ECONOMICS 620

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The September Effect

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March 15, 2024

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by

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Submitted to The Department of Business and Economics

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Date: March 15, 2024

I hereby recognize and pledge to fulfill my responsibilities as defined in the Honor Code and to maintain the integrity of both myself and the College as a whole.

Preston Pierce

Acknowledgements

Dedicated to my parents Carm and Regina Pierce for always supporting me.

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Abstract

There is extensive research in the field of stock market anomalies as well as more specifically the September Effect. This anomaly has been both supported and contested by research in economic studies all around the world and over many sectors. However, even more interestingly many works have attempted to find the reasoning behind the anomaly. The research has many applications in the field of economics especially surrounding the efficient market hypothesis. I delve into the occurrence of the September Effect on indexes in recent history and test some of the more convincing arguments and hypotheses within my specific framework. In order to produce my results I review current literature, look into algorithm correlation between the market and September, and produce indicators that I believe can help support or discredit the current theories in order to give a clearer sense of stock market anomalies, the September Effect and the the efficient market hypothesis. Readers should have a better understanding of these topics and take away new information surrounding the correlations between the September Effect and indicators believed to be related.

Chapter 1: Introduction

The September Effect is one of many well known calendar anomalies that occur throughout a year in the global stock market. An anomaly is known as a variation from the currently accepted paradigms that is too significant to be overlooked, too methodical to be written off as random error, and too fundamental to be handled by loosening the normative framework. More specifically, a financial market anomaly, according to conventional finance theory, is a circumstance in which the performance of a stock or group of stocks deviates from the assumptions of the efficient market hypothesis (Latif, Arshad, Fatima, & Farooq, 2011) (The efficient market hypothesis is explained more thoroughly down below).

Calendar anomalies are a specific subgroup of these anomalies which are associated with certain time periods, such as the day-to-day, monthly, and annual fluctuations in stock prices. Calendar anomalies conflict with the weak form of market efficiency because this hypothesis assumes that markets are efficient and cannot be predicted based on past prices. The existence of seasonality contradicts this assumption because it enables investors to earn abnormal returns based on recurring and consistent price fluctuations at predictable times.

The September Effect is categorized as a calendar anomaly because there is no exact event or link attributed to the anomaly, however, it has still recurred significantly over recent history. In the specific case of the September Effect we observe the historically weak stock market returns during the month of September. As you can see in figure 1.1, September is historically the worst month for equities across the globe with at least 60% of countries reporting negative returns (Ganti & Team, T. I. 2022). Likewise, stocks have been down in the US 55% of the time in September since 1928 and the S&P 500 has had an average of -0.61% returns from 1960 to 2021 which is .6% less than the next lowest (Leem, 2020).

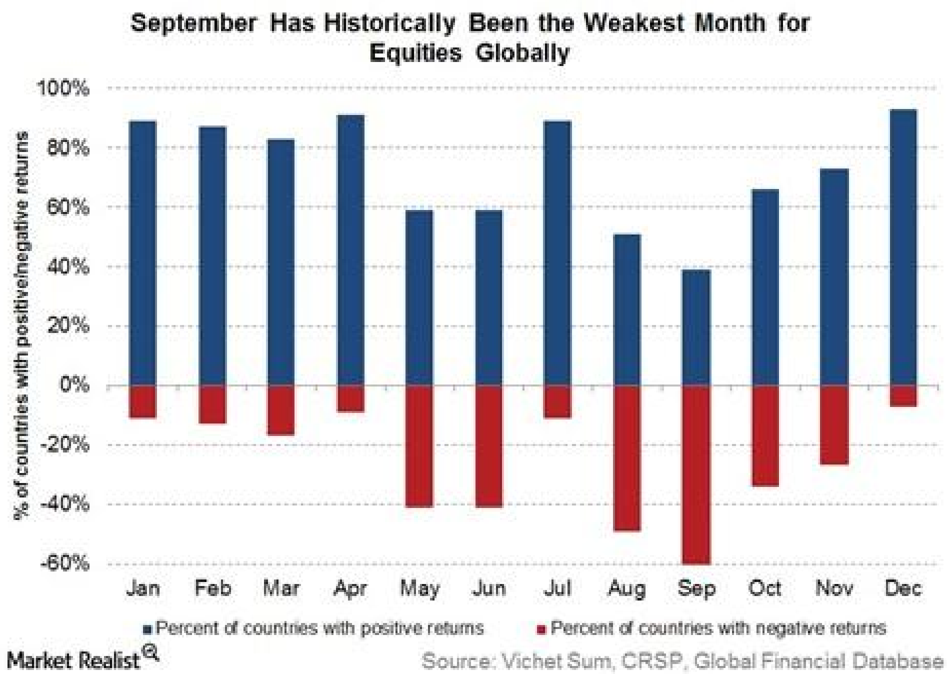

Figure 1.1 - A graphical representation of the percent of countries with either negative or positive returns per month from 1928 to 2022 (Bechard, 2023).

Some people attribute these findings to chance since after all one of the months has to be the lowest performing and because there are periods that the effect cannot be seen such as long term in Europe or short term pockets such as from 2014 to now. However, with all of this data evidence, it is difficult to deny that there is in fact a correlation between September and poor stock performance. That being said, if there is a correlation, what is a rational reason as to why? Presumably, it will be a combination of many things contributing to this anomaly or possibly it could in fact just be chance. Nevertheless it is important to consider the anomaly from all aspects and perspectives. Therefore, it is this paper's goal to look into possible reasonings behind The September Effect and consider the validity of the predictions presented.

Data Support

While some academics have disputed its existence, there is a growing body of empirical evidence that supports the notion that the September Effect is a statistically significant phenomenon. This analysis aims to provide an in-depth and detailed description of the current statistical data that supports the September Effect, taking into consideration different markets, sectors, industries, and time periods.

One of the earliest studies that examined the September Effect was by Lakonishok and Smidt (1988), who analyzed the monthly returns of US stocks from 1904 to 1986. They found that September had the lowest average return of all months. Since then, numerous studies have confirmed the September Effect across different markets worldwide. For instance, Bouman and Jacobsen (2002) examined the monthly returns of 108 stock markets worldwide from 1693 to 1998 and found that September had the lowest average return of any month. Similarly, Lucey and Zhao (2008) analyzed the monthly returns of 34 countries' stock markets and found that September was the weakest month (Balaban, Hakkio, & Rush, 2018).

The September Effect has also been observed across different sectors and industries. A study by Chen and Singal (2003) examined the monthly returns of ten industry portfolios in the US from 1926 to 1997 and found that September had the lowest average return of all months for seven of the ten industries. Similarly, O'Connor et al. (2015) analyzed the monthly returns of different sectors in the US from 1926 to 2014 and found that the September Effect was more pronounced in the technology sector than in other sectors.

The September Effect has been documented in different time periods as well. For example, a study by Jacobsen and Zhang (2013) examined the monthly returns of 82 countries' stock markets from 1988 to 2011 and found that the September Effect was still present during this period. Moreover, a study by Balaban et al. (2018) analyzed the monthly returns of the US stock market from 1926 to 2016 and found that the September Effect was statistically significant in both the pre- and post-World War II periods (Balaban, Hakkio, & Rush, 2018).

Nonetheless, it appears that the September Effect is trending away especially in the US. The September Effect was stronger in the beginning half of the century and less so in the second half. From 1928 to 2021 the S&P's average return during September was -1 % while the DJIA's average return was -0.8%, and the S&P's was -0.5% since 1950 (Bechard, 2023). This data supports that the September Effect is still a relevant anomaly, however, it also suggests that it was strongest at the beginning of the past century and may be fading away.

Efficient Market Hypothesis

One of the most important things about anomalies in the stock market is that they violate the Efficient Market Hypothesis in at least one of the three possible ways. Also known as the EMH, the efficient market hypothesis is based on two assumptions. The first is that available information is already incorporated into a stock price, and the second is that investors are unable to earn a risk-weighted excess return. This essentially means that stock prices reflect the intrinsic value of a company and investors are unable to earn higher returns than that of the market. Many current equations and economic assumptions are based off of this hypothesis, making it a fundamental part of our current economic understanding. Therefore, any anomalies that violate these assumptions are heavily scrutinized by economists.

The three possible ways to violate the EMH are weak, semi-strong, and strong forms of violation (Degutis & Novickytė, 2014). The weak form of EMH implies that all historical price information such as past stock prices and trading volume is taken into account for the price of the stock. This would inhibit anyone from gaining excess returns by employing historical analysis. The semi-strong form implies that all historical data and current public information such as announcements of acquisitions, dividend pay-outs, and changes in accounting policy is reflected in the stock prices. This differs from weak in the fact that semi-strong assumes information is constantly being integrated fluidly into stock prices and there is no delay. Therefore, it assumes people can't utilize brand new information to make gains before that information affects the market. Finally, the strong form assumes that current stock prices incorporate information which does not necessarily have to be public. This form of market efficiency assumes it is impossible to earn excess profit while even trading on insider information. This assumption is considered to be unlikely, nevertheless since insider trading is illegal, violations of the strong form (where people could make financial gains based on private information) are mostly mitigated and violations are typically met with federal punishment. The weaker the form, the stronger the evidence is for the existence of EMH since each level of new information is harder for the market to account for. Nonetheless, there is strong evidence or examples for all three efficient market forms. (Degutis & Novickytė, 2014).

Advocates of the EMH would argue that even if the September Effect occurred at some time in history, overtime the market would rid itself of this inefficiency. There are two general efficient market assumptions that would aid this correction. First, violation of the Efficient Market Hypothesis would leave opportunities for arbitrage from the information gap. Arbitrageurs would exploit this situation by buying undervalued stocks before September and selling them afterward. These actions would drive up the prices of these stocks and reduce the magnitude of the effect. Furthermore, the EMH assumes that investors are rational, informed, and profit maximizing. Therefore, if the September effect was based on irrational behavior, rational investors would counteract it. As an example, they might conduct thorough analyses of company fundamentals rather than relying on calendar-based trading strategies. The influence of rational investors would eventually outweigh any irrational trading behaviors, likewise leading to the disappearance of the September effect. As a result, the persistent nature of the September Effect is a large issue for the Efficient Market Hypothesis.

