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Are Donald Trump and Hillary Clinton Controlling the Stock Market? An Analysis of the 2016 Presidential Election's Impact on Stock Market Volatility

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An Analysis of the 2016 Presidential Election's Impact on Stock Market Volatility

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Abstract

Hillary Clinton and Donald Trump ran highly controversial campaigns in the 2016 Presidential Election, which then leaves us with the question of what impact is this having on the current economy? Prior analysis of political influence on the stock market tells us that isolating political impact on the stock market is nearly impossible. However, there are clearly defined 4-year cycles in stock prices that seem to correspond with election years. In this paper, I create my own index of stocks in the four major U.S. industries and measure both day-to-day and intraday volatility in stock prices across three comparable time periods: the year leading up to the 2016 election, all election years excluding the 2016, and all non-election years. I found that the 2016 election year was significantly less volatile than both prior election years as well as non-election years, suggesting that the 2015-2016 election year was not a closely contested race.

Acknowledgements

I would like to first dedicate this paper to Maxwell Sacks, whose continual support and interest in this research was an irreplaceable factor to its success. I would also like to dedicate this paper to my parents, Katherine and James Tambone, who never stopped believing in my ability to be a successful economist.

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I. Introduction

News stations are blowing up. Social media is in frenzy. Our phones *bing* every day with the latest and greatest Trump or Clinton announcement. We cannot ignore it: the 2016 Presidential election is iconic and scandalous.

During the exciting and anxious time of presidential campaigns, as the current President wraps up the projects they began, the nation becomes highly critical of every single government policy. Yet, despite all this criticism, our focus seems to be on the past and future economy, but never the current economic status of the United States as it undergoes the drawn-out campaign process. What is actually happening to our economy during this time is relatively unknown. Hilary Clinton and Donald Trump ran highly critical campaigns during the 2016 Presidential election. They have critiqued Obamacare, tax structures and the "corporate tax loopholes," immigration policies, trade relations with various countries, social security, gun rights, abortion, coal mines, access to education, and so much more. It appears like even when they make highly political and controversial commentary, such as Trump's views on Mexican immigration, the country listens and responds. Presidential elections are a time when people are especially tuned into politics and new policies.

Literature discusses that there is an inherent relationship between political uncertainty and stock prices, since businesses delay investing during uncertain periods, just like how consumers decrease spending. The literature also shows us that there is an observable 4-year trend in stock prices, also called the "Presidential Election Cycle" where stock prices decline in the first two years of a candidacy, since investors are uncertain about what changes the new President will make, and increase in the later years as this uncertainty dissipates. The most common way to measure this uncertainty seems to be through stock price volatility.

Nevertheless, data does not exist for volatility during the 2016 election year, nor is there U.S.-specific or Presidential election-specific data.

With all this paper aims to tackle these issues by asking: to what extent does this Presidential election impact patterns in the stock market? More specifically, is the 2016 election year different than prior election years in terms of stock market volatility? I used daily stock prices for 24 stocks in the four major U.S. industries to measure average volatility for the 2016 election year compared to prior election years as well as non-election years. I hypothesize that there will be a statistically significant difference in stock market volatility between this election year versus prior election years. Moreover, I predict that the 2016 election year will experience higher volatility than normal, since having primary candidates who are so vocal about controversial topics may cause uncertainty about the U.S.'s future, and thus confuse investors and increase volatility.

The empirical analysis is consistent with the findings of prior literature and concludes that election years are indeed more volatile than non-election years. Also interesting is that the 2016 election year was statistically less volatile than prior election years, suggesting that the 2016 election was perhaps not a closely contested election. These results are consistent across all four major U.S. industries: energy, manufacturing, transportation, and healthcare. They are also consistent for intraday volatility, and even maintain consistency after extending the election period by one day to capture post-election volatility. Thus, the empirical findings support my hypothesis that the 2016 election is experiencing unusual volatility compared to prior elections, but contrasts my prediction that there is higher volatility in the 2016 election year.

II. Literature Review

In a May New York Times article titled "Election Years Roil Markets with Waves of Unease," Sorkin (2016) questions if the decrease in mergers and acquisitions activity, virtually no IPO's, company's cutback in spending, stock market volatility, and GDP stall could possibly be explained by Hillary Clinton and Donald Trump! Already, it is observed that major companies such as Verizon, McDonald's, Delta Air Lines, and Exxon Mobil are dramatically cutting their capital spending. In fact, firms reduce investment expenditures by an average of 4.8% relative to nonelection years (Julio and Yook, 2012). Likewise, merger volume in the first quarter of 2016 is down 38% from last year (Dealogic, 2016).

Research shows that during presidential election years, especially those with abnormally large uncertainty about the nation's future, industries become paralyzed as large deals and investments are put on hold. Historically, the stock market trends down during the last year of a President's term, putting a psychological damper on deal making and IPOs. For example, Stephen Suttmeier (2016), a technical analyst at Bank of America Merrill Lynch Global Research observed that the Standard & Poor's index has fallen on average 2.8% since 1928 on election years where the current President is not seeking re-election. This is the only year of a President's term where, on average, there are negative returns. By comparison, in years when a President is up for reelection, the S&P 500 has average returns of 12.6% and the average for all years between 1928-2014 is 7.5%. A combination of these findings and the fact that the 2016 election period has Republican nominee unlike anyone who has run before (between Trump's limited political experience and racist campaign) leaves the following question: are we experiencing something comparable to what is observed on average in the stock market during

Presidential elections, or will the abnormal activity observed by Sorkin and atypical nominee cause the 2016 Presidential election's impact on the stock market to be distinct?

The economic and political literature below addresses two main areas of research surrounding this question: 1) what historical impact has the U.S. Presidential election cycle had on the stock market, and 2) what evidence exists about the extent to which investors are influenced by political factors, including Presidential elections?

Part I: Historical Election Cycle's Impact on the Stock Market

Kitchin (1923) observed that between 1890-1922, there was a 40-month business cycle in the stock market in both the United States and Great Britain. Because 40 months is roughly the same length as a President's term, he coined this pattern the "Presidential Election Cycle." Many researchers have found that the cycle still exists today. For example, Stovall (1992) noticed that the Presidential Election Cycle in the United States had an especially large presence in the stock market from 1868-1945. This pattern consists of low returns for the first two years of a President's term and high returns in the last two years.

In the scholarly article "Mapping the Presidential Election Cycle in US Stock Markets," Wong and McAleer (2009) suggest that one reason for this initial decline in stock prices is that the new President may make unpopular policy changes to adjust the economy. However, by mid-term, stock prices will rise due to a now stronger (and ideally improved) economy. In effort to quantify these observations, they looked at weekly data from the Standard & Poor's 500 Composite Price Index from January 1, 1965 to December 31st 2003 for all empirical analysis. When graphing this index, they found the same trend as above: a four-year cycle with the stock index falling during the first half of a Presidency, reaching a trough in year two, and finally rising in the second half. The authors also used the Exponential Generalized Autoregressive

Conditional Heteroscedasticity model (EGARCH) where there are Presidential dummy variables to represent each year of the President's term, a time variable for the upward trend from 1965 to 2000, and a dummy variable, which is the prevailing administration political party. They then applied the Augmented Dickey-Fuller transformation to the S&P stock returns and plotted this data via a periodogram to more clearly reveal the dominant peaks. This plot confirmed that although there are several cycles in stock market prices, nothing was as prominent as the 4-year Presidential Election Cycle since the strongest spikes in pricing were spaced on average of 200 weeks, or roughly 4 years. Thus, this article confirms that there is a trend between the election cycle and stock market.

In attempts to prove robustness of this trend, Gartner and Wellershoff (1995) looked at how this changed over time and between administrations of different party backgrounds. They started by graphing the nominal and real U.S. Industrial Share Prices per year and visually observed the trend for both nominal and real share prices. From this, they created a formula comprised of time, white noise, and an election year dummy variable that captures the ups and downs of stock prices in 4 years to predict log stock prices, and a dummy variable to capture the stock market crash of 1987. They found that the election-cycle dummy has a negative impact on real stock returns and that this pattern is highly insensitive to specific changes in the estimation equation and robust over time and between administrations of different political parties. Yet, this model, like all other models, still is unable to isolate the impacts of the Presidential election on the stock market from other influential factors.

Moreover, one way to also look at this trend is by observing volatility. Bialkowski, Gottschalk, and Wisniewski (2008), for example, investigated whether a sample of 27 OECD countries experience higher stock market volatility during national elections. They established that volatility around elections is warranted because election uncertainty especially affects risk-averse investors and market-wide fluctuations in response to election shocks will augment the volatility of all shocks, making it reasonable that option prices may increase during the voting period. Through their event-study framework, they found that investors, unable to accurately predict election results, are typically surprised by the vote. As a result, stock prices react strongly to this surprise and cause temporary levels of volatility; this volatility typically doubles during the week before elections. Moreover, stock market participants react more volatilely during closely contested elections. What this article lacks is both US specific results and results driven by data instead of hypotheses; my model will provide a model to this U.S. volatility as a means of grounding this evidence in data.

