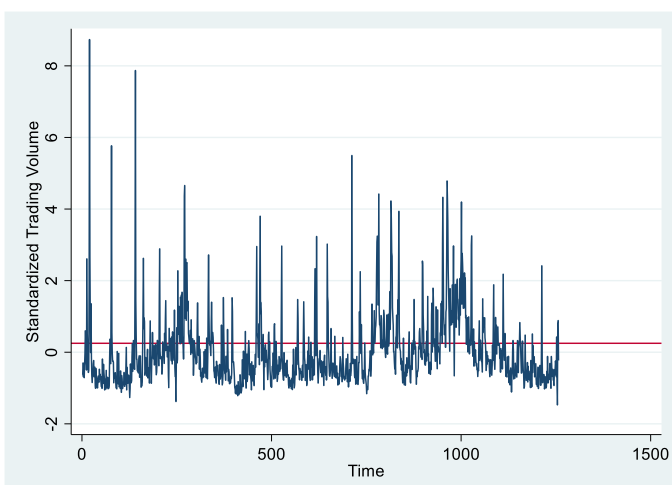

Figure 3 – AMZN Standardized Transaction Volume over Time, $y = 0.25$

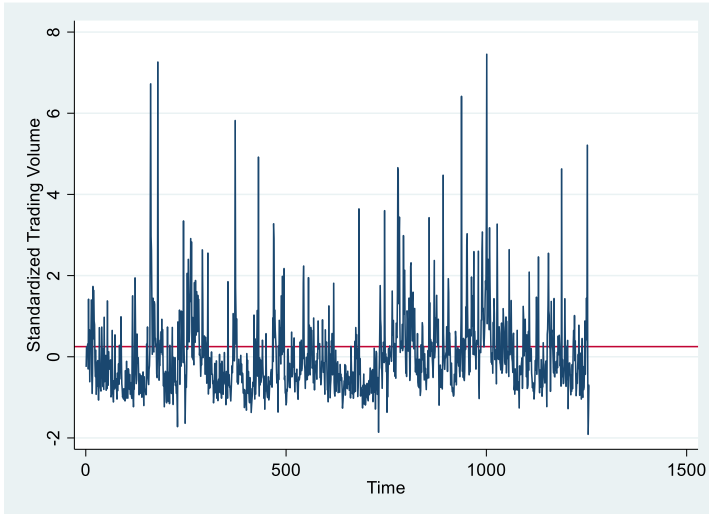

Figure 4 – BRK-B Standardized Transaction Volume over Time, $y = 0.25$

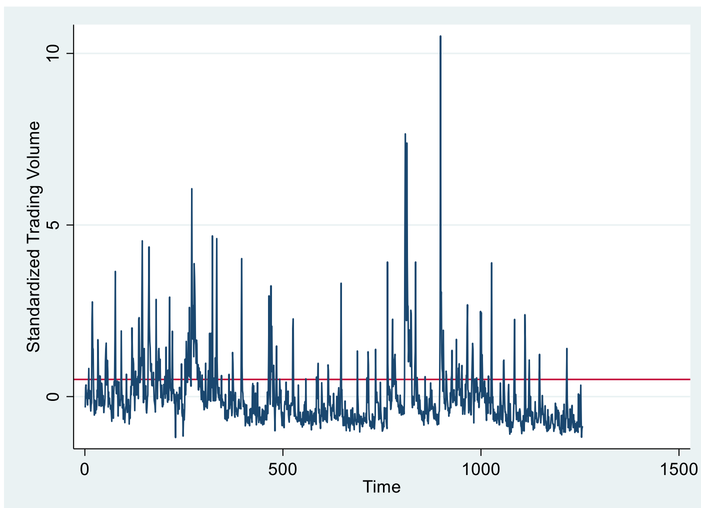

Figure 5 – FB Standardized Transaction Volume over Time, $y = 0.5$

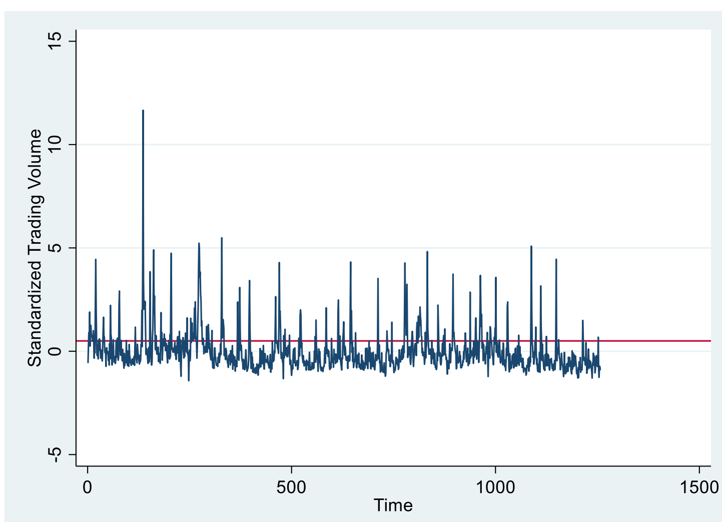

Figure 6 – GOOGL Standardized Transaction Volume over Time, $y = 0.5$

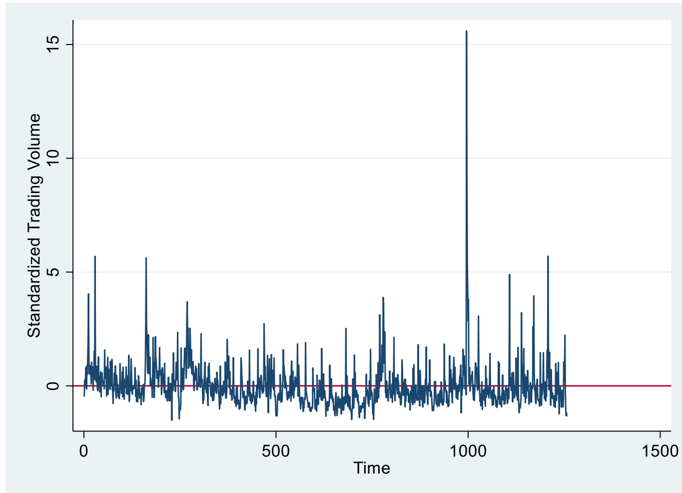