The September anomaly would allow investors to use market timing to their advantage and increase their returns based on the historical fact that September is the worst performing month. This is a violation of the weak EMH. If the weak version is violated then so is the semi-strong and if the semi-strong is violated then so is the strong. As a result all three versions of the EMH are violated and something is amiss. Therefore, it is this paper's goal to look into possible reasons behind this specific September violation as well as the validity of the predictions presented.

CHAPTER 2: LITERATURE REVIEW

There is much to be considered when it comes to why a violation of the EMH would occur like this. What are the true contributors? What is random? How does it occur in different areas? How does it occur in different stocks? How does knowing these things support or disprove what we believe? How does including behavioral finance help understanding of the phenomenon? This is all taken into consideration while reviewing a few topics of interest around the September Effect.

Behavioral Finance

A potential alternative to the traditionally accepted efficient market hypothesis is a theory called behavioral finance. This theory is based on an interdisciplinary field that combines finance, economics, and psychology to study how psychological factors affect financial decision-making. It is based on the premise that investors are not always rational and make decisions that deviate from traditional finance theory assumptions, such as the efficient market hypothesis and rational expectations theory (Barberis & Thaler, 2003). In this section, a description of behavioral finance is provided with its core concepts and theories.

Behavioral finance is focused on understanding how emotions, biases, and other psychological factors influence investors' decision-making. As mentioned, the theory recognizes that investors are not always rational and often are influenced by a variety of cognitive and emotional biases. There are many forms and examples of these biases. Some of the most common ones studied in behavioral finance include overconfidence, loss aversion, herding behavior, anchoring, and confirmation bias.

Overconfidence bias is when investors believe that their abilities and knowledge are superior to others, which can lead them to make excessive trades or invest in speculative assets. Loss aversion, on the other hand, is the tendency to feel more pain from losses than pleasure from gains, which can result in investors holding on to losing positions for too long or selling winning positions too early.

Herding behavior refers to the tendency of individuals to follow the actions or decisions of a larger group, without necessarily considering whether those actions or decisions are rational or appropriate. Alternatively, anchoring is a cognitive bias in which individuals rely too heavily on the first piece of information they receive (the "anchor"), and subsequently adjust their beliefs or decisions based on that initial anchor, even if it is irrelevant or arbitrary. Finally, confirmation bias is the tendency to seek out, interpret, or remember information in a way that confirms one's preexisting beliefs or hypotheses, while disregarding or discounting information that contradicts those beliefs or hypotheses (Barberis & Thaler, 2003).

The field of behavioral finance gets its roots from the work of Daniel Kahneman and Amos Tversky, who in the 1970s and 1980s challenged the traditional assumptions of rationality and efficiency in economic decision-making. They were the ones to propose that people’s decision-making is influenced by a range of cognitive biases, such as availability bias and representativeness bias, which can lead to errors in judgment and decision-making.

A key concept in behavioral finance is the prospect theory, developed by Kahneman and Tversky in 1979. Prospect theory is a behavioral model that explains how people make decisions under uncertainty and risk. It suggests that people evaluate potential gains and losses in a non-linear way, meaning that losses have a greater impact on people's emotional state than equivalent gains (Barberis & Thaler, 2003). This leads to risk and loss aversion when faced with potential losses, and risk-seeking behavior when faced with potential gains. Prospect theory also suggests that people tend to overweight small probabilities, which can lead to excessive risk-taking or fear of rare events.

Framing effect is another important concept in behavioral finance. This refers to the way that information is presented or framed to investors. The same information can be presented in different ways, and the way it is framed can influence investors' perceptions and decision-making. For example, presenting a stock as having a 90% chance of success may be more appealing to investors than presenting the same stock as having a 10% chance of failure.

There are several practical applications for behavioral finance in the financial industry. For example, it can be used to develop investment strategies that take into account the cognitive biases and heuristics that investors exhibit. One such strategy is the use of momentum investing, which involves buying stocks that have recently performed well and selling stocks that have recently performed poorly (Barberis & Thaler, 2003). This strategy is based on the idea that investors tend to exhibit herding behavior and overreact to recent news, leading to momentum in stock prices.

Behavioral finance can also be used to develop financial products that are designed to appeal to investors' psychological needs. For example, target-date funds are designed to address investors' tendency towards procrastination and decision paralysis by automatically adjusting the asset allocation of the fund as the investor's target retirement date approaches.

There are also many ways behavioral finance offers a unique perspective on the September Effect that highlights the role of psychological factors in investors' decision-making. This last part of the analysis will examine how behavioral finance contributes to the September Effect, and the implications of this for investors and financial professionals.

One key factor that may contribute to the September Effect is the loss aversion, which is the tendency for investors to hold on to losing positions for too long and sell winning positions too early (Muradoglu & Taskin, 2015). This behavior can lead to a selling pressure in September as investors attempt to realize losses before the end of the tax year. Losses in the summer can cause people to prematurely sell in September due to these factors. The topics of loss aversion and taxes are addressed further in the market psychology and tax related selling literature review sections.

The September Effect may also be influenced by herding behavior, where investors follow the crowd rather than making independent investment decisions. In September, investors may be influenced by the perception that it is a seasonally weak month for the stock market and may be more likely to sell their positions to avoid potential losses. This behavior can lead to a self-fulfilling prophecy, where the selling pressure in September reinforces the perception of weakness in the market (Muradoglu & Taskin, 2015). Therefore, there is reason to believe that the September Effect can be partially explained by behavioral finance. Psychological factors, such as the disposition effect, the endowment effect, and herding behavior, may contribute to the selling pressure in September and lead to suboptimal investment decisions. The lack of rational investors also gives a logical reason to why we might see the efficient market hypothesis fail for anomalies such as the September Effect.

Post School Holiday Effect

The beginning conjecture brought to attention that the September Effect reflects a broader “post school holiday effect” where market returns after long school holidays are significantly lower than alternative times. The hypothesized reasoning behind the claim is that investors are less attentive to news. This inattentiveness compounded with effects of short sale constraints cause this low spot we know as the September Effect as well as contributing to other market decreases. Fang, Lin, and Shao find a striking pattern at a closer look. In the 47 countries observed, returns are, on average, 1% lower in the months post major school holidays. More importantly, this lower return is not only driven by September, even though the September anomaly is pervasive in the northern hemisphere. When September is not considered, a return gap of 0.6% between postschool holiday months and other times still occurs making the difference remain highly significant (Fang, Lin & Shao, 2017).

A variation of validation tests were conducted in order to exploit variations in school calendars that might affect the data. To illustrate, while the school year begins in September for most states, some have school years that begin in early August. However, it is observed that for stock headquarters in these states it is actually August that underperforms more than September (Fang, Lin & Shao, 2017). Effects are taken into consideration where they stagger holidays based on regions to reduce tourist congestion in places such as France. These holidays are considered to have less effect because of the implicit assumption that investors exhibit local bias where local stocks are mostly kept by local investors. Thus, local bias and the postschool holiday effect are tested together. These all combined attempt to give a convincing set of data supporting the post holiday effect of the literature.

The reason for this phenomenon, as discussed above, is hypothesized to be due to investor inattention and delay in the incorporation of news into price. It is assumed that school holidays cause many traders to be away from the market. As a result they pay less attention to information and are less likely to trade. This implies that new information is incorporated into the price slower than other times. It is also implied that negative information is more difficult to take advantage of than positive information, and so the slow incorporation of negative news into prices is particularly severe. This as a whole is what leads to lower returns in the month after major school holidays.

In order to test this hypothesis, activity was looked at for investors. It was found by the authors that trading volume is 7.8% lower while school holidays are taking place compared to time in school. The trading volume is still 2.4% lower during school holidays when there was a release of earnings news. In addition, the delayed response ratio is used to measure the comparison of delayed response to the total stock response to earning announcements. The DRR calculated was about 60% higher for negative news announced during school holidays than at other times (Fang, Lin & Shao, 2017). On the other hand, the delayed price response for positive news during school holidays is not significant. Therefore, it can be assumed that market reaction to negative news significantly slows down during school holidays while positive news does not which would support the claim. Stocks news type and trading volume during the holidays were even considered. This showed that low returns are concentrated among the stocks that release news during school holidays and especially concentrated among stocks that release negative news and have lower trading volume during school holidays.

Something interesting that is found is that the postschool holiday effect is stronger in larger stocks with greater institutional holdings. This cross-sectional pattern is different then many other anomalies typically concentrated among small, illiquid stocks with low institutional holdings. However, this could make sense due to the fact that shorting activities can be reduced by inattention which typically accrue in the larger stocks (Fang, Lin & Shao, 2017).

Tax Related Selling

Another one of the many hypotheses looked into about the September Effect is based on the idea of realizing capital losses. Essentially if an investor has held a particular stock or index for long enough and has seen losses on that particular asset, they can then sell before the turn of the year in order to report those losses as tax relief. One scholarly journal examines the correlation between tax-related selling and the September Effect. The authors explore the possibility that the September Effect is driven by this occurrence of individual investors selling stocks in order to realize capital losses for tax purposes.

The authors begin their endeavor by noting that the January effect, in which small stocks tend to outperform large stocks in January, has been widely studied and is thought to be driven by tax considerations, as investors may sell stocks that have declined in value in order to realize tax losses before the end of the calendar year. The authors argue that the September Effect may be driven by a similar tax motive, as investors may sell stocks that have declined in value over the summer months in order to realize capital losses for tax purposes (Edelen, Garbade, & Kadlec, 1999). Although this wouldn't seem quite as correlated as selling in January, it relates enough to be a plausible explanation.

To test this hypothesis, the authors used a sample of individual investors from a large discount brokerage firm and examined their trading patterns in September and October, as well as their trading patterns in the preceding months. What they found was that individual investors are more likely to sell stocks that have declined in value over the summer months in September and October than in other months of the year (Edelen, Garbade, & Kadlec, 1999). Furthermore, they find that the magnitude of this effect is greater for stocks that have higher tax implications, such as those that have been held for longer periods of time or those that have larger unrealized gains. Therefore, it would be expected to find similar assets underperforming in the month of September as those stocks begin to be sold.