Part II: Politics' Influence on Investors

In Hong and Kostovetsky's (2012) highly sited article "Red and Blue Investing: Values and Finance," they look at the stock holdings of U.S. mutual fund managers who make campaign donations to Democrats and how this affects their portfolios. They found that managers who donate to the Democratic party or to a Democratic campaign underweight, relative to Republican donors, stocks that are considered "socially irresponsible," such as guns and tobacco, which are typically associated with the Republican Party. Conversely, Democratic managers overweight stocks of socially responsible firms. This finding was similar for hedge fund managers.

In response to this research, Jiang, Kumar, and Law (2015) sought to expand this research on political preferences beyond just buy side (as with Hong and Kostovetsky) to sell-side equity analysts. Similarly, they examined whether Republican analysts contain portfolios heavily influenced by conservative traits. Specifically, their sample of equity analysts and earnings forecasts came from the Thomson Reuters' Institutional Brokers Estimate System. This data was merged with the Center for Research on Security Prices data set to obtain stock prices around the forecasts. From this, a regression was created to estimate a series of market reactions and to examine whether the market reaction was stronger or weaker for these analysts. They found that Republican investors are more cautious in incorporating new information into their earnings forecasts and stock choices.

In order to claim that politics influence investments, it is important not only to notice a trend in portfolio allocation and political party, but also the changes in the overall quantity of investing during an election. There is a lot of economic uncertainty in the U.S. economy, especially policy uncertainty in the wake of the financial recession. In a scholarly article by Brandon Julio and Youngsuk Yook (2012), the authors attempt to measure this effect of uncertainty on investment expenditures by establishing two key points. First, election results are relevant to corporate decisions since their results will have a direct effect on industry regulation, taxation, and monetary policy. Secondly, because it is so hard to study the impact of political uncertainty on investment due to endogeneity between uncertainty and economic growth as a result of economic downturn itself, elections are essentially a natural experiment to study political influences because they disentangle some of this endogeneity. In a sample of several large countries, it was discovered that corporate investment is lower before national elections. When controlling for investment opportunities and the economic environment, investment rates drop on average 4.8% in the year leading up to an election. This evidence supports the political uncertainty hypothesis, which states that political uncertainty leads firms to reduce investment expenditures until electoral results are announced. Cumulatively, this research shows that politics matter in a firm's investment decisions.

Furthermore, the most simplistic valuation model used to interpret movements in stock prices states that real stock prices equal the present value of expected future real dividends, discounted by a constant real discount rate (Investopedia). This model was largely disproved by Shiller (1981), who observed that stock prices were too volatile (5x-13x too high) and that there must be missing information in the model. In other words, this model is overly simplistic and Shiller implies that political factors may be the missing key to this unexplained volatility. Sweet, Ozimek, and Asher (2016) explain that political factors can influence stock market volatility because political uncertainty can cause businesses to delay hiring, firing, and ultimately investments since part of "gaining the system" in the stock market is based on anticipating changes (such as Presidential policies). On the flip side, there is also a consumer impact since they may be more frugal during periods of heightened uncertainty.

Nevertheless, disentangling political fluctuations from general economic uncertainty is extremely challenging. Many economists continually struggle to with the complexity of stock market behavior and the inability of present value models to fully describe this behavior. As a result, researchers such as Wisniewski (2009) explore the impact of variables related to politics on the valuation of companies. Wisniewski found that political factors describe the behavior of the stock market beyond present value models. Stocks are typically more expensive, relative to fundamentals, when there is a Democratic President. Also, when there are periods of strong support for a President, this typically inflates stock prices, potentially because investors feel optimistic about the future of the economy. Investors are also optimistic when voters cast their ballots, as indicated by overpricing in the years of Presidential elections. Thus, present value models would be more accurate if they included political factors.

With this in mind, I seek to observe patterns in the stock market through examining volatility in the 2016 election year versus prior election years and non-election years. Although it is difficult to isolate political impacts, this election year contains such interesting nominees in the Democratic (Hillary Clinton, who has 40+ years of political experience) and Republican (Donald Trump, who has no political experience) parties, that I anticipate volatility to be exceptionally high since Trump's experience and banter may cause high levels of uncertainty.

III. Model & Data

In the previous section, economists such as Joseph Kitchin, Michael McAleer, and Wing-Keung Wong suggest that there is indeed an observable four-year pattern in stock prices that mirrors the Presidential cycle. Brandon Julio and Youngsuk Yook explained how election results are relevant to investors since their results will have a direct effect on industry regulation, taxation, and monetary policy and thus can potentially impact the stock market. Additionally, Bialkowski, Gottschalk, and Wisnieswski proved that country's stock markets react more volatilely during closely contested elections. Yet the first problem with these findings is that they are not always U.S. specific. For example, Bialkowski, Gottschalk, and Wisniewski studied election cycles in a sample of 27 OECD countries and did not give country-specific results. In fact, Kitchin conducted the most recent U.S. specific measure of stock price cycles during Presidential candidacies in 1923. Although others such as Stovall have added additional data to Kitchin's model, this data ends over 50 years ago. Another missing component to this research is that it sometimes examines elections holistically, not specific to Presidential elections, such as in Julio and Yook's research. Thus, while previous research provides purpose and interest to examine if these patterns still exist, this will be the first and most current examination of stock prices during U.S. Presidential election years vs. non-election years. Also, since prior research has not paid enough attention to industry specific differences, this model will examine whether different industries experience volatility during election years in similar or different ways and directions.

As a means of modeling whether stock prices in the 2016 election year are different than stock prices in prior election years, 24 stocks were selected from the four major U.S. industries: energy, manufacturing, transportation, and healthcare. It is important to note that while agriculture is also regarded as a major U.S. industry, it is excluded from our data due to the limited number of public U.S. agricultural companies. Each industry contains 6 stocks which were further diversified by company age to vary the types of companies representing each industry. Table 1 contains information about the stocks selected, listed from oldest to newest company per industry. Daily stock prices were pulled from Yahoo Finance and are considered a time series dataset.

Table 1a.

Industry	Stock	Ticker	Year Founded	Year began issuing stock
Energy	Exxon Mobile	XOM	1870	1970
	Enterprise Products Partner	EPD	1968	1998
	Valero Energy Corp.	VLO	1980	1982
	SunPower	SPWR	1985	2005
	First Solar	FSLR	1990	2006
	SolarCity	SCTY	2006	2012
Manufacturing	Delux Corp.	DLX	1915	1987
	Toro Co.	TTC	1914	1987
	Monster Beverage Corp.	MNST	1935	1995
	Polaris Industries	PII	1954	1987
	Apple	AAPL	1976	1980
	Thor Industries	THO	1980	1987
Transportation	UPS	UPS	1907	1999
	General Motors	GM	1908	2010
	Delta Airlines	DAL	1924	2007
	Southwest Airlines	LUV	1967	1980
	FedEx	FDX	1971	1978
	United Continental Holdings	UAL	2010*	2006
Healthcare	McKesson	MCK	1833	1994
	CVS Health	CVS	1963	1984
	Cardinal Health	CAH	1971	1987
	United Health Group	UNH	1977	1992
	Express Scripts	ESRX	1986	1992
	AmerisourceBergen	ACB	2001*	1995

* Merger and Acquisition date. Companies issued stock prior to the M&A, hence why the "year began issuing stock" is earlier than the "year founded."

The data set starts at the year when the stock was first issued, and thus each stock has a slightly different number of observations ranging from 46 years of daily statistics (ex. Exxon

Mobile) to 4 years (ex. SolarCity), with the independent variable being the date and the dependent variable being the closing stock price for that day. Although a variety of stock prices are published for each day including the opening price, highest price, lowest price, and closing price, for this model the closing price was used. The closing price most accurately reflects the price at which someone bought the stock since stocks are typically purchased throughout the day, rather than when the stock market first opens, and since it is price most commonly used in the models listed in the Literature Review. However, for intraday volatility, the stock high and low for the day were used to capture the daily swing. This model can be found in the "Robustness Checks" section in "Results."