Figure 7 – JNJ Standardized Transaction Volume over Time, $y = 0$

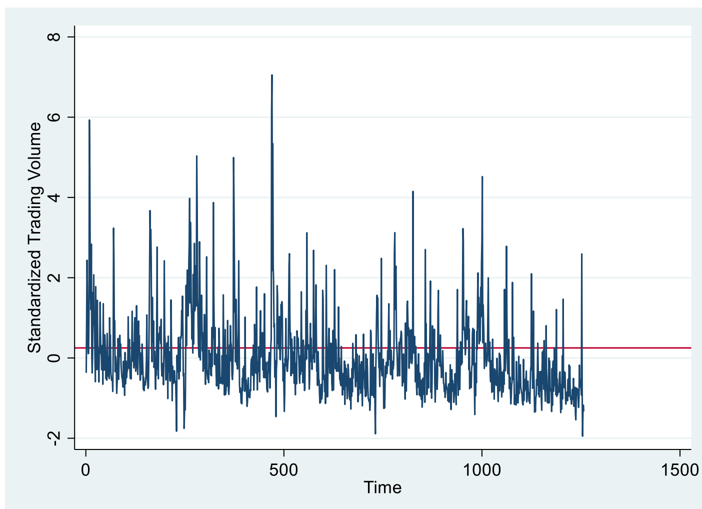

Figure 8 – JPM Standardized Transaction Volume over Time, $y = 0.25$

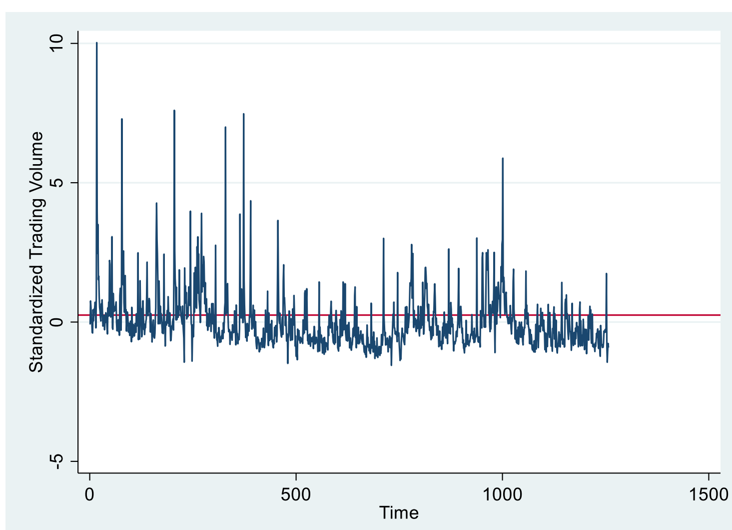

Figure 9 – MSFT Standardized Transaction Volume over Time, $y = 0$

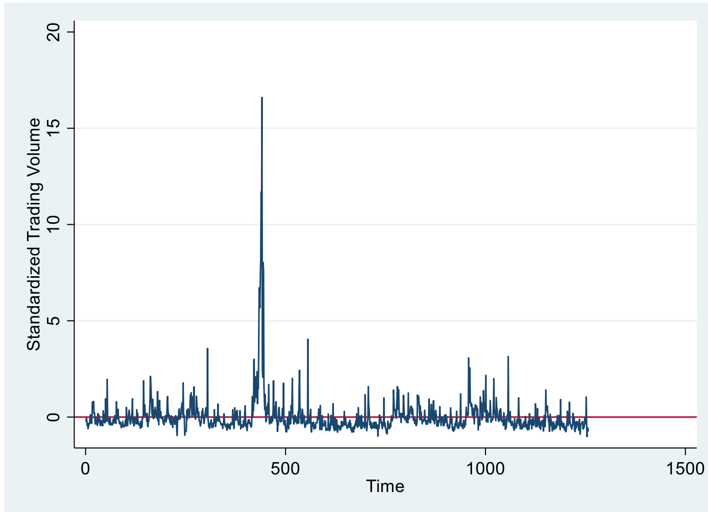

Figure 10 – PG Standardized Transaction Volume over Time, $y = 0$

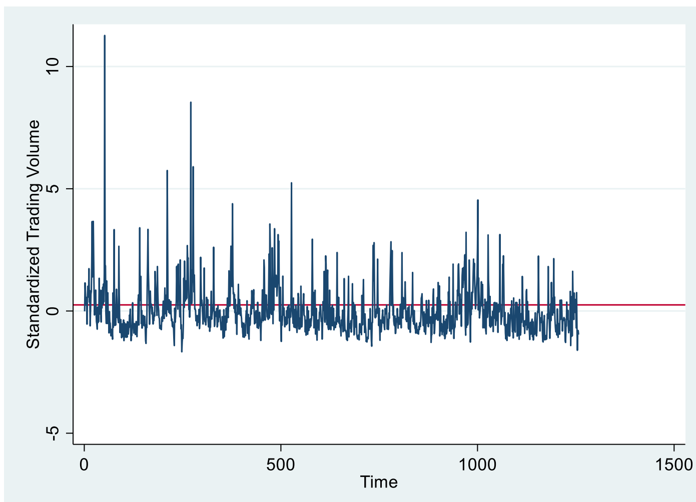

Figure 11 – V Standardized Transaction Volume over Time, $y = 0.25$

```
Selection-order criteria
Sample:  5 - 1257                          Number of obs      =      1253
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-9141.09				127319	14.5923	14.5939	14.5964
1	-5560.34	7161.5*	1	0.000	420.127*	8.87843*	8.88151*	8.88663*
2	-5560.02	.63048	1	0.427	420.586	8.87953	8.88415	8.89182
3	-5558.47	3.1082	1	0.078	420.215	8.87864	8.8848	8.89503
4	-5558.09	.75817	1	0.384	420.631	8.87963	8.88733	8.90012