To adjust for possible errors in their analysis, the authors use a number of statistical techniques, including controlling for market returns and controlling for the characteristics of the stocks being sold. They also conduct a number of sensitivity analyses to test the robustness of their results. All of these corrections help validate the initial finding of the research about heavy selling of the summer's losing stocks in the early fall months.

The authors conclude that tax-related selling by individual investors is a significant contributor to the September Effect. They argue that this finding has important implications for investors and policy makers, as it suggests that tax policies can have a significant impact on stock market returns.

Halloween Effect

The second literature considered has to do with the correlation between the September anomaly and another anomaly called the Halloween Effect. This anomaly is derived from the idea that equity returns tend to outperform between November and April compared to May through October. Therefore, people sell in May and don't return till the end of October to avoid the worst months. Since September is included in this bad bunch it is likely that these anomalies could amplify the effects of each other based on their individual stigmas.

All of the hypotheses surrounding the effect have to do with seasonality. Weather, seasonal disorders, and vacation times are all considered possible causes. They also rely on a general and market-wide behavioral explanation. This makes sense because the anomaly has been found to be a market-wide phenomenon, however, there is no strong evidence suggesting that it is a market-wide phenomenon or that the cause of the effect is limited to one of the possible causes described above. Economic seasonal effects are also considered such as production and consumption cycles, holiday sales, travel seasons, school cycles and shifts in business priorities (Jacobsen & Visaltanachoti, 2009). However, for the specific literature the focus is mainly on the effect in different industries.

The Halloween effect is compared and contrasted across 17 sectors and 49 industries in the United States (Jacobsen & Visaltanachoti, 2009). The motivation is to see whether it should be considered for a market-wide explanation or if the focus for the Halloween effect should be industry specific. It is found that there were noticeable differences between summer and winter returns for various sectors and industries over the period observed from 1926 to 2006. The effect is almost absent in sectors having to do with consumer consumption, but appears to be strong in production sectors (Jacobsen & Visaltanachoti, 2009).

This anomaly is similar to the September Effect in that it breaks the weak EMH. This is because it is shown that the seasonal changes can be used for a sector and industry allocation strategy. This would consist of investors switching from production industries to consumption industries during the year in order to outperform the general market index. Since changes in liquidity can be market-wide and specific to sectors, liquidity is considered as an alternative explanation to the typical seasonality.

The Halloween Anomaly is also similar to that of the September Effect in that the seasonal effect hasn't disappeared after being discovered. Many well-known anomalies in finance literature do not continue past their sample periods. This makes the Halloween and September Effects interesting anomalies to study together and to see how the correlation may go further.

Market Psychology

As described by Prospect Theory, there is a strong psychological impulse occurring from incorrect intuitions and biases present in the individual's investment context that amplifies people's negative response to potential loss. Psychologically speaking, losses feel larger than same-sized gains. Therefore, losing 200 dollars creates approximately twice the pain as winning 200 dollars creates pleasure. Fair bets should balance in our favor more than 50% to get us into action (Mitroi & Stancu, 2014). Loss aversion also creates a reluctance in us to make decisions that include change. This is due to a focus on what might be lost more than on what might be gained either as a predisposition to a trend or anticipation of a reversal. A controlling bias that sways investors and keeps them subjective and emotional. Hence when it comes to personal financial decisions, it is generally preferred to follow the status quo and be herded along with our peers.

This irrational fear of loss contained in Prospect Theory and loss aversion are very relevant to the idea of the September Effect. Since September is known for its poor performance, people are likely to make irrational decisions around September based on Prospect Theory. For example a typically rational investor who knows about the September Effect would be more inclined to sell positions in order to avoid loss. If many individuals traded on these bases it would have a large negative effect on the market for September. Consequently, more people sell and cause prices to only continue falling throughout the month. Those affected by loss aversion would suffer the worst and likely not sell till the end of the month when it was too late.

When investing it's not only our own bias that we need to watch out for. It's the other guys that not only brings risk to the system but also changes how markets work and function. Understanding biases becomes the key to success. These biases are misled judgment, which lack objectivity and increase when money is involved. These emotional fixations are led by crowd emotions and push out any independent thinking. Personal experiences also have an effect on these biases. A previous failure or success colors our investment approach to the market. A failure makes us more hesitant to risk, while a win makes us more willing to risk (Mitroi & Stancu, 2014). Furthermore, removing a bias is difficult, because we are so influenced by the events and news around us.

This philosophy can contribute to market inefficiencies and calendar anomalies such as the September Effect. One of the key behavioral traits that contributes to the September Effect is herding behavior. Herding refers to investors' tendency to follow other investors' actions rather than conduct independent analysis while making investment decisions. When investors engage in herding behavior, it can lead to a disproportionate influence on the stock market trend, as decisions made by some investors can have a ripple effect across other market participants. Moreover, market psychology can also affect investors' reaction to news and market events. In the context of the September Effect, negative news or events in September may lead to a disproportionately detrimental reaction by investors, leading to a decline in stock prices (Lo & MacKinlay, 1999). Due to the fact that investors tend to make their investment decisions in light of recent events, it may be more likely that they will overreact to negative news in September, which may lead to a more pronounced September Effect than in earlier months. This combined with the fact that we have an unproportionate tendency to react stronger to negative news already makes for a strong case that market psychology could be a big part of inducing the September effect.

Elections Effect

A final source considered how theories about political business cycles commonly look into implications concerning the temporal relationships of elections and turning points in the business cycle. For instance, theories about opportunistic political business cycles suggest that the beginning of an expansion phase of the business cycle, also known as a business cycle trough, is likely in the period before an election. This is based on the assumption that an incumbent will attempt to maximize chance of reelection. Furthermore, a business cycle peak, the start of the contraction phase in a business cycle, will typically follow close after an election as the pre-election impact is quickly reversed. It is not plausible for someone to always predict future market changes correctly, but the stock market does have patterns that could meaningfully add to investors' profits as we have already seen. Since history can be a good guide and a useful tool in considering entry and exit points in the stock market and a major factor of the real economy is the economic policies of an incumbent government, it only makes sense that the two should be considered together as an impact on stock market movements. Nonetheless, this critical connection is limited in studies.

Duration analysis was used in order to test if the occurrence of a turning point in the United States stock market cycle can be significantly affected by the happenings of an election. A turning point in the stock market is when there is either the end of a bear market or the end of a bull market. The reason duration analysis was used for the study is it is well suited when considering the temporal links between stock market turning points and elections. It provides a way to directly test the determinants when looking at the probability that an end of a market cycle phase will occur in any period conditional upon the phase lasting up until that period (Wang, 2019). The determinants that were focused on in the study was the occurrence of turning point timing related to the outcome of elections. This form of analysis also enables an estimate for the effect elections have on the chance that the end of a stock market cycle phase occurs holding other factors constant. Specifically, the duration analysis helps control for duration dependence that comes about when there is a change in probability at the end of a stock market cycle as the cycle itself progresses.

Empirical results reported in the paper provide no statistical evidence that an ongoing bear market is more probable to end in a period before an election compared to other periods no matter the political party of the president. Meanwhile, there is a significant increase in the likelihood of the end of a bear market ceteris paribus in the 24-month and the 16-month periods before an election when a Republican is incumbent (Wang, 2019). Data in the study fails to provide significant evidence that bull markets endings increase in the post-election period.

The result of post-election effects were examined further by disaggregating the post-election time period according to the winning party. The results showed that there was a significant increase in the chance of a market summit occurring directly after a Republican candidate victory and a significant lowering in the probability of a market trough in the two years after the election of a Republican president. However, there is no sufficient evidence for variation in the stock market behavior after Democratic election victories. The results also demonstrate that political alignment between the White House and Congress, known as political control, has a critical role in the timing of the turning points relative to the elections. On the contrary, when considering exclusively a president who does not have political control, the end of bear markets, known as market troughs, are less likely to occur prior to elections. Since the literature was based off of a limited number of stock market cycles, two robustness tests were conducted in the study. First, to make sure the results are indeed related to the presidential elections and not coming from some outliers in the data, the observations from the 1929 stock market crash period and the 2008 market crash period were excluded from the sample to help find consistent results. The study was then replicated using the nominal stock prices as an alternative way to show the general market condition, and the new results reaffirm the initial findings.

The hypothesis proposed in this literature was of two fold. Firstly, Compared to other times, a bear market is more likely to end in the period leading up to an election; and a bull market is more likely to complete in the period immediately after an election regardless of the political party of the president. Secondly, the probability of the end of a bull market is higher in the wake of a Republican election victory than at other times and is lower after a Democratic election victory. The likelihood of the end of a bear market is lower after an election of a Republican president than at other times and is higher after a Democratic election victory than in other periods (Wang, 2019).

The focus of this study was a set of covariates that represented specified periods before or after elections. The prior to elections and post-election periods were represented by dummy variables that are used as time-varying covariates. That means covariates that can change over the course of a spell. All these covariates represent one of three different time frames and likewise are set equal to one of the 8-month, 16-month, or 24-month periods used to observe either before or after an election. The use of different time frames for the covariates lets there be investigation into the political effect on the hazard in regards to the length of the period. The coefficients that were used across different specifications of time frames are directly comparable since the hazard is an estimate of the probability in the completion of a market cycle phase within the following month conditional on the fact that it has already lasted up until that month being observed.

To show how the hazards may depend on the underlying state of the economy, the literature considers the change time-varying interest rates can have in some specific scenarios as well. Interest rate levels may be changed by a low-frequency component and therefore could possibly not contain the supportive information over a sample period as long as the one in the report. Alternatively, interest rate changes are more likely to track business cycle variation across the fuller sample. As a result, the data includes both levels and changes in interest rates. The coefficients prior to the elections and covariates after an election represent the transfer in a hazard during the chosen period before or after an election, respectively, when holding constant the effect of duration dependence and minimizing the effect for the underlying economy by including interest rates. The pre-election and post-election covariates used in tests of the first hypothesis do not distinguish between political parties. Hypothesis one therefore predicts positive coefficients on the pre election covariates in hazard estimates for bear markets. This suggests that the bear markets that have lasted until the period before an election tend to end at that point more than at other times (Wang, 2019). The predicted post-election market downturn from the hypothesis is supported with positive coefficients on post-election covariates in hazard estimates for bull markets.