The data was broken into three time periods: 1*, 1, and 2. Period 1* and 1 are the election years and period 2 is the non-election years. I based my time periods off Manfred Gartner and Klaus W. Wellershoff's model, whose election period ends when the Presidential election takes place in November, rather than when the newly elected President takes office in January. This is in order to isolate the effects of uncertainty of who will be elected President from when the election is over and this uncertainty ends. For example, period 1*, which is the 2015-2016 election year, is from November 8, 2015 – November 8, 2016, which is the one year prior to the 2016 Presidential election date through the election day. If the beginning or end of a period fell on a day that the stock market was closed, the period was rounded up to the next day the stock market was open. Period 1 contains every one-year period between the Election Day and the year prior to the Election Day for every Presidential election since the stocks were first issues, excluding this current election year. Period 2 contains stock prices between these election years (both 1* and 1). It is important to note that in years where a President was re-elected for a second term, that re-election period was not considered an "election year" or "period 1" since research explains that there is much less uncertainty during these elections since they are typically not as closely contested and thus have much less volatility. It is also important to note that the year leading up to Richard Nixon's resignation and Gerald Ford's Presidency is counted as an election year, since per that same ideology, there was great uncertainty in what would happen to the government and thus resulted in higher volatility. Table 2. contains the data ranges for each section.

Table 2.

Year Type	Date ranges included (does not exclude closed market days)
1*	11/8/15-11/8/16
1	8/9/73-8/9/74, 11/2/75-11/2/76, 11/4/79-11/4/80, 11/8/87-11/8/88, 11/3/91-11/3/92, 11/7/99-11/7/00, 11/4/07-11/4/08
2	11/6/69-8/8/73, 8/10/74-11/1/75, 11/3/76-11/3/79, 11/5/80-11/7/87, 11/9/88-11/2/91, 11/4/92-11/6/99, 11/8/00-11/3/07, 11/5/08-11/7/15

One way to capture fluctuations in stock market prices across time is to measure stock volatility between days, which was measured via a modified percent change model:

$$Day - to - Day\ Volatility\ (V) = \frac{|P_2 - P_1|}{P_1}$$

In the day-to-day volatility model, P2 is the closing price of the stock today and P1 is the closing price from the prior day. Later, I will adapt a similar model for intraday volatility where P1 is the daily low for the stock and the P2 is the daily high for the stock. Again, this modified model is written out in the "Robustness Checks" section of "Results." This measurement is based on a model used by Bialkowski, Gottschalk, and Wisniewski, who used the historical volatility method as a way of measuring stock price volatility. The historical volatility method is the standard deviation of daily stock returns. In order to find day-to-day fluctuations instead of intraday fluctuations, this model was adapted slightly as well as simplified.

After the day-to-day volatility was calculated for each stock and for each day, I found the average volatility for each time period: 1*, 1, and 2. I also found the average daily volatility for each sector by calculating:

$$Average\ Volatility\ by\ Sector = \frac{V_1 + V_2 + V_3 + V_4 + V_5 + V_6}{6}$$

where V is the day-to-day volatility for each stock and "sector" refers to Energy, Manufacturing, Transportation, or Healthcare data. This sector average was then also classified by average volatility for each time period (1*, 1, and 2). These results, as well as their corresponding F-tests, can be observed in the "Results" section. Furthermore, average volatility for all 24 stocks was calculated using a similar formula:

$$Averaage\ Volatility\ for\ Data\ Set = \frac{V_1 + V_2 \ldots + V_{24}}{24}$$

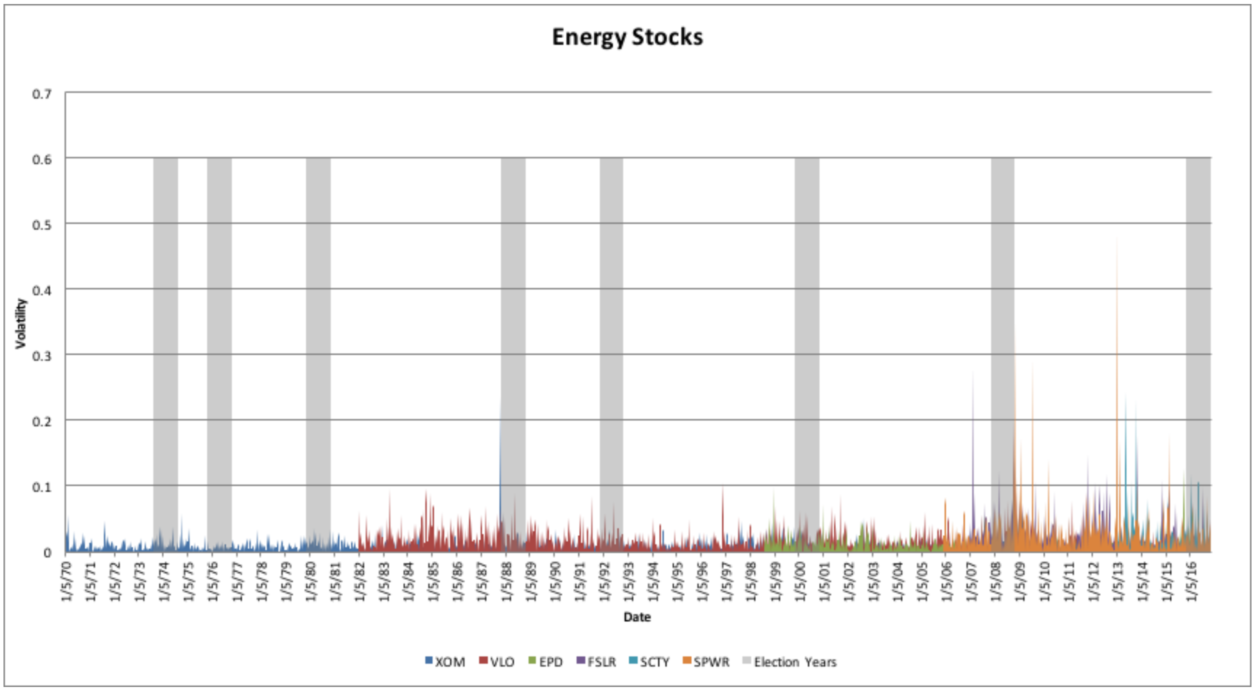
Table 3 includes summary statistics of the data. The summary statistics for "All Data" used the formula titled "Average Volatility for Data Set" and the summary statistics for energy, manufacturing, transportation, and healthcare stocks used the formula titled "Average Volatility by Sector." This data tells us that volatility measurements around 0.015-0.020 are fairly typical for these stocks. By contrast, the standard deviation in table 3 as well as graphs 1-4, which graph daily volatility for each industry, show us that abnormal volatility occurs typically at volatility measures of 0.1, with major spikes around or above 0.3.

Table 3. Summary Statistics

	Mean Volatility	Standard Deviation	Minimum Volatility	Maximum Volatility
All Data	0.0166	0.0131	0	0.5418
Energy Stocks	0.0147	0.0144	0	0.5073
Manufacturing Stocks	0.0216	0.0220	0	0.2998
Transportation Stocks	0.0172	0.0161	0	0.4635
Healthcare Stocks	0.0154	0.0120	0	0.2203

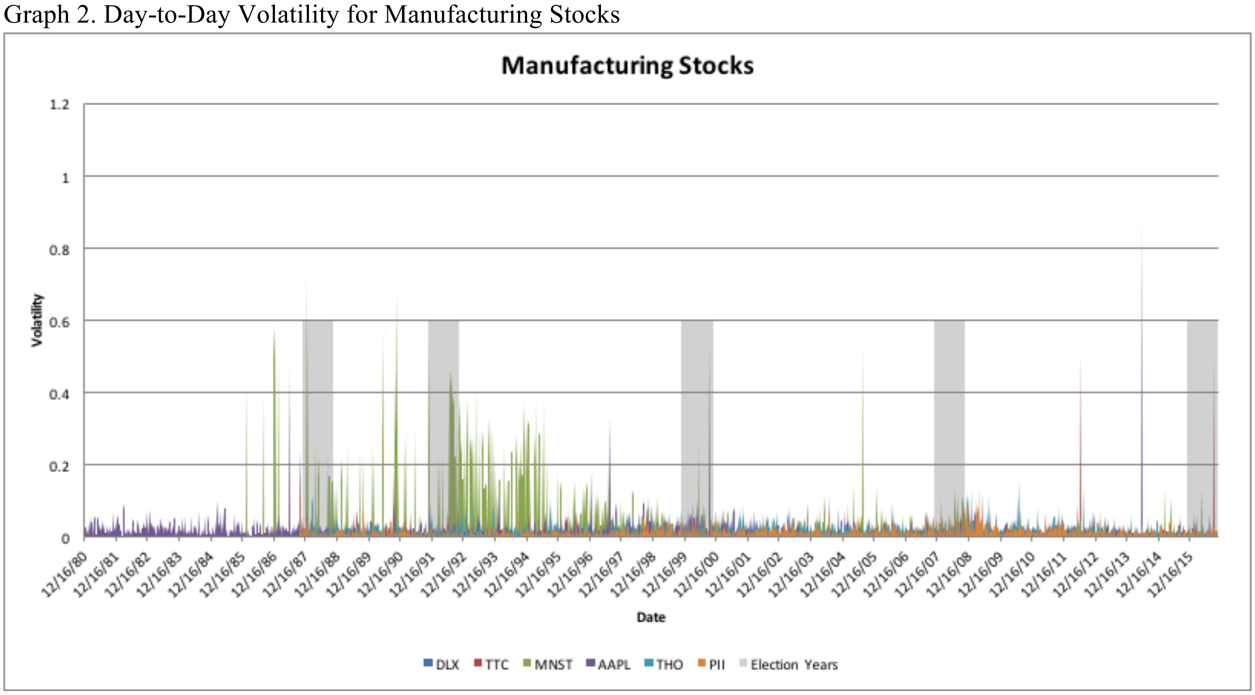
Before delving further into the data specifications, I was curious to see what the volatility looked like for each industry and whether election years for the stocks selected experienced higher or lower volatility than non-election years. Day-to-day volatility was plotted on the yaxis, and date on the x-axis. Below are the graphs of each industry, with election years highlighted in grey:

Graph 1. Day-to-Day Volatility for Energy Stocks



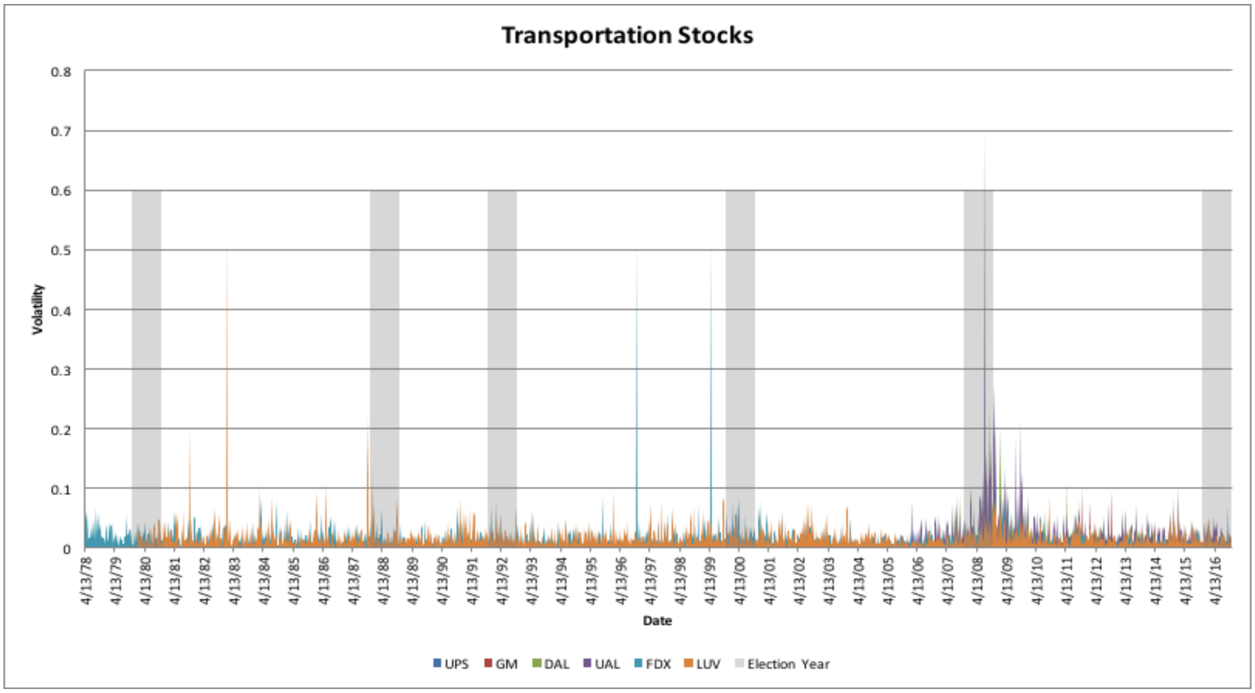
Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 2. Day-to-Day Volatility for Manufacturing Stocks



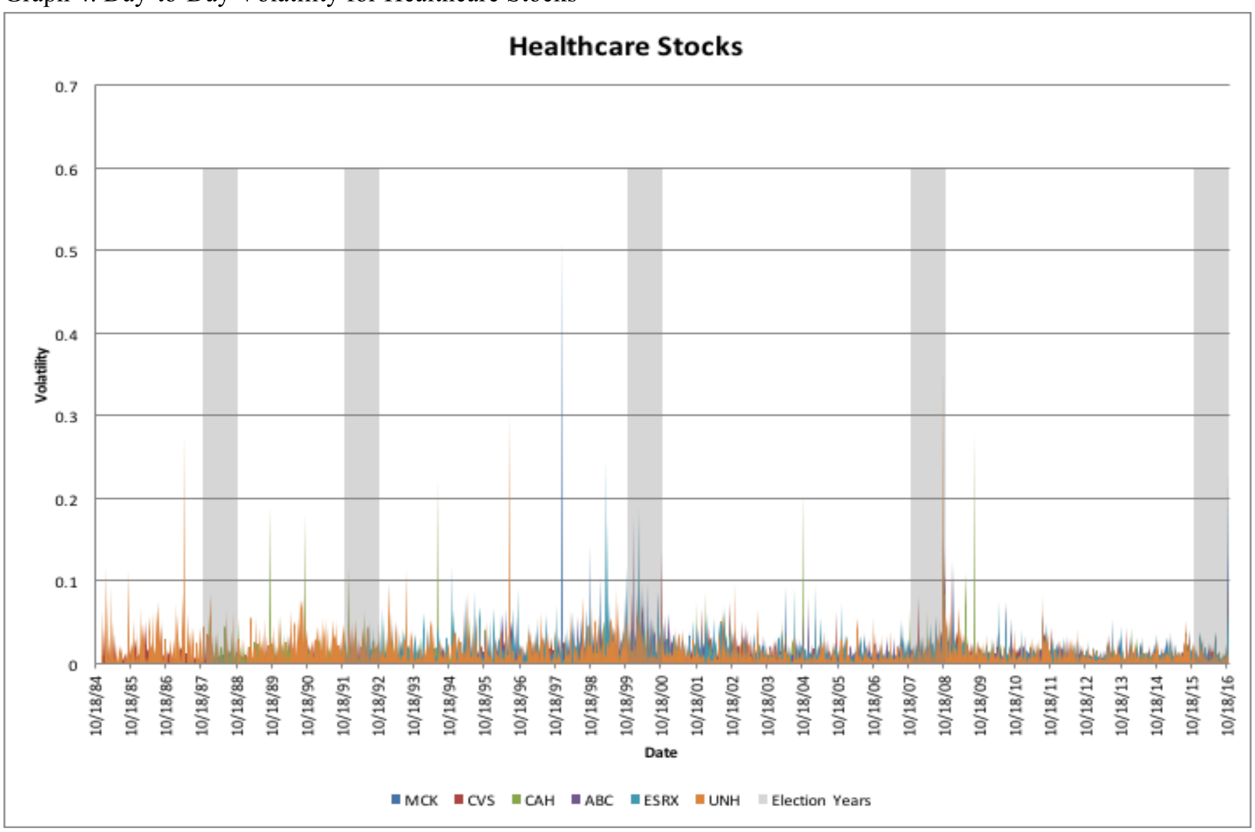
Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 3. Day-to-Day Volatility for Transportation Stocks



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 4. Day-to-Day Volatility for Healthcare Stocks