```
Endogenous:  Market_Close_N
 Exogenous:  _cons
```

Table 1 – Optimal Number of Lags for ADF test

Augmented Dickey-Fuller test for unit root   Number of obs = 1255

	Test Statistic	Z(t) has t-distribution 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-0.191	-2.329	-1.646	-1.282

p-value for Z(t) = 0.4244

D. Market_Close_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Market_Close_N						
L1.	-.0003101	.0016256	-0.19	0.849	-.0034993	.0028791
LD.	-.0217703	.0282665	-0.77	0.441	-.0772253	.0336847
_cons	1.737561	4.025912	0.43	0.666	-6.160717	9.635839

Table 2 – ADF Test Results [Model 1 in Equation 7]

Augmented Dickey-Fuller test for unit root   Number of obs = 1255

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.140	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0970

D.Market_C~N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Market_Clo~N						
L1.	-.0162987	.0051903	-3.14	0.002	-.0264813	-.006116
LD.	-.0144702	.0282496	-0.51	0.609	-.069892	.0409517
_trend	.0165287	.0050978	3.24	0.001	.0065275	.0265298
_cons	30.5337	9.744913	3.13	0.002	11.41553	49.65188

Table 3 – ADF Test Results [Model 2 in Equation 8]

Phillips-Perron test for unit root   Number of obs = 1256
Newey-West lags = 1

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-0.310	-20.700	-14.100	-11.300
Z(t)	-0.153	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.9438

Close	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Close						
L1.	.9997174	.0016238	615.66	0.000	.9965317	1.002903
_cons	1.618697	4.022451	0.40	0.687	-6.27278	9.510173

Table 4 – PP Test Results [Model 1 in Equation 7]