The set of post-election covariates used to test the second hypothesis includes separate covariates for the period after the election based on the party of the given president whether republican or democratic. Hypothesis two says that the post-election effect is based upon which party it was that won the election. Consistent with this hypothesis, estimates of hazard function for bull markets include positive coefficients on the covariates showing the period that follows the election of a Republican president and negative coefficients on the covariates representing the period after the choosing of a Democratic president. Furthermore, the hypothesis also predicts the estimates of hazard functions for bear markets which include negative coefficients on the covariates representing the period after a Republican president comes into office and positive coefficients on the covariates that represent the period post-election of a Democratic president.

In conclusion there is an obvious correlation between elections and turning points of elections. Similarly to the September Effect no obvious reason is provided for this phenomenon and it is not for certain, however, it seems likely a big part of it is due to anticipation of change. As a result, the market follows the speculation creating sometimes drastic changes in momentum. Since September lies so close to the election period it is likely sucked into this phenomenon of the hazards and the negative effects are amplified. Since this instigator is only once every four years it is probable the overall effects are minimal, however, it still must be considered and applied.

Literature Review Conclusion

In conclusion, from what we can observe various factors contribute to the September Effect anomaly in financial markets. Even in just a brief overview of the extensive literature on the September Effect there are several tentative conclusions that can be drawn. Elections play a significant role in affecting investors' sentiments, leading to market inefficiencies during this period. Market psychology, including herding behavior and investors' reactions to negative news and market events, exacerbate the September Effect. Additionally, the Halloween Effect and Post-School Holiday Effect have also been observed to contribute to the September Effect, where investors tend to engage in seasonal trading behavior leading to market inefficiencies.

Understanding the role of these factors, their interplay, and how they can lead to market inefficiencies and the occurrence of anomalies such as the September Effect can help investors better manage risks and implement more effective investment strategies. As such, it is crucial that investors and practitioners consider these factors when analyzing market trends and making investment decisions because these factors contribute to market inefficiencies and lead to the occurrence of anomalies such as the September Effect, which cannot be fully explained by efficient market theory.

The presence of inefficiencies in the market indicates that investors can potentially outperform the market by exploiting these anomalies, a notion that contradicts the theory of an efficient market. This suggests that market efficiency may not hold in all circumstances and that external factors can generate market anomalies, leading to the occurrence of supposed seasonal patterns such as the September Effect. Thus, understanding the influence of these factors can help investors create better and more effective investment strategies that take account of potential market inefficiencies, regardless of the time of year. Therefore, the efficient market hypothesis does not fully explain the September Effect, and additional factors outside the scope of theoretical models must be considered when analyzing financial markets.

We addressed many of the prominent literatures and hypotheses surrounding the September Effect as well as some of the background into why this is a significant anomaly worth researching. Although much was considered, there is still a significant amount to be discussed and further pursued if we have any chance of a complete explanation for such a phenomenon. I think an important part of the literature that has not been extensively addressed is comparing and contrasting time series where the September Effect was prevalent to those where it is not. By doing so you could isolate factors that might be contributing more to the effect than others by looking at the occurrence of the anomaly compared to those specific factors such as election times.

It follows that the irregularity in some of these factors such as the elections, post holiday times, sector, and location plays a large role in the lack of consistency. We see in the election portion of the review that depending on certain cabinets, house controle and party choices there can be significantly different results on the market. Furthermore, since this only occurs once every 4 years it is assumed that this should not always be considered as a significant factor.

Likewise, there is a large amount of variation in the timing of school holidays and favorable traveling times in different areas of the world and even some variation within very similar areas. For example, the schools that went back in August saw lower returns rather than September. We also saw that when considering the halloween effect the strength of the anomaly changed from industry to industry and throughout different sectors. It is plausible that these variations could be very useful in the regression to isolate the correlation and causation.

At the end of the day it's important to consider that despite many studies and analyses, it is difficult to pinpoint a single cause for this effect. Instead, there are likely many factors that contribute to the September Effect, and these factors can vary from year to year and across different markets, sectors, and industries. Furthermore, the September Effect is not consistently observed across all markets, sectors, or time periods. For example, some studies have found that the September Effect is more pronounced in small-cap stocks, while others have found that it is more pronounced in large-cap stocks. This shows that as you look at the market there is a great amount of volatility across the market and more observations are needed to be considered. Additionally, the strength and even the direction of the September Effect can vary from year to year, making it difficult to draw definitive conclusions.

In conclusion, the September Effect is a complex phenomenon that is likely influenced by many different factors, including changes in investor sentiment, corporate news, seasonal trends in investor behavior, and macroeconomic events. While researchers have made progress in identifying possible causes of the September Effect, it remains difficult to pinpoint a single cause or to draw definitive conclusions about its nature and underlying drivers. As such, investors should be cautious when interpreting the September Effect and should consider a range of factors when making investment decisions. Likewise, the continued pursuit of identifying causation for the September Effect and other failures of the efficient market hypothesis is crucial to our understanding and maintenance of economics and finance as we know it.

CHAPTER 3: DATA

As the paper moves into the portion of the project relying on personal research, the best way to effectively calculate the cause of the September Effect is considered. Therefore, a brief overview of the data chosen to be included beginning first with the dependent variable. Although an index is often looked at as sufficient for a sampling of the market, the September Effect is an anomaly that has been observed across a wide array of industries and sectors. Therefore, three indexes were included to produce a more fitting dependent variable. The S&P 500, Nasdaq, and Dow Jones are represented in the sample, all widely recognized as good index representations of the overall U.S. stock market. Since this anomaly is so extensive, I also chose to look at these three indexes as a way to narrow the data observed down to mainly the US (with some international representation from the Nasdaq). Each index has its own unique characteristics and methodology and provides a comprehensive view of the performance of the U.S. equity market. By including all three, the index's uniqueness is utilized as an advantage to more sufficiently cover areas affected by the anomaly. A short summary of each index is provided.

The S&P 500 is a market-capitalization-weighted index that includes 500 of the largest publicly traded companies in the United States (Lo & MacKinlay, 1999). It is widely considered to be a benchmark for the overall stock market and is used as a performance measure by many investors and financial professionals. The S&P 500 includes companies from a broad range of industries, including technology, healthcare, financials, and consumer goods, among others.

The Nasdaq Composite Index is a market-capitalization-weighted index that includes all the companies listed on the Nasdaq stock exchange. Unlike the S&P 500, which includes only

U.S.-based companies, the Nasdaq Composite includes both U.S.-based and international companies (Lo & MacKinlay, 1999). The Nasdaq Index is a good explanation of the stock market as a whole because it is a broad-based index that includes many different publicly traded companies across various sectors such as technology, healthcare, retail, and finance. The Nasdaq Composite is especially viewed as a gauge of the technology sector, as many technology companies are listed on the Nasdaq exchange. The Nasdaq index is also highly liquid and widely followed by investors and market analysts, making it a reliable indicator of overall market trends and sentiment. Overall, the Nasdaq Index is trusted and widely used as a proxy for the broader stock market, making it a useful tool for investors and analysts to track and analyze market trends and returns.

The Dow Jones Industrial Average is a price-weighted index that includes 30 large-cap blue-chip companies that are considered leaders in their respective industries. The Dow Jones Industrial Average is one of the oldest and most widely recognized stock market indexes in the world (Lo & MacKinlay, 1999). It is often used as a barometer of the overall health of the U.S. economy, as the companies included in the index are considered to be representative of key sectors such as manufacturing, transportation, and energy.

The independent variable began as a collection of these three indexes from 2000-2022. This time series data sourced from Bloomberg and beginning in December of 1999, the market values of one share for each index were collected at the end of every month (Bloomberg, 2014). The closing share values of the day were used to keep the data consistent and to include each month's total change. These monthly closing share values for the three indexes were then summed together with those of the corresponding month. This created an overall market value for each month. In order to find the percent change based on these values the following equation was used:

$$((C_p - L_p)/L_p)*100 \qquad (3.1)$$

Where C_p equals the current month price being calculated and L_p equals the last month price. These calculations are the reason December of 1999 data was required. The resulting product is an average percent change every month for the three indexes. These percent changes are what is ultimately used as the dependent variable.

The first independent variable included is a dummy variable to represent September against every other month. This was done by assigning September the value of one while all other months were kept with zero. This method was chosen opposed to creating twelve individual dummy variables to represent the months for several reasons. First, this form gives a simpler regression to isolate September against all other months and see the comparison as a whole. Second, it allows for an easier platform to work off of when considering other factors. Third, it avoids removing September to account for collinearity and to enable the comparison between other months. In this hypothetical scenario it is possible to see how the individual months compare to September and one another, but not the significance of September on the corresponding data which is a crucial observation. Instead this September dummy variable allows us to estimate the effect of September specifically on the stock market returns while still determining its comparison to other months and statistical significance.

The next independent variable is the dummy variable associated with the Halloween Effect. November to April, which based on this anomaly is the better performing half of the year, will be kept with a zero while May to October is given a one value. This variable is an important piece of data to the regression analysis. Since September is included in the worst six months of this dummy variable, it is likely to produce some overlap with the September variable creating multicollinearity in our regression. However, this could actually push to test the validity of the September dummy variable. What this means is, since the variables are so correlated, it is possible the September Effect is just a byproduct of the Halloween Effect or the opposite. Conversely, if these factors can co-exist it only adds to the September variable's validity and the overall significance of the model.