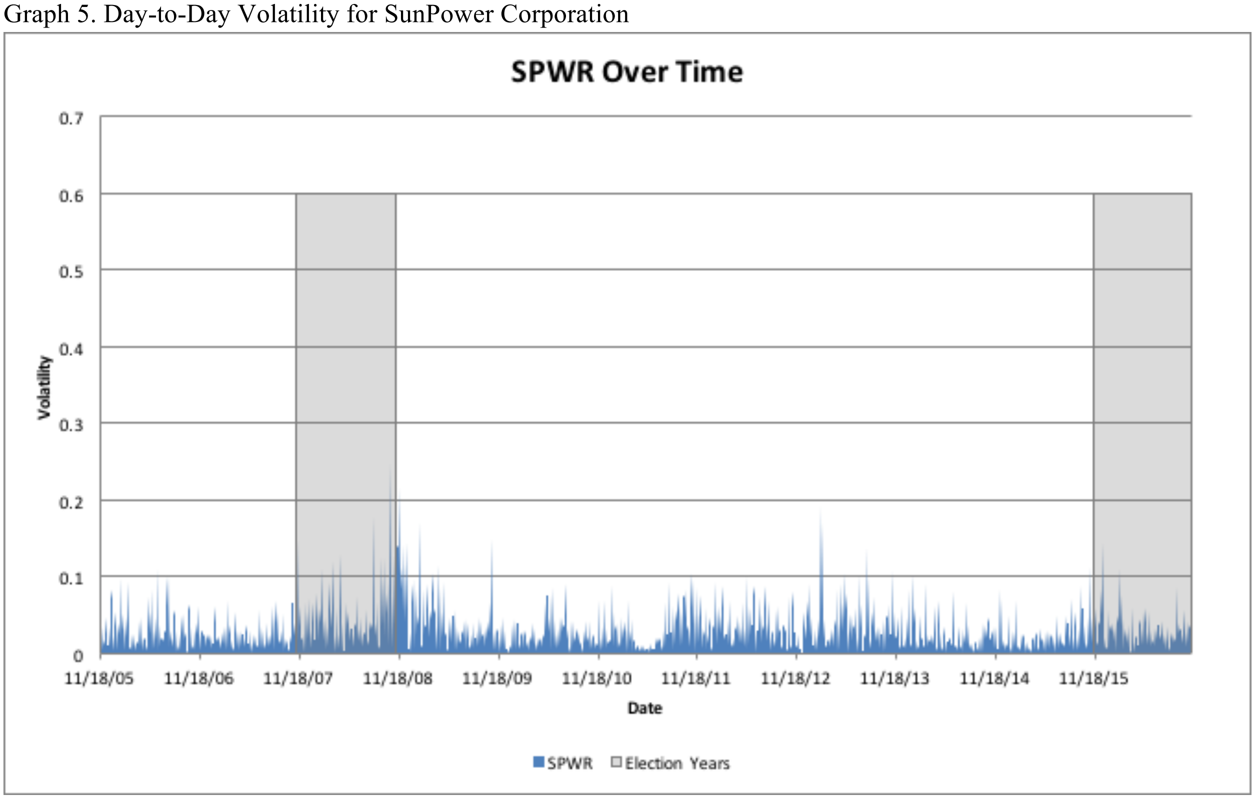


Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Although it is hard to make conclusions based on such busy graphs, it appears that the grey regions, or election years, often capture several of the volatility spikes, which would mean that election year's experience higher volatility than non-election years. For example, graph 3, which captures the volatility for the transportation stocks, shows that although there are large spikes in volatility in non-election years as well as election years, the greatest spikes appeared right around the 2008 election. Similarly, the spikes for the '88 and '00 elections seem to be higher than their non-election year counterparts.

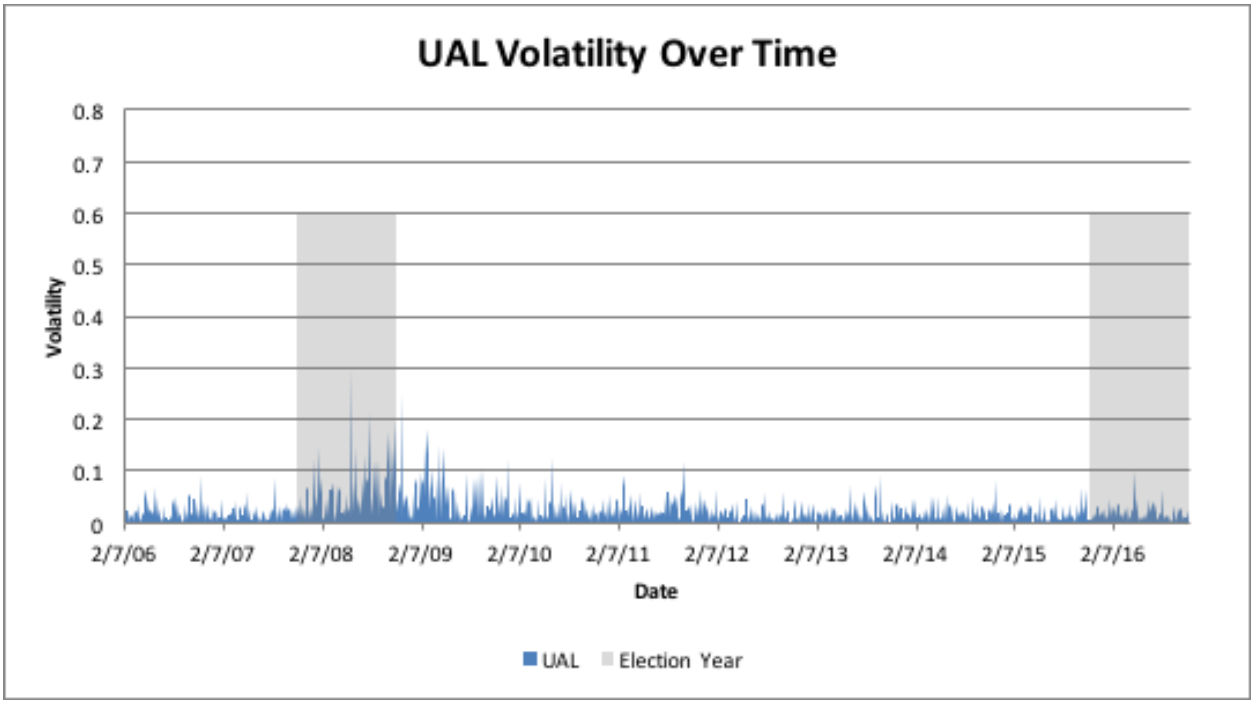
To simplify these graphs and to examine more closely the relationship between volatility this election year versus prior election years, I selected two companies from two different industries that have only issued stock for two election cycles. Below are the graphs of SunPower Corporation (SPWR), an energy stock, and United Continental Holdings (UAL), a transportation stock:

Graph 5. Day-to-Day Volatility for SunPower Corporation



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 6. Day-to-Day Volatility for United Continental Holdings



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Both graph 5 and 6 show similar results: volatility seems to increase throughout the 2008 election year, peeking right around or right after the election, and then decreasing again. However, the 2016 election does not experience a similar spike in stock prices. In the next section, I will see if these same results are observable for all stocks.

IV. Results

Section 1. Part A. Day-to-Day Volatility

Once the volatility formula was calculated for each stock and for each day, these values were divided into their 1*, 1, and 2 groups. From there, the average was taken for each group (1*, 1, and 2). This is shown in the left section of table 4 where the period is in the left column and the average for that period across all stocks is in the right column. In order to compare these values, the differences between periods were also calculated as shown in table 2. The third row is the difference between the average volatility for 1(election years excluding the 2016 election) and 1* (2016 election year) and the forth row is the difference between the average volatility for 1 and 2. It is important to note that the value is positive for each but bigger between 1 and 1*, meaning that the average volatility for period 1 was higher than that for 1* and 2 (non-election years) and that there was a greater difference between the 1* and 1 than there was for 1 and 2. Next, these averages were taken for each industry, in order to see if there were any industry-specific differences. Table 5 shows the average for 1*, 1, and 2 in each industry and the differences between these averages. Something noteable about table 5 is that the differences for energy indicate that the volatility is only slightly higher in period 1 compared to period 1*; this difference is a lot larger for other industries.

Next, a series of f-tests were conducted to compare the variances between time periods, as exemplified by the right two columns of table 4 and 5. F-tests were calculated at an alpha of 0.01 and all were found to be statistically significant, excluding the difference between group 1* and 2 in energy, since they had p-values above 0.01. The null hypothesis is that there is no difference between the variance in 1 and 1*, 1 and 2, and 1* and 2 and the alternative hypothesis is that there is a difference in variance. Because of the f-values and p-values, we have evidence to reject the null hypothesis. Additionally, several of the readings included in the literature review indicated that election years experience higher volatility than non-election years. In other words, period 1 experiences higher volatility than period 2. This was consistant with my findings and also proved to be statistically significant.