```
Phillips-Perron test for unit root              Number of obs    =      1256
                                                Newey-West lags =         1
```

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
		Interpolated Dickey-Fuller		
Z(rho)	-21.026	-29.500	-21.800	-18.300
Z(t)	-3.264	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0724

Close	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Close						
L1.	.9830296	.0051642	190.36	0.000	.9728982	.993161
_trend	.0172653	.0050742	3.40	0.001	.0073104	.0272201
_cons	31.67626	9.699497	3.27	0.001	12.64721	50.7053

Table 5 – PP Test Results [Model 2 in Equation 8]

Source	SS	df	MS
Model	.00168764	1	.00168764
Residual	1704.93729	1,254	1.35959912
Total	1704.93898	1,255	1.35851712

Number of obs	=	1,256
F(1, 1254)	=	0.00
Prob > F	=	0.9719
R-squared	=	0.0000
Adj R-squared	=	-0.0008
Root MSE	=	1.166

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0109066	.3095675	-0.04	0.972	-.6182338	.5964206
_cons	.5175413	.6044654	0.86	0.392	-.6683337	1.703416

Table 6 – Equation 16 Results for AAPL

Source	SS	df	MS
Model	.891692598	1	.891692598
Residual	2631.11113	1,254	2.09817475
Total	2632.00283	1,255	2.09721341

Number of obs	=	1,256
F(1, 1254)	=	0.42
Prob > F	=	0.5146
R-squared	=	0.0003
Adj R-squared	=	-0.0005
Root MSE	=	1.4485

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0878514	.1347602	-0.65	0.515	-.3522317	.176529
_cons	.7597043	.1445388	5.26	0.000	.4761398	1.043269

Table 7 – Equation 16 Results for AMZN

Source	SS	df	MS			
Model	.012295236	1	.012295236	Number of obs	=	1,256
Residual	494.039285	1,254	.393970721	F(1, 1254)	=	0.03
				Prob > F	=	0.8598
Total	494.05158	1,255	.393666598	R-squared	=	0.0000
				Adj R-squared	=	-0.0008
				Root MSE	=	.62767

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	.0078089	.044203	0.18	0.860	-.0789111	.0945288
_cons	-.0277359	.0431216	-0.64	0.520	-.1123343	.0568625

Table 8 – Equation 16 Results for BRK-B

Source	SS	df	MS			
Model	.020955111	1	.020955111	Number of obs	=	1,256
Residual	2745.86951	1,254	2.18968861	F(1, 1254)	=	0.01
				Prob > F	=	0.9221
Total	2745.89047	1,255	2.18796053	R-squared	=	0.0000
				Adj R-squared	=	-0.0008
				Root MSE	=	1.4798

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0207314	.2119212	-0.10	0.922	-.4364905	.3950278
_cons	.4026436	.1955725	2.06	0.040	.0189583	.7863289

Table 9 – Equation 16 Results for FB

Source	SS	df	MS			
Model	.334213844	1	.334213844	Number of obs	=	1,256
Residual	1518.72551	1,254	1.21110487	F(1, 1254)	=	0.28
				Prob > F	=	0.5995
Total	1519.05973	1,255	1.21040616	R-squared	=	0.0002
				Adj R-squared	=	-0.0006
				Root MSE	=	1.1005

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.1154491	.2197704	-0.53	0.599	-.5466074	.3157092
_cons	.4803696	.2128545	2.26	0.024	.0627795	.8979598

Table 10 – Equation 16 Results for GOOGL

Source	SS	df	MS			
Model	.051320718	1	.051320718	Number of obs	=	1,256
Residual	936.97378	1,254	.747188023	F(1, 1254)	=	0.07
				Prob > F	=	0.7933
Total	937.025101	1,255	.746633547	R-squared	=	0.0001
				Adj R-squared	=	-0.0007
				Root MSE	=	.8644

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0270186	.1030937	-0.26	0.793	-.2292738	.1752365
_cons	-.5104958	.1928992	-2.65	0.008	-.8889366	-.132055

Table 11 – Equation 16 Results for JNJ

Source	SS	df	MS	Number of obs	=	1,256
				F(1, 1254)	=	3.97
Model	3.01183466	1	3.01183466	Prob > F	=	0.0466
Residual	951.53145	1,254	.75879701	R-squared	=	0.0032
				Adj R-squared	=	0.0024
Total	954.543285	1,255	.760592259	Root MSE	=	.87109