The final data included in the regression is trade volume. Using the same three indexes as the dependent variable, the Nasdaq, S&P 500, and Dow Jones indexes are split into three independent variables. Each independent variable's data was drawn from yahoo finance trade volumes starting January 2000 through December of 2022. The volumes for each index were collected as a total for every month. This data was included not only for its relevance to the existing variables, but also plays an important role in looking at the Post School Holiday Affect. A large factor considered in this hypothesis is the effect of negative news based on trade activity and attention. Hence trade volumes are a good way to get a glimpse at this specific hypothesis's relevance and significance.

CHAPTER 4: METHODS

As discussed above, the goal of our research is to look at the significance of the September Effect and possible hypotheses surrounding it using the data collected. The first step is determining the significance of September on the percent change of our sample market. Hence, we take the isolated September dummy variable in a simple regression against the Index variable we have created in order to see if just September has a significant effect on our data. This a crucial part of the research because if we cannot find a correlation then further research into causation is unsupported. Therefore, if we cannot find correlation then we accept the null hypothesis that the Efficient Market Hypothesis is true and September has no predictable effect on the market. If correlation is found, reject the null hypothesis, conclude that Efficient Market Hypothesis is false, and continue to look for causality. This regressions equation is:

$$IN = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 SEP \qquad (4.1)$$

Where "IN" represents the Market Index percent change and "SEP" is the September dummy variable. For the purpose of the paper, we assume that we rejected the Null Hypothesis moving forwards in order to look into causality.

Once the Null Hypothesis is rejected more independent variables can be included into the regression. These variables are included in the regression for the possible correlation they are hypothesized to have with the September Effect. These variables include the rest of the collected data. Trade Volumes for Nasdaq, S&P 500, and Dow Jones as well as a dummy variable representing the Halloween Effect are all included. These additional variables are added to the regression equation:

$$IN = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 SEP + \boldsymbol{\beta}_2 NAS + \boldsymbol{\beta}_3 S\&P + \boldsymbol{\beta}_4 DJ + \boldsymbol{\beta}_5 HAL \qquad (4.2)$$

Where “NAS” equals the Nasdaq volume, “S&P” equals the S&P volume, “DJ” equals the Dow Jones volume, and “HAL” equals the Halloween Effect dummy variable. This equation is then run for the new and more extensive model results.

The model, having all of the collected variables included, will need to be tested in order to check for certain biases that could be skewing results. There are many factors that can potentially create misleading results based on specific information within the data. Correcting for these potential biases would improve the accuracy and precision of the estimates and consequently, allow for better inference about the significance of the September Effect. Homoscedasticity, correlation, and multicollinearity will all be tested and accounted for, beginning first with homoscedasticity.

Homoscedasticity is tested by examining the residuals for variation. The most important part of the tests is to determine whether the variance of the residuals in a regression model is constant. Two tests will be run in order to determine the likelihood of homoscedasticity in the regression. The white test will be used first.

White's test can be run against the regression to check if the null hypothesis is true and that homoscedasticity exists. If this is true, any experimentally observed effect is due to chance alone and no correction is needed. If the null hypothesis is rejected it means that heteroskedasticity exists and that residuals vary greatly and there may be a factor that can explain the phenomenon. In order to run this test we input “imtest, white”. This will produce a

P-value to observe. If that value is less than .05 the null hypothesis is rejected at a 95 percent confidence interval and we assume the model contains heteroskedasticity and the model needs correcting. If the value is greater than .05 the null hypothesis stands and nothing needs to be done.

The Second test run is called the Breusch-Pagan test. This test is very similar to the white test, but still can be used in order to solidify the conclusions drawn about homoscedasticity and heteroskedasticity. The main difference between the tests is that it does not include the squares and interactions of explanatory variables like the white test does. This makes the Breusch-Pagan test a simpler version of the white test. It does not account for as many types of heteroskedasticity as the white test, but it handles larger amounts of variables much better. To run this test the command “estat hettest” is used against the regression. This test also produces a relevant P-value that you analyze just like the white test.

One solution to solve heteroskedasticity is logging appropriate variables of the regression. This can be any large, non consecutive numbers that don't include percentages or non-positive numbers. Once logged those variables are interpreted as a percentage to the regression. This can help take very large numbers with great variations and make them more manageable for the regression. Applicable variables to be logged in this case would be the trade volumes for the three indexes. If log variables do not improve the regression, using a robust command after the regression is another way to solve the issue. By including “,vce (robust)” at the end of the regression, the standard errors are switched to robust standard errors solving the problem of heteroscedasticity.

The next step is testing for trends in the regression. Adding a trend coefficient to the linear regression of the September Effect would help to account for any linear trend or pattern over time that may be influencing the relationship between the month of September and percent change or the index. This could be particularly relevant if there is a gradual increase or decrease in the dependent variable over time, as this may impact the magnitude or direction of the September Effect. By including a trend coefficient, the regression model would be able to estimate the impact of both the month of September and any linear trend simultaneously, providing a more accurate and comprehensive analysis. Additionally, it helps to identify whether the September Effect is becoming stronger or weaker over time, which could have important implications for forecasting or prediction purposes.

The final analysis of the regression is to test for multicollinearity. What this means for a regression is that two or more independent variables are correlated to one another. High multicollinearity can cause problems with the results of the model due to the cross over in information. The addition of highly correlated variables can vastly skew the coefficients of one another and cause other issues with the model's outputs. In order to test for multicollinearity two tests can be run against the regression. The first tests the possible correlation percentages between each pair of individual variables. If these numbers are close to 1 or -1 there could be risk of collinearity for the associated two variables. To run this test the term "pwcorr" followed by all the variables is run against the regression. The next test weighs the extremity of the correlation on a zero to ten scale and more certainly aids in removing unnecessary variables. For this test the input is "vif" and each variable has a specific output associated with it. If the value is between 0 and .25 there is high risk of multicollinearity and the variable should be removed. From .25 to 5 risk is low, from 5 to10 risk is mild and 10 or above is untolerable and should be removed from the model. This also aids in building a more reliable and accurate regression by removing unneeded data.

All put together the final equation is:

$$IN = \boldsymbol{\alpha} + \boldsymbol{\beta}_1 SEP + \boldsymbol{\beta}_2 logNAS + \boldsymbol{\beta}_3 logS\&P + \boldsymbol{\beta}_4 logDJ + \boldsymbol{\beta}_5 HAL + \boldsymbol{\beta}_6 TREND \quad (4.3)$$

Where log represents the log versions of the three index trade volumes.

CHAPTER 5: RESULTS

As described in the methods, the first regression run was a simple linear regression between the September dummy variable and my dependent variable of average Index percent change. The purpose of this regression was to find the type of correlation September had on this market sample and the significance of it. The described results are below.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.139887653							
R Square	0.019568555							
Adjusted R Square	0.015990338							
Standard Error	4.484405589							
Observations	276							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	1	109.9769996	109.9769996	5.4688007	0.020078183			
Residual	274	5510.110815	20.10989348					
Total	275	5620.087814						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.67638742	0.281932164	2.399114065	0.017103119	0.121358951	1.231415889	0.121358951	1.231415889
SEPT	-2.283922147	0.976641664	-2.338546707	0.020078183	-4.206597163	-0.361247132	-4.206597163	-0.361247132

Table 5.1 - A simple linear regression run on Excel isolating the September variable against the monthly percent change index dependent variable.

The first consideration is the values for our September Effect independent variable. The main focus when looking at the variable is in two parts. How does the independent variable affect the dependent variable and how reliable is the estimate on that correlation? The effect is represented by the correlation coefficient present in the far left column of the model. The number included in that column is the effect that the independent variable has on the dependent variable when the independent variable increases by one unit. Therefore, if this coefficient is negative there is a negative correlation on the independent variable and if the coefficient is positive then the correlation is positive. There are several indicators that can be used to determine if the correlation coefficient is significant to the model or not. This includes the P-values denoted as |P|

> t , t statistics denoted by t, and t-stat interval denoted by [95% conf. Interval]. Each indicator takes a slightly different approach to validating or discrediting the variable coefficients. Each indicator is sufficient to check for coefficient significance and typically give the same results, however, checking with multiple indicators increases the confidence level of the conclusions drawn. Hence, P-value and T-stats will both be considered for the regression result analysis.

The September variable is the only one included in the regression. The coefficient associated with this variable is -2.28. Therefore, September has a negative correlation such that the market percent change is expected to be 2.28 percent less in September than the other months. This value is taken in a percentage because of the nature of our dependent variable which was calculated as a monthly percent change. This result still supports the original hypothesis of the September Effect where September has a negative effect on the market. In order to check the significance the P-value and t-stats interval are considered. The P-value for the September variable is 0.020. Since this value is less than 0.05 we can reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -4.21 to -.361. Since the range does not contain zero, as the null hypothesis would suggest, we can once again reject and use the alternative hypothesis. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the September variable correlation coefficient is statistically significant to the model.

Next addressed is the general overview indicators for the regression and their significance to the overall model. The R-squared shows the percent of variation in the dependent variable that is explained by the provided independent variables of the regression. As seen in table 5.1, R-squared is equal to 0.0196. The interpretation of these results are that variations in SEPT account for 1.96% of the variation in IN. Just below we see the adjusted R-squared indicator. This is very similar to R-squared, however, it accounts also for the number of independent variables included in the regression and adjusts accordingly. As a result, if insignificant independent variables are included in the regression the adjusted R-squared will be negatively affected where R-squared will not. Therefore, adjusted R-squared is typically lower than R-squared especially as the number of included independent variables increase. The adjusted R-squared for the model is 0.0159. The interpretation of these results are that our independent variables account for explaining 1.6% of the dependent variable variation. Both of these numbers are relatively low representation of the dependent variable. This indicates that there are likely other factors that can explain the variation more completely or that the data is highly random such as the Efficient Market Hypothesis would suggest and any correlations found will seem relatively small.