Table 4. Volatility across all stocks

Total Averages		Difference Between Periods		F Observed	P-Value
1* 2016 Election Year	0.0141	1-1*	0.0130***	0.0807	0****
1 All Election Years Except 2016	0.0271	1-2	0.0088***	4.302	0****
2 Non-Election Years	0.0182	1*-2	-0.0042***	0.3472	0****

***Denotes significance at the 1% level (two-tailed test)
****Value was so small that excel rounded it to 0.

Table 5. Volatility by industry

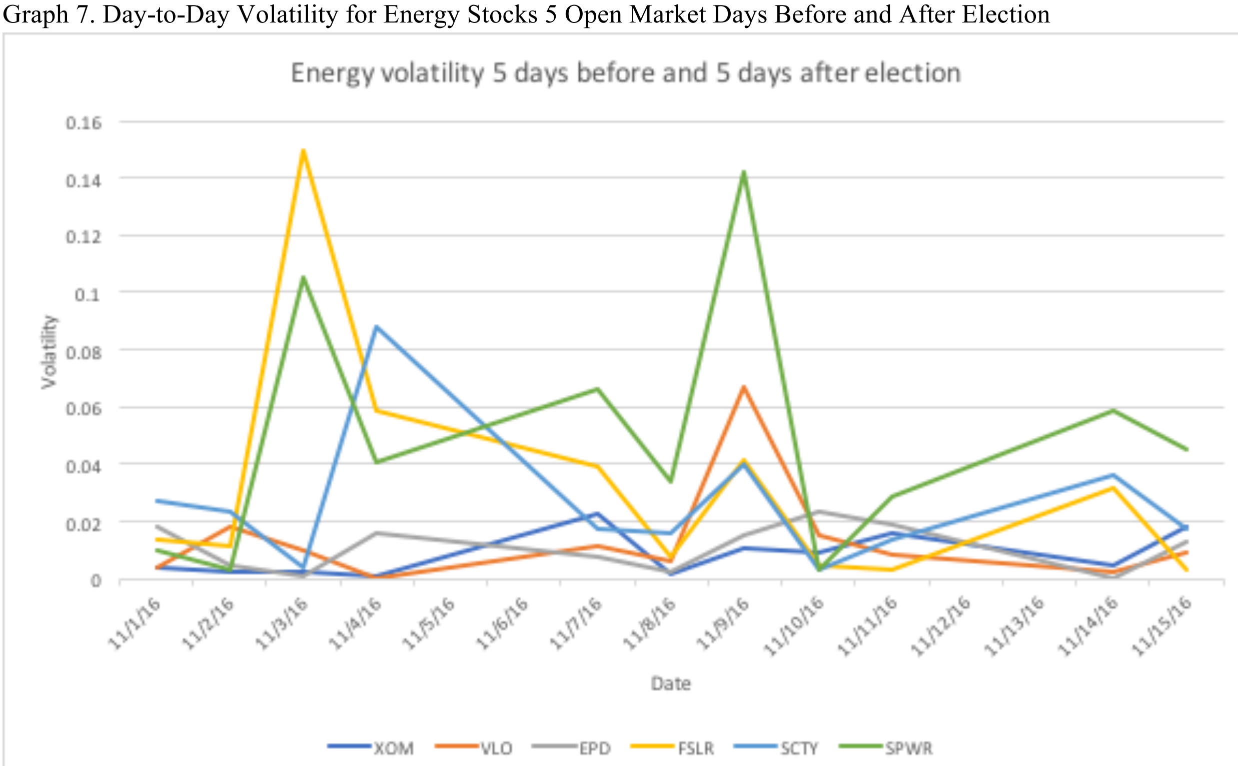
Average by Industry by Period			Difference by Industry by Period		F-Test Results	
Sector	Period	Average Volatility	Groups	Average Difference	F Observed	P-Value
Energy	1*	0.0211	1-1*	0.0016***	0.4900	4.301E-12
	1	0.0227	1-2	0.0016***	1.8831	1.3074E-77
	2	0.0211	1*-2	0.0000	0.9227	0.1971
Manufacturing	1*	0.0123	1-1*	0.0152***	0.0997	0****
	1	0.0274	1-2	0.0071***	1.4593	2.1265E-17
	2	0.0203	1*-2	-0.0081***	0.1454	0****
Transportation	1*	0.0126	1-1*	0.0221***	0.1562	0****
	1	0.0347	1-2	0.0179***	0.4389	0****
	2	0.0167	1*-2	-0.0041***	2.8110	6.241E-23
Healthcare	1*	0.0104	1-1*	0.0099***	2.5928	2.9775E-18
	1	0.0203	1-2	0.0055***	1.4581	5.1779E-17
	2	0.0149	1*-2	-0.0045***	0.5623	3.4565E-09

***Denotes significance at the 1% level (two-tailed test)
****Value was so small that excel rounded it to 0.

Part B. 5 Days Before and After Election

Because the difference between period 1* and 1 was so similar for the energy sector and to further examine the immediate impact of the 2016 election, I decided to calculate and graph the day-to-day volatility for the 5 days that the stock market was open before and after the 2016 Presidential election to see if there was a pattern of increased or decreased volatility immediately before and after the election. First, I examined the volatility for the energy stocks, as shown in graph 7. As you can see, volatility is relatively high around 11/2/16, settles for a few days before the election, and then spikes up on 11/9/16, before flattening again on 11/10/16. The most consistent trend for all stocks seems to be on 11/9/16, the day after the election, since every single stock went up in volatility that day. However, it appears that volatility before the election was also high, which could explain the unusually high 2016 election year (1*).

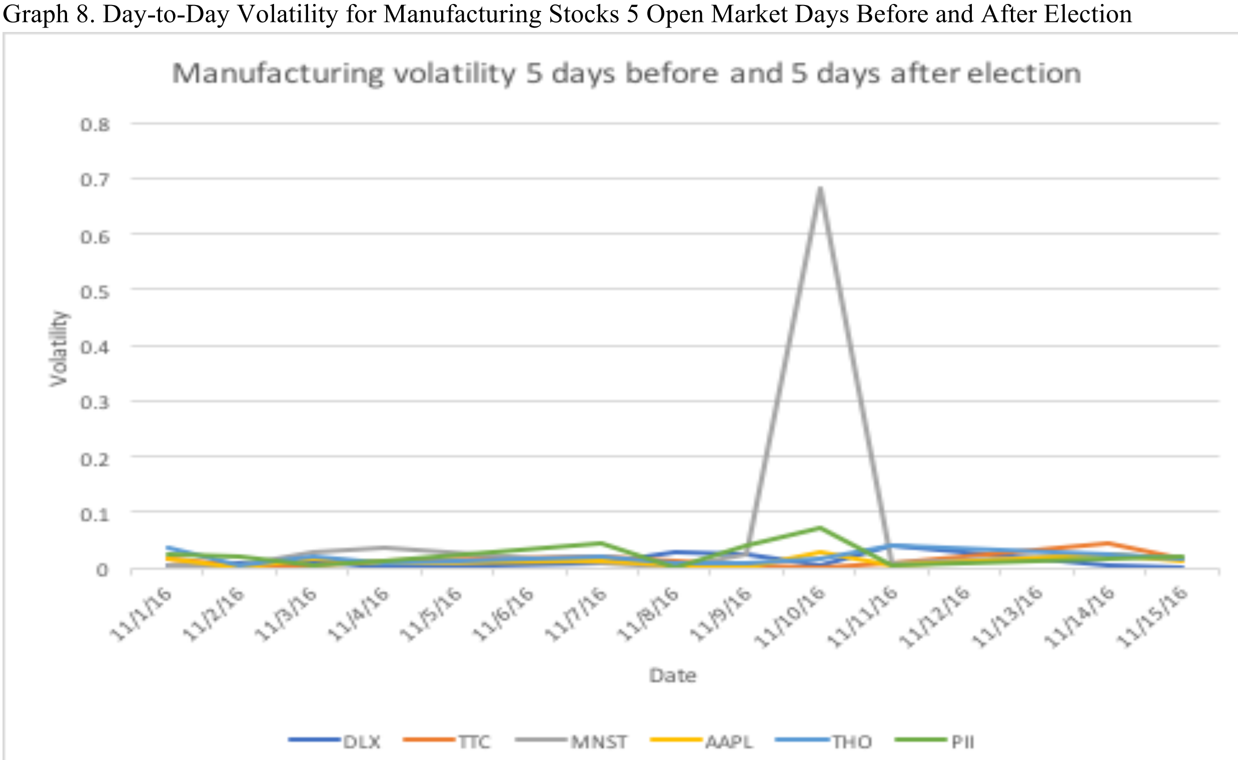
Graph 7. Day-to-Day Volatility for Energy Stocks 5 Open Market Days Before and After Election