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.1262748	.0633817	-1.99	0.047	-.2506206	-.0019289
_cons	.5001565	.0703489	7.11	0.000	.362142	.638171

Table 12 – Equation 16 Results for JPM

Source	SS	df	MS	Number of obs	=	1,256
				F(1, 1254)	=	0.00
Model	.002765728	1	.002765728	Prob > F	=	0.9565
Residual	1162.95359	1,254	.927395206	R-squared	=	0.0000
				Adj R-squared	=	-0.0008
Total	1162.95635	1,255	.926658449	Root MSE	=	.96301

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.004882	.0893981	-0.05	0.956	-.1802685	.1705044
_cons	.5972975	.0935281	6.39	0.000	.4138087	.7807863

Table 13 – Equation 16 Results for MSFT

Source	SS	df	MS	Number of obs	=	1,256
				F(1, 1254)	=	2.34
Model	1.81638122	1	1.81638122	Prob > F	=	0.1262
Residual	972.486601	1,254	.775507656	R-squared	=	0.0019
				Adj R-squared	=	0.0011
Total	974.302982	1,255	.776337038	Root MSE	=	.88063

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0877495	.0573369	-1.53	0.126	-.2002363	.0247373
_cons	-.5450651	.1709638	-3.19	0.001	-.8804718	-.2096585

Table 14 – Equation 16 Results for PG

Source	SS	df	MS	Number of obs	=	1,256
				F(1, 1254)	=	0.04
Model	.030671993	1	.030671993	Prob > F	=	0.8353
Residual	889.920954	1,254	.709665833	R-squared	=	0.0000
				Adj R-squared	=	-0.0008
Total	889.951626	1,255	.709124802	Root MSE	=	.84242

AbnormalReturn_N	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
FitStandardizedTradingVolume_N	-.0301943	.1452382	-0.21	0.835	-.315131	.2547424
_cons	.3001601	.1538937	1.95	0.051	-.0017575	.6020777

Table 15 – Equation 16 Results for V

	(1) AbnormalRe~N
EPS_N	0.116*
	(2.30)
ROE_N	-0.00790
	(-1.07)
CurrentRat~N	0.563
	(1.45)
DebttoEqui~N	0.0578
	(0.20)
VIX_N	0.00536
	(0.58)
_cons	-0.303
	(-0.56)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 16 – Equation 19 Results for AAPL

	(1) AbnormalRe~N
EPS_N	0.115
	(1.82)
ROE_N	-0.0291
	(-1.83)
CurrentRat~N	-0.640
	(-0.38)
DebttoEqui~N	0.473
	(1.52)
VIX_N	-0.0180
	(-1.73)
_cons	1.447
	(0.77)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 17 – Equation 19 Results for AMZN

	(1)
	AbnormalRe~N
EPS_N	0.0109*
	(2.01)
ROE_N	0.00596
	(0.85)
CurrentRat~N	0.178
	(0.83)
DebttoEqui~N	0
	(.)
VIX_N	-0.00147
	(-0.34)
_cons	-0.154
	(-1.50)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 18 – Equation 19 Results for BRK-B

	(1)
	AbnormalRe~N
EPS_N	0.00687
	(0.05)
ROE_N	-0.000816
	(-0.06)
CurrentRat~N	-0.0366
	(-1.34)
DebttoEqui~N	-3.312
	(-1.35)
VIX_N	-0.00593
	(-0.55)
_cons	0.890*
	(2.10)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 19 – Equation 19 Results for FB

	(1)
	AbnormalRe~N
EPS_N	0.00890
	(0.90)
ROE_N	-0.0168
	(-1.00)
CurrentRat~N	-0.0363
	(-0.89)
DebttoEqui~N	-2.781
	(-1.16)
VIX_N	-0.00969
	(-1.17)
_cons	0.961**
	(2.70)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 20 – Equation 19 Results for GOOGL

	(1)
	AbnormalRe~N
EPS_N	0.00241
	(0.10)
ROE_N	0.00729*
	(2.09)
CurrentRat~N	0.0627
	(1.19)
DebttoEqui~N	-0.111
	(-0.50)
VIX_N	0.000492
	(0.08)
_cons	-0.795***
	(-3.71)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 21 – Equation 19 Results for JNJ

	(1)
	AbnormalRe~N
EPS_N	-0.0175
	(-0.26)
ROE_N	-0.00369
	(-0.88)
CurrentRat~N	0.0605
	(0.60)
DebttoEqui~N	0.308*
	(2.31)
VIX_N	0.00118
	(0.17)
_cons	0.297
	(1.01)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 22 – Equation 19 Results for MSFT

	(1)
	AbnormalRe~N
EPS_N	0.146
	(0.87)
ROE_N	-0.00537
	(-0.62)
CurrentRat~N	-0.0342
	(-1.22)
DebttoEqui~N	-0.0256
	(-0.22)
VIX_N	0.0000992
	(0.02)
_cons	0.364*
	(2.54)
N	1256

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 23 – Equation 19 Results for V