The F test shown as Prob > F is an indicator that describes the significance of the overall model. If this value is too large then it must be assumed that the overall data of the model cannot be trusted. There are different intervals that can be used to interpret these values. The most typical are 90%, 95%, and 99% confidence intervals. As we see in Table 5.1 the F test given for the regression is 0.020. Since this value is greater than .01 the regression cannot reject the null hypothesis at a 99 percent confidence interval and any correlation found must be attributed to chance for that confidence level. However, since the value is less than 0.05 we can reject the null hypothesis at a 90 and more effectively 95 percent confidence level and accept correlation within the model at that confidence level. In cases such as this where only one independent variable exists, the P-value of the F test is equal to the P-value of the independent variable, in this case SEPT.

Hence, the null hypothesis is rejected and we conclude that September is negatively correlated to the percent change of the sample market. Thus, there is reason to continue research on further explanation and a multivariable regression is run to determine more information surrounding the correlation.

```
. reg INDEX SEPT NASDAQVOL DJVOL SPVOL HALLEFFECT
```

Source	SS	df	MS
Model	209.022156	5	41.8044312
Residual	5411.06566	270	20.0409839
Total	5620.08781	275	20.436683

Number of obs =	276
F(5, 270) =	2.09
Prob > F =	0.0674
R-squared =	0.0372
Adj R-squared =	0.0194
Root MSE =	4.4767

INDEX	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SEPT	-2.237928	1.023149	-2.19	0.030	-4.252291	-.2235643
NASDAQVOL	2.15e-11	1.72e-11	1.25	0.213	-1.24e-11	5.55e-11
DJVOL	-3.60e-10	1.64e-10	-2.20	0.029	-6.82e-10	-3.75e-11
SPVOL	-3.16e-12	1.05e-11	-0.30	0.764	-2.39e-11	1.76e-11
HALLEFFECT	-.1411553	.5666238	-0.25	0.803	-1.256718	.9744075
_cons	1.731616	.8933072	1.94	0.054	-.0271171	3.49035

Table 5.2 - A multilinear regression run on Stata from data collected in excel.

The first independent variable included in the regression is the September dummy variable. The coefficient associated with this variable is -2.24. Therefore, September has a negative correlation such that the market percent change is expected to be 2.24 percent less in September than the other months. This result still supports the original hypothesis of the September Effect where September has a negative effect on the market. In order to check the significance the P-value and t-stat interval are considered. The P-value for the September variable is 0.030. Since this value is less than 0.05 we can reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -4.25 to -.22. Since the range does not contain zero, as the null hypothesis would suggest, we can once again reject and use the alternative hypothesis. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the September variable correlation coefficient is statistically significant to the model.

The next three variables are the index trade volume variables. The coefficient associated with the nasdaq variable is $2.15e^{-11}$. Therefore, the Nasdaq has a slight positive correlation such that the market percent change is expected to be $2.15e^{-11}$ percent more for every trade in the nasdaq. The P-value for the Nasdaq variable is 0.213. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-1.24e^{-11}$ to $5.55e^{-11}$. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Nasdaq variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the Dow Jones volume variable is $-3.60e^{-10}$. Therefore, the Dow Jones has a slight negative correlation such that the market percent change is expected to be $3.60e^{-10}$ percent more for every trade in the Dow Jones index. The P-value for the Dow Jones variable is 0.029. Since this value is less than 0.05 the null hypothesis is rejected for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-6.82e^{-10}$ to $-3.75e^{-11}$. Since the range does not contain zero, once again the null hypothesis is rejected. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the Dow Jones variable correlation coefficient is statistically significant to the model.

The coefficient associated with the S&P variable is $-3.16e^{-12}$. Therefore, the S&P has a slight negative correlation such that the market percent change is expected to be $-3.16e^{-12}$ percent more for every trade in the S&P. The P-value for the S&P variable is 0.764. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-2.39e^{-11}$ to $1.76e^{-11}$. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the S&P variable correlation coefficient is statistically insignificant to the model.

Finally, we include our halloween effect dummy variable. The coefficient associated with the variable is -.141. Therefore, the Halloween Effect has a slight negative correlation such that the market percent change is expected to be -.141 percent lower during the months of May to October. Currently September is also included here, so the effect of September on returns is equal to -2.24 - 0.14 which is equal to the overall effect of -2.38 for September. However, the P-value for the dummy variable is 0.803. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -1.26 to .974. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Halloween Effect variable correlation coefficient is statistically insignificant to the model.

For the multilinear model, R-squared is equal to 0.0372. Thus our independent variables account for explaining 3.7% of the dependent variable variation. The adjusted R-squared for the model is 0.0194 so the independent variables explain 1.9% of the dependent variable variation adjusting for the number of independent variables. Both of these numbers are still a low representation of the dependent variable because there is still a lot of the variation not explained . This indicates that there are still likely other factors that can explain the variation more completely even after adding variables or once again that the data is highly random such as the Efficient Market Hypothesis would suggest.

As we see in Table 5.2 the F value given for the regression is 0.0674. Since this value is greater than .05 the regression cannot reject the null hypothesis at a 95 or 99 percent confidence interval and any correlation found must be attributed to chance. However, since the value is less than 0.10 we can reject the null hypothesis at a 90 percent confidence level and accept correlation within the model at that confidence level.

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(17)      =     80.03
         Prob > chi2   =    0.0000
```

Figure 5.1 - White Test ran in Stata on Table 5.2 regression.

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of INDEX

         chi2(1)      =    21.41
         Prob > chi2  =   0.0000
```

Figure 5.2 - Breusch-Pagan test ran in Stata on Table 5.2 regression.

The regression is then tested for homoscedasticity. First the White test is run as shown in Figure 5.1. The P-value shows as 0.0000. Since the value is less than .05 we reject the null hypothesis of homoscedasticity. Similarly, the Breusch-Pagan test is run as in Figure 5.2. The P-value is once again 0.0000 and the null hypothesis is rejected. As a result we conclude that our regression contains heteroskedasticity and corrections must be made.

```
. gen logNAS = log(NASDAQVOL)

. gen logDJ = log(DJVOL)

. gen log = log(SPVOL)
```

Figure 5.3 - The log index trade volume variables generated in Stata to adjust for large values and heteroskedasticity.

```
. reg INDEX SEPT HALLEFFECT logNAS logDJ logSP
```

Source	SS	df	MS
Model	181.424247	5	36.2848495
Residual	5438.66357	270	20.1431984
Total	5620.08781	275	20.436683

Number of obs	=	276
F(5, 270)	=	1.80
Prob > F	=	0.1128
R-squared	=	0.0323
Adj R-squared	=	0.0144
Root MSE	=	4.4881

INDEX	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SEPT	-2.217062	1.026514	-2.16	0.032	-4.238052	-.196073
HALLEFFECT	-.1237527	.5678946	-0.22	0.828	-1.241817	.9943119
logNAS	.6570105	1.168018	0.56	0.574	-1.642571	2.956591
logDJ	-1.277894	.7496842	-1.70	0.089	-2.753864	.1980763
logSP	.2009439	.648625	0.31	0.757	-1.076062	1.47795
_cons	8.05117	20.52198	0.39	0.695	-32.35229	48.45463

Table 5.3 - A multilinear regression run on Stata from data collected in excel with the addition of the log index trade volume variables instead of the original value driven variables.

The first correction for homoscedasticity is taking the log of the three index trading volumes. After the new variables are generated as above in Figure 5.3 the old volume variables are replaced and a new regression is run as in Table 5.3. R-squared is equal to 0.0323. Thus our independent variables account for explaining 3.23% of the dependent variable variation and is slightly lower than the previous regression. The adjusted R-squared for the model is 0.0144 so the independent variables explain 1.44% of the dependent variable variation adjusting for the number of independent variables which is also slightly lower. This indicates that on top of there still likely being other factors that can explain the variation more completely, the previous variables may have explained the dependent variable slightly better.

The given F value for the regression is 0.1128. Since this value is greater than .10 the regression cannot reject the null hypothesis at any of the three percent confidence intervals and any correlation found must be attributed to chance. This furthermore suggests that the index trade volume's original form was a better representation of the overall model. Still we will look into the variables.

The September dummy variable's coefficient is -2.22. Therefore, September has a negative correlation such that the market percent change is expected to be 2.22 percent less in September than the other months. This result still supports the original hypothesis of the September Effect where September has a negative effect on the market, however, since the overall model is rejected this is less significant. The P-value for the September variable is 0.032. Since this value is less than 0.05 we can reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -4.24 to -.196. Since the range does not contain zero, as the null hypothesis would suggest, we can once again reject and use the alternative hypothesis. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the September variable correlation coefficient is statistically significant to the model.

Next we include our halloween effect dummy variable. The coefficient associated with the variable is -.124. Therefore, the Halloween Effect has a slight negative correlation such that the market percent change is expected to be .124 percent lower during the months of May to October. The P-value for the dummy variable is 0.828. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -1.24 to .994. Since the range does contain zero, once again the null hypothesis stands. Due to both the P-value and t-stat intervals not rejecting the null hypothesis it is concluded that the Halloween Effect variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the log nasdaq variable is .657. Therefore, the log Nasdaq has a slight positive correlation such that the market percent change is expected to be .657 percent more for every percent increase in the nasdaq trade volume. The P-value for the Nasdaq variable is 0.574. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -1.64 to 2.96. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Nasdaq variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the Dow Jones variable is -1.28. Therefore, the Nasdaq has a slight negative correlation such that the market percent change is expected to be 1.28 percent less for every percent increase in the Dow Jones index trade volume. The P-value for the Dow Jones variable is 0.089. Since this value is greater than 0.05 the null hypothesis is not rejected for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -2.75 to .198. Since the range contains zero, once again the null hypothesis is not rejected. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Dow Jones variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the S&P variable is .201. Therefore, the S&P has a slight positive correlation such that the market percent change is expected to be .201 percent more for every percent increase in the S&P trade volume. The P-value for the S&P variable is 0.757. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -1.08 to 1.48. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the S&P variable correlation coefficient is statistically insignificant to the model.

```
. imtest, white

White's test for Ho: homoskedasticity
         against Ha: unrestricted heteroskedasticity

         chi2(17)      =     81.28
         Prob > chi2   =    0.0000
```

Figure 5.4 - White Test ran in Stata on Table 5.3 regression.

```
. estat hettest

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of INDEX

         chi2(1)      =    11.03
         Prob > chi2  =   0.0009
```

Figure 5.5 - Breusch-Pagan test ran in Stata on Table 5.3 regression.