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

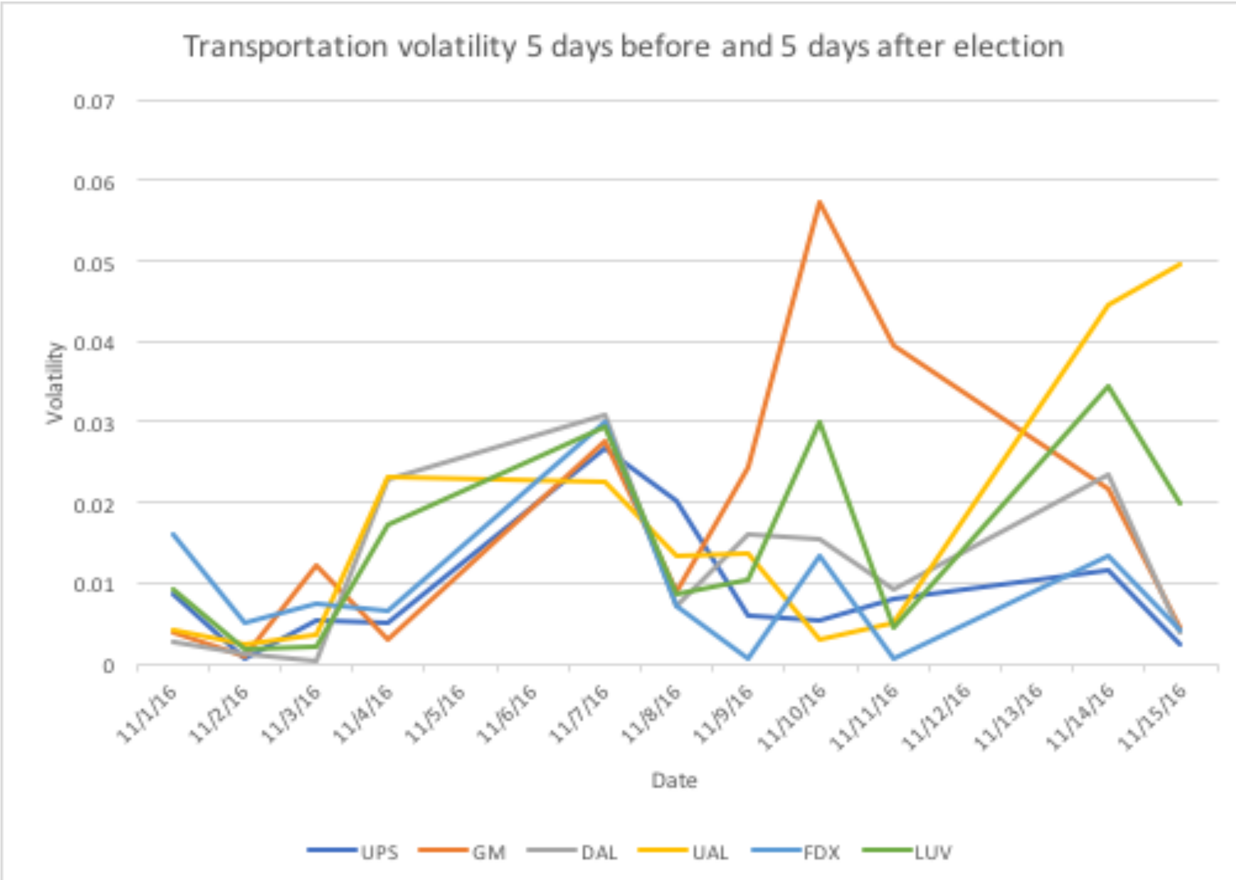
Next, the same was done for manufacturing stocks (graph 8), transportation stocks (graph 9), and healthcare stocks (graph 10). The manufacturing stocks show that there was no change in volatility immediately before or after the election, with the exception of Monster Beverage Corporation (MNST), which had a spike two days after the election. The transportation stocks show one spike on 11/10/16 but this was not unanimous for every stock selected. For example, although GM spiked in volatility, the other 5 stocks either stayed the same or decreased in volatility. As the week went on, volatility increased for some of these stocks, however this was several days after the election. Finally, healthcare stocks showed a spike in volatility on the 8th and 9th of November and seemed to calm down by the 10th, which could potentially be a result of the election. Overall, the varied shapes of these graphs prove to be rather inconclusive; however, it seems as though most industries experience some increased volatility immediately on or after the election, even if not for all stocks within the industry.

Graph 8. Day-to-Day Volatility for Manufacturing Stocks 5 Open Market Days Before and After Election



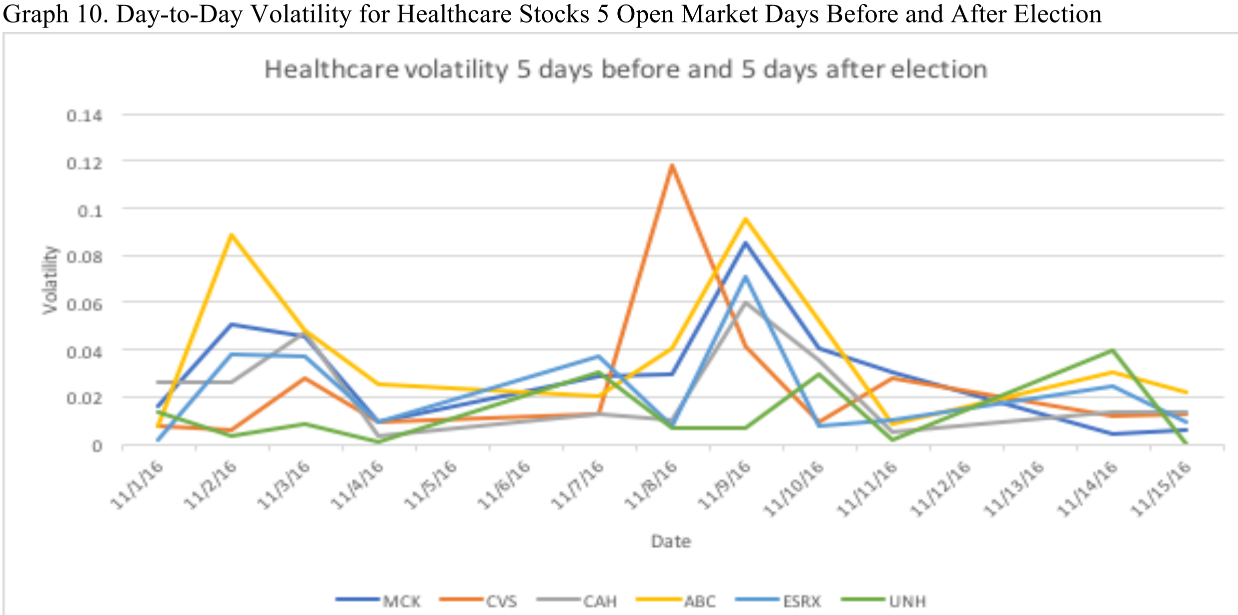
Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 9. Day-to-Day Volatility for Transportation Stocks 5 Open Market Days Before and After Election



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Graph 10. Day-to-Day Volatility for Healthcare Stocks 5 Open Market Days Before and After Election



Source: Closing stock prices are from Yahoo Finance. Volatility was calculated using the day-to-day volatility model.

Section 2. Robustness Checks.

Part A. Robustness Check #1: Intraday Volatility

As a means of being robust and further examining election volatility, intraday volatility was calculated to observe whether the results would change if the volatility between stock prices throughout the day was captured instead of between days. For example, potentially a stock price moved around a lot throughout the day, as the result of people buying and selling the stock, but the closing price ended up about the same as the day before, which would give us superficially low volatility measures. The formula used to calculate the intraday volatility is:

$$Intraday\ Volatility = \frac{|P_2 - P_1|}{P_1}$$

In the formula, P2 is the highest price of the stock observed that day and P1 is the lowest observed price of the stock that day. As with day-to-day volatility, intraday volatility was calculated for each stock, day, and time period, and then averages were calculated accordingly. Table 6 is comparable to Table 4 in that it measures the average intraday volatility for 1*, 1, and 2, as well as the differences between these groups. Also, like Table 4, Table 6 shows that when looking at intraday volatility, we still see that the average volatility of all election years except 2016 (1) has the highest volatility, followed by non-election years (2), followed by the 2016 election year (1*). Table 7 is comparable to Table 5 and like Table 5, shows the exact same trend. The differences observed in both Table 6 and 7 are statistically significant, as shown in the right two columns of Table 6 and Table 7. It is important to note that Energy has the most similar period 1* and period 1 volatility.

Table 6. Intraday volatility across all stocks

Total Averages		Difference Between Periods		F Observed	P-Value
1* 2016 Election Year	0.0252	1-1*	0.0212***	0.2114	0****

1 All Election Years Except 2016	0.0464	1-2	0.0151***	0.4384	0****
2 Non-Election Years	0.0313	1*-2	-0.0061***	2.074	2.736E-13
***Denotes significance at the 1% level (two-tailed test) ****Value was so small that excel rounded it to 0.					

Table 7. Intraday volatility by industry						
Average by Industry by Period			Difference by Industry by Period		F-Test Results	
Sector	Period	Average Volatility	Groups	Average Difference	F Observed	P-Value
Energy	1*	0.0390	1-1*	0.0024***	0.5606	9.1316E-09
	1	0.0414	1-2	0.0027***	1.9173	2.8544E-82
	2	0.0387	1*-2	0.0003	1.0749	0.2009
Manufacturing	1*	0.0209	1-1*	0.0153***	0.1344	0****
	1	0.0362	1-2	0.0061***	0.8421	9.5491E-05
	2	0.0307	1*-2	-0.0092***	6.2668	6.2832E-56
Transportation	1*	0.0226	1-1*	0.0435***	0.0785	0****
	1	0.0661	1-2	0.0361***	0.2220	0****
	2	0.0300	1*-2	-0.0074***	2.8282	3.6519E-23
Healthcare	1*	0.0183	1-1*	0.0191***	0.1786	0****
	1	0.0374	1-2	0.0111***	0.5284	0****
	2	0.0263	1*-2	-0.0080***	0.3380	0****
***Denotes significance at the 1% level (two-tailed test) ****Value was so small that excel rounded it to 0.						

Part B. Robustness Check #2: Day-to-Day Volatility with Extended Period 1

Next, I wondered if the reason why the 2016 election year was less volatile was because the stock market closed before the poll figures were totaled. Perhaps, people who did not react to the poll results the day of the election instead reacted the day after the election, which may cause heightened volatility a day after the election. This was partially observed for some stocks in Graph 7-10, which showed increase volatility the day after the election as opposed to the day of the election. Thus, I adjusted my election year period slightly by extending the end of the election period by one day, as to include the day after the election, and used the same day-to-day volatility model as in my original research. Similarly, the start of the period was moved up by one day to ensure that the election period is exactly 1 year. Table 8 shows the adjusted time periods that were included in group 1*, 1, and 2.

Table 8.

Year Type	Date ranges included (does not exclude closed market days)
1*	11/9/15-11/9/16
1	8/10/73-8/10/74, 11/3/75-11/3/76, 11/5/79-11/5/80, 11/9/87-11/9/88, 11/4/91-11/4/92, 11/8/99-11/8/00, 11/5/07-11/5/08
2	11/6/69-8/9/73, 8/11/74-11/2/75, 11/4/76-11/4/79, 11/6/80-11/8/87, 11/10/88-11/3/91, 11/5/92-11/7/99, 11/9/00-11/4/07, 11/6/08-11/8/15

Like the robustness check for intraday volatility, these figures hardly moved, and some did not move at all, further proving that these results are indeed accurate. For example, for all industries, period 1* had the smallest volatility and period 1 had the largest volatility, as shown in table 10. There was also no movement in volatility above 0.0001. These results are the same for the data as a whole, as shown in table 9. However, it is important to recognize that because the data set is so large, even a large spike in volatility the day after the election would have a very small impact on the overall volatility, since it is averaged by a 200+ day period. Nevertheless, these results show that the year leading up to the 2016 election experienced less volatility than prior election years, which is meaningful and interesting.

Table 9. Day-to-day volatility across all stocks with extended period 1					
Total Averages		Difference Between Periods		F Observed	P-Value
1* 2016 Election Year	0.0141	1-1*	0.0130***	0.0840	0****
1 All Election Years Except 2016	0.0271	1-2	0.0089***	0.2319	0****
2 Non-Election Years	0.0182	1*-2	-0.0041***	2.7573	2.0776E-22
***Denotes significance at the 1% level (two-tailed test) ****Value was so small that excel rounded it to 0.					

Table 10. Day-to-day volatility by industry with extended period 1						
Average by Industry by Period			Difference by Industry by Period		F-Test Results	
Sector	Period	Average Volatility	Groups	Average Difference	F Observed	P-Value
Energy	1*	0.0211	1-1*	0.0017***	0.4891	3.4888E-12
	1	0.0228	1-2	0.0017***	0.5168	0****
	2	0.0211	1*-2	0.0000	1.0566	0.2817
Manufacturing	1*	0.0123	1-1*	0.0152***	0.0351	0****
	1	0.0274	1-2	0.0071***	0.2419	0****
	2	0.0203	1*-2	-0.0081***	6.8896	1.5423E-60
Transportation	1*	0.0126	1-1*	0.0221***	0.1553	0****
	1	0.0347	1-2	0.0180***	0.5239	0****
	2	0.0167	1*-2	-0.0041***	3.3743	8.9459E-30
Healthcare	1*	0.0105	1-1*	0.0098***	0.4342	8.5487E-15
	1	0.0203	1-2	0.0054***	0.6886	1.1102E-16
	2	0.0148	1*-2	-0.0044***	1.5860	1.1609E-06
***Denotes significance at the 1% level (two-tailed test) ****Value was so small that excel rounded it to 0.						

Part C. Summary of All Findings

This empirical investigation started with calculating the average volatility for each period (1*, 1, and 2) across all stocks and industries. These averages show that the highest volatility is during period 1, or election years prior to the 2016 election year. The second highest volatility was during period 2, or the non-election years and the lowest volatility was during period 1*, or this election year. This shows us that not only is there a difference between volatility in election years versus non-election years, which is consistent with the findings in the Literary Review, but that there is an even greater difference between volatility this election year compared to prior years. Specifically, this election period is much less volatile then past years.

To see if there were industry-specific differences, the next step was to compare average volatility by period and sector. Table 5 shows these differences by sector: energy, manufacturing, transportation, and healthcare. Although manufacturing, transportation, and healthcare are consistent with period 1 experiencing the highest volatility and period 1* experiencing the lowest volatility, energy experienced slightly different result: period 1* experienced almost the same volatility as period 1. This suggests that there is a lot of volatility in the energy section this election year, especially compared to other industries. Thus, with potentially an exception in the energy sector, this data clearly suggests that the 2016 election was accompanied with lower volatility than usual.

It is important to note that the same results and thus conclusions can be made when examining intraday volatility, by extending the election period, and by examining volatility 5 days before and after the election, proving that these trends are robust. Finally, f-tests were conducted for every test to see whether these differences were significant. Almost every single difference was statistically significant with p-values below 0.01. In conclusion, the 2016 election year was statistically less volatile than both prior election years and non-election years. Additionally, my data supports the findings of previous literature in that election years, overall, tend to experience more volatility than non-election years.

V. Conclusion

Political influences on the stock market are historically considered marginal, if that. Yet, stock market fluctuations surrounding national U.S. Presidential elections show that election years perform in a much different fashion than non-election years and as such, the political impact on stock prices may have more a significant and larger impact than what is typically accounted for.

This study investigated the impact that the 2016 Presidential election had on stock prices and whether this is distinct from both prior election years as well as non-election years. The value-add to this analysis is twofold: it provides U.S. and Presidential specific results, as well as the first analysis of the 2016 Presidential election's impact on the stock market. While a few economists have addressed these prior two concerns, it is typically as a means of predicting the President, rather than looking for market trends based on perceived election results, or the results are not U.S. specific. The 2016 Presidential election is also unique opportunity to study an election year that is described by most as "distinct," since it presents two very different candidates: the potentially first female President, whom has been in government for 40 years and has already served as a First Lady, but is highly controversial because of her illegal email server, and a man with a lot of business and entertainment experience but no political experience, who is known for his racist and sexist statements as a means of drawing attention. Consequently, this paper explored whether the stock market trend during the pre-election period was as original as the candidates.

The impact of the election on stock prices is assessed by measuring the volatility of closing stock prices for 24 different stocks in the four main U.S. industries: Energy, Manufacturing, Transportation, and Healthcare. These stocks are representative of the U.S.

economy and are diversified not just by their industry sector but also by the age of the company, to create a balance of older and newer firms. After collecting an array of stocks, the next step was to break the data into three time periods: the first being the year preceding the 2016 Presidential election, the second being all prior election years, excluding the 2016 election, and the third being all non-election years. After noticing a graphic difference between these periods, a volatility model was created to assess this variation. The day-to-day volatility model examined the percent change between prior day closing stock prices and current day closing stock prices.

The empirical results of this were all statistically significant and were consistent with the findings of prior literature: election years experience higher volatility than non-election years. In other words, the highest volatility is in election years excluding the 2016 election. This was followed by non-election years, and the least-volatile time period was actually the year leading up to 2016 election. Thus, not only is there a significant difference between the volatility in election and non-election years, but there is also a significant difference between this election year and prior election year volatility. Volatility immediately before and after the election was also examined and showed that while there was indeed some heightened volatility after the election, this was not unanimous for all stocks.

To prove robustness of results, I next examined intraday volatility, or the daily swings between high and low stock prices, as well as lengthening the election period, to see if my model was potentially not capturing volatility accurately enough. Both robustness checked proved to be entirely consistent with my original findings, which further supports the observed pattern. These findings are also important because we know from Bialkowski, Gottschalk, and Wisniewski (2008) that there is higher stock market volatility during closely contested elections. Thus, these results could indicate that the 2016 election was not a closely contested race.

Surprisingly, when broken down by industry, every sector followed this same pattern except energy, which had an almost identical 2016 election year volatility compared to prior election year volatility. This leads me to the biggest challenge of my model, which is that it does not control for external factors. For example, perhaps this energy results could be the direct or partial result Clinton's popular campaign for increased usage in solar energy or overall industry volatility, especially with OPEC. Or, perhaps the decreased 2015-2016 stock market volatility could be a result of the way that information is received. For example, now that social media is very popular, people's opinions are readily accessible, which could be affecting the way that people feel about candidates or could affect whom they perceive as the leading candidate, which may sway their investment choices. Thus, further research could attempt to capture externalities to isolate the impact of a Presidential election on stock prices. Finally, further research should attempt to include agricultural