The regression is then tested for homoscedasticity again. First the White test is run as shown in Figure 5.4. The P-value shows as 0.0000. Since the value is less than .05 we again reject the null hypothesis of homoscedasticity. The Breusch-Pagan test is run as in Figure 5.5. The P-value this time is 0.0009. The logged indexes slightly improved this P-value, however, not by enough and the null hypothesis is still rejected. In order to confirm the heteroskedasticity we also graph the residuals against the fitted values as seen in Figure 5.6. We see signs of heteroskedasticity where the residuals are larger near the mean of the distribution and less so at the extremes. Furthermore, there exists a systematic pattern of fitted values. As a result we conclude that our regression still contains heteroskedasticity and that the log corrections should be removed due to decreased regression significance.

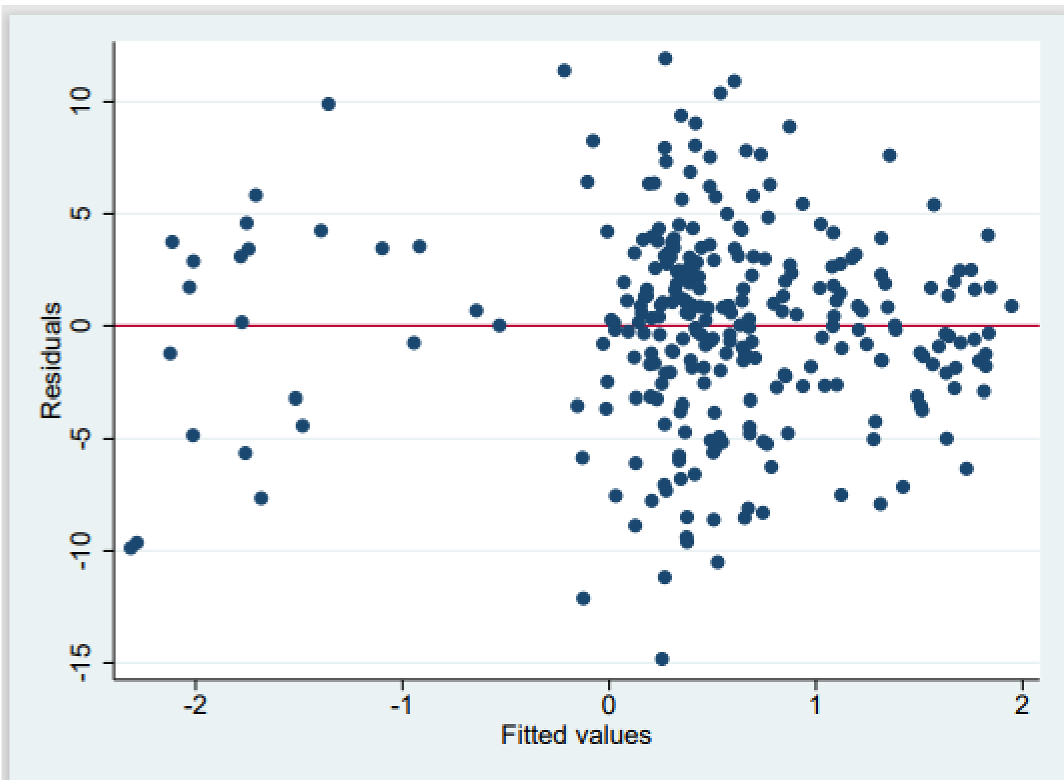

Figure 5.6 - A graphical representation of the heteroskedasticity present in Table 5.3.

```
. reg INDEX SEPT NASDAQVOL DJVOL SPVOL HALLEFFECT,  vce(robust)

Linear regression                                      Number of obs =     276
                                                       F(  2,   270) =       .
                                                       Prob > F      =       .
                                                       R-squared     =  0.0372
                                                       Root MSE      =  4.4767
```

INDEX	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
SEPT	-2.237928	1.134834	-1.97	0.050	-4.472177	-.0036783
NASDAQVOL	2.15e-11	2.06e-11	1.04	0.297	-1.91e-11	6.21e-11
DJVOL	-3.60e-10	2.00e-10	-1.80	0.074	-7.54e-10	3.46e-11
SPVOL	-3.16e-12	1.45e-11	-0.22	0.828	-3.17e-11	2.54e-11
HALLEFFECT	-.1411553	.5503532	-0.26	0.798	-1.224685	.9423741
_cons	1.731616	1.089103	1.59	0.113	-.4125969	3.87583

Table 5.4 - A version of table 5.2 with robust standard errors to correct for heteroscedasticity.

Since the heteroskedasticity of the market could not be corrected with log index trade volumes, the standard errors must be converted into robust standard errors in order to account for the phenomenon. Essentially to add the robust standard errors to the model the empirical variability of the model residuals are used to adjust the original standard errors. Empirical variability is the difference between observed outcome and the outcome predicted by the statistical model. This process corrects the heteroskedasticity and our model.

```
. reg INDEX SEPT NASDAQVOL DJVOL SPVOL HALLEFFECT trend
```

Source	SS	df	MS
Model	318.078163	6	53.0130271
Residual	5302.00965	269	19.7100731
Total	5620.08781	275	20.436683

Number of obs	=	276
F(6, 269)	=	2.69
Prob > F	=	0.0149
R-squared	=	0.0566
Adj R-squared	=	0.0356
Root MSE	=	4.4396

INDEX	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
SEPT	-2.341553	1.015622	-2.31	0.022	-4.341132	-.3419732
NASDAQVOL	1.43e-12	1.91e-11	0.07	0.940	-3.62e-11	3.91e-11
DJVOL	-2.79e-10	1.66e-10	-1.68	0.094	-6.06e-10	4.81e-11
SPVOL	-1.84e-11	1.23e-11	-1.50	0.135	-4.27e-11	5.80e-12
HALLEFFECT	-.1227158	.5619811	-0.22	0.827	-1.229156	.9837249
trend	-.0118063	.0050192	-2.35	0.019	-.0216882	-.0019244
_cons	4.98126	1.641158	3.04	0.003	1.750112	8.212409

Table 5.5 - A version of table 5.2 with the trend variable added to account for correlation patterns over time.

Since the dependent variable and index trade volumes are all time series data it is very easy for there to be trends over time in the data. For example the trade volumes are bound to increase over time as the market continues to grow. Adding the trend variable to our regression acts as a proxy for these variables that are highly correlated to time, but the effects are too difficult to directly see.

For the multilinear model including the trend variable in Table 5.5 the R-squared is equal to 0.0566. Thus our independent variables account for explaining 5.7% of the dependent variable variation. The adjusted R-squared for the model is 0.0356 so the independent variables explain 3.6% of the dependent variable variation adjusting for the number of independent variables. Both of these numbers are still a low representation of the dependent variable, however, these are the highest percentage of explanations received from the models yet. The F value given for the regression is 0.0149 which similarly to R-squared is an improved significance to the model. Since this value is less than .05 the regression can reject the null hypothesis at a 95 percent confidence interval and accept correlation within the model at that confidence level.

The first independent variable included in the regression is the September dummy variable. The coefficient associated with this variable is -2.34. Therefore, September has a negative correlation such that the market percent change is expected to be 2.34 percent less in September than the other months. The P-value for the September variable is 0.022. Since this value is still less than 0.05 we can reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -4.34 to -.34. Since the range does not contain zero we can once again reject the null hypothesis and use the alternative hypothesis. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the September variable correlation coefficient is statistically significant to the model.

The main difference in the three index trade volume variables is the significance of the Dow Jones coefficient. In the original multilinear regression the Dow Jones coefficient is $-3.60e^{-10}$. Therefore, the Dow Jones has a slight negative correlation such that the market percent change is expected to be $3.60e^{-10}$ percent more for every trade in the Dow Jones index. The P-value for the Dow Jones variable is 0.029. Since this value is less than 0.05 the null hypothesis is rejected for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-6.82e^{-10}$ to $-3.75e^{-11}$. Since the range does not contain zero, once again the null hypothesis is rejected. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the Dow Jones variable correlation coefficient is statistically significant to the old model. However, when the trend variable is added to the regression the statistical significance is affected. The P-value increases to .094 which is larger than .05 and is rejected at the 95% confidence level. Likewise, the t-stat interval for the Dow Jones is $-6.06e^{-10}$ to $4.81e^{-11}$ in the trend model. This interval contains zero and therefore is rejected at a 95% confidence interval. This means that the trend corrected a falsely significant variable that was skewed due to time correlation. In order to ensure this change was correct the significance of the variable is addressed. The P-value of the trend variable is .019 which is below .05 and accepted at a 95% confidence level. The t-stat interval of the trend variable is -.0217 to -.002. This interval does not contain zero and therefore the variable is again accepted at a 95% confidence level. Thus we can conclude that the trend variable is statistically significant and has a correcting effect on the variables, specifically the Dow Jones trade volume variable.

```
. pwcorr INDEX SEPT NASDAQVOL DJVOL SPVOL HALLEFFECT trend
```

	INDEX	SEPT	NASDAQ~L	DJVOL	SPVOL	HALLEF~T	trend
INDEX	1.0000						
SEPT	-0.1399	1.0000					
NASDAQVOL	-0.0006	-0.0332	1.0000				
DJVOL	-0.1037	-0.0303	0.5955	1.0000			
SPVOL	-0.0161	-0.0168	0.5100	0.3046	1.0000		
HALLEFFECT	-0.0483	0.3015	-0.0066	-0.0586	0.0121	1.0000	
trend	-0.0996	-0.0095	-0.6004	-0.2439	-0.6629	-0.0126	1.0000

Table 5.6 - A correlation test ran on table 5.5 to check for multicollinearity likelihood between variables.

```
. vif
```

Variable	VIF	1/VIF
NASDAQVOL	2.38	0.420584
trend	2.24	0.446561
SPVOL	1.87	0.533822
DJVOL	1.63	0.614634
HALLEFFECT	1.11	0.904473
SEPT	1.10	0.906326
Mean VIF	1.72	

Table 5.7 - A test for multicollinearity severity of variables ran on Table 5.5.

The regression must be now checked for multicollinearity. In order to do so the commands shown in Table 5.6 and Table 5.7 can be used. Table 5.6 produces a table of correlation percentages represented in decimals between 1 and -1 where 1 would be 100% positive correlation and -1 would be 100% negative correlation. As we see in the table many of the variables are suggested to have slight negative correlations to one another. The strongest correlations in the table are found between the trend variable and two of the trade volumes which it is proxying for. The first is the Nasdaq trade volume at a -60% correlation and the second is a 66.3% correlation with the S&P trade volume variable. This makes sense due to the fact that we expected these variables to interact in order to correct the time correlations. The Table 5.7 tests each variable to see the correlation strength and outputs a correlation strength denoted by VIF. The VIF scale has 3 ranges that help determine if each variable needs to be removed due to multicollinearity. The interval with the weakest multicollinearity is between .25 and 5 where all of the model variables are located. Hence, we do not have any significant multicollinearity and all the variables can stay included.

```
. reg INDEX SEPT NASDAQVOL DJVOL SPVOL HALLEFFECT trend, vce(robust)

Linear regression                                      Number of obs =     276
                                                       F(  3,   269) =       .
                                                       Prob > F      =       .
                                                       R-squared     =  0.0566
                                                       Root MSE      =  4.4396
```

INDEX	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
SEPT	-2.341553	1.114345	-2.10	0.037	-4.535499	-.1476065
NASDAQVOL	1.43e-12	1.92e-11	0.07	0.941	-3.64e-11	3.93e-11
DJVOL	-2.79e-10	1.95e-10	-1.43	0.155	-6.63e-10	1.06e-10
SPVOL	-1.84e-11	1.81e-11	-1.02	0.308	-5.40e-11	1.71e-11
HALLEFFECT	-.1227158	.5452413	-0.23	0.822	-1.196199	.9507673
trend	-.0118063	.0055688	-2.12	0.035	-.0227702	-.0008424
_cons	4.98126	1.977849	2.52	0.012	1.087228	8.875293

Table 5.8 - A variation of Table 5.5 that includes robust standard errors to account for heteroskedasticity in the final model.

Now that the regression is checked and free of multicollinearity and time trends the robust standard errors are added back to account for the heteroskedasticity on the final regression. For the multilinear model including the trend variable and robust standard errors as in Table 5.8 the R-squared, F variable and coefficients all remain constant to the Table 5.5 regression. R-squared remains equal to 0.0566. Thus our independent variables account for explaining 5.7% of the dependent variable variation. The adjusted R-squared for the model is 0.0356 so the independent variables explain 3.6% of the dependent variable variation adjusting for the number of independent variables. The F value given for the regression is 0.0149 which is less than .05 so the null hypothesis is rejected at a 95 percent confidence interval and correlation within the model is accepted.

The first independent variable included in the regression is one again the September dummy variable. The coefficient associated with this variable is -2.34. Therefore, September has a negative correlation such that the market percent change is expected to be 2.34 percent less in September than the other months. The P-value for the September variable is 0.037. Since this value is still less than 0.05 we can reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -4.54 to -.148. Since the range does not contain zero we can once again reject the null hypothesis and use the alternative hypothesis. Since both the P-value and t-stat interval reject the null hypothesis it is concluded that the September variable negative correlation coefficient is statistically significant to the final model.

The coefficient associated with the nasdaq variable is $1.43e^{-12}$. Therefore, the Nasdaq has a slight positive correlation such that the market percent change is expected to be $1.43e^{-12}$ percent more for every trade in the nasdaq. The P-value for the Nasdaq variable is 0.941. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-3.64e^{-11}$ to $3.93e^{-11}$. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Nasdaq variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the Dow Jones variable is $-2.79e^{-10}$. Therefore, the Dow Jones has a slight negative correlation such that the market percent change is expected to be $-2.76e^{-10}$ percent more for every trade in the Dow Jones index. The P-value for the Dow Jones variable is 0.155. Since this value is more than 0.05 the null hypothesis is accepted for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-6.63e^{-10}$ to $-1.06e^{-10}$. Since the range does contain zero, once again the null hypothesis is accepted. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Dow Jones variable correlation coefficient is statistically insignificant to the model.

The coefficient associated with the S&P variable is $-1.84e^{-11}$. Therefore, the S&P has a slight negative correlation such that the market percent change is expected to be $-1.84e^{-11}$ percent more for every trade in the S&P. The P-value for the S&P variable is 0.308. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from $-5.40e^{-11}$ to $1.71e^{-11}$. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the S&P variable correlation coefficient is statistically insignificant to the model.

Finally, we include our halloween effect dummy variable. The coefficient associated with the variable is -.123. Therefore, the Halloween Effect has a slight negative correlation such that the market percent change is expected to be .123 percent lower during the months of May to October. The P-value for the dummy variable is 0.822. Since this value is more than 0.05 it can't reject the null hypothesis for this coefficient at a 95% confidence level. The t-stat interval for this variable ranges from -1.196 to .951. Since the range does contain zero, once again the null hypothesis stands. Since both the P-value and t-stat interval do not reject the null hypothesis it is concluded that the Halloween Effect variable correlation coefficient is statistically insignificant to the model.

CHAPTER 6: CONCLUSION

The purpose of this project was to look into the September Effect as a stock market phenomenon and more specifically the validity of the anomaly, the possible contributing factors and how this information would affect the stock market as a whole. Looking now at the final regression and its associated conclusions, there are many interesting findings that are worth noting. My first significant finding is a consistent rejection of the null hypothesis for the September dummy variable concluding that there was a significant correlation between that variable and the monthly percent change of the average index. Seeing this result in the simple linear regression that began our results, the significance was never lost. Even as the model became less reliable due to the logged index trade volume variables, the only variable that stayed relevant was the September variable. Likewise, through all of our regression corrections the September dummy variable continued to be significant. There are many applications this has to both the paper and larger economic topics.

Setting out on this topic it was never guaranteed a correlation between September and negative stock returns would ever be found. However, the detection of this phenomenon allowed for a further look into economic research and reasoning. Most importantly it gave an unexpected conclusion to ponder. There is evidence that September can have a significant negative effect on markets. It opened up an opportunity to search through more than just a question of correlation but also causality. This allowed for more interesting data to be collected and tested. In turn this led us to our final regression where September has a coefficient of -2.34. This coefficient is no slight deviation from the typical month; it is a large and significant decrease in the market based on the model. So what does this mean?

If indeed there is a large and significantly negative correlation between September and the market that means that in this case the efficient market hypothesis has a weak or semistrong violation. This violation tells us that information is not being appropriately collected and utilized to adjust the market. Information is missing from the market leaving a gap between the intrinsic value and stock value that people can take advantage of. This lag of information discrediting the efficient market hypothesis is detrimental to many economic theories and models that rely on the theory to operate.

Luckily there are many factors about the final regression that we must consider before we can draw that conclusion. First let's consider the further supporting factors to September having a negative effect on the market and violating the efficient market hypothesis. The model's f-value is equal to .015. This is well within the 95% confidence interval. Since the overall model is significant and September is the only significant independent variable, it suggests that September truly has a significant impact on the market in this model. Furthermore, we look at the intercept coefficient which has a P-value that is correlated with the market and its coefficient is positive as we would expect from a growing stock market on a regular basis. Finally the halloween variable is considered. If the halloween effect was also a significant variable, the variable would likely be highly correlated with September and September could just be a residual effect of that larger calendar anomaly. However, this is not the case. The halloween coefficient is not significant in any cases. Since the September variable is significant despite this, it solidivise even further that it is September specifically that is having an effect on the model market.

There are also regression factors that tend to not support the September findings. First we look at the R-squared value of .0566 and even a lower adjusted R- squared value of .0356. This means that the current variables account for somewhere between 5.7% and 3.6% of the total variance. This leaves a lot of area for interpretation as mentioned before. It is likely that there are other factors with greater correlation to the coefficient that were left out and should be included that would change the results. This can create a bias for the given data making conclusions less certain. Another factor that questions the confidence of the equation is the insignificance of the trading volumes. One of the largest theories surrounding the September Effect is an abnormal amount of negative information hitting the market due to an uptick in trading volume after a slower period. Since these variables are insignificant we have no real good reasoning behind our findings. We once again are without any evidence for a conclusive reason behind the anomaly.

It is very interesting to see a significant negative variable show up in the data, however, without more factors represented and explaining more of the variation it is difficult to claim any confident conclusions on the basis of September's negative effect on the market. Furthermore, without any significant causality variables, the mystery still remains what could be behind the September Effect. More research is needed to make any absolute conclusions.

Moving forward it would be practical to involve other variables besides the September dummy variable to explain the variation involved in the market's monthly percent change and see how that would affect the model. It could also be reasonable to include a lagged variable for the market trade values since the effects are typically following a slow trade month. In conclusion, more research is needed to be certain about drawing any conclusions. However, seeing a

September variable represent the anomaly so well based on the index market changes gives a good reason to continue searching and may be an indication that a solution is near.

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About the Author

Being a student here at Allegheny has been full of new experiences for me. Coming from Washington state I knew no one and nothing about the area I was coming to. On top of this I started my college career right in the mix of the Covid 19 pandemic where everything had an extra element of unknown and chaos. I had no idea what to expect. I traveled here with two certainties in my mind. That I was here to play baseball and I was doing my 3 years of physics here and then going home to finish my 3-2 engineering program back home in Washington. Yet here I am 4 years later writing my senior comp as an economics major with a math minor. Although I may not be where I expected, through it all I have grown in ways I never could have imagined and believe that has been as invaluable to me as anything. I enjoyed playing baseball with all my teammates, spending time with the people I grew close to and sitting in Brooks. I am not yet sure where my professional life will take me, but I hope to combine my economic and sports trainer background as I venture back to the west coast to begin my next chapter of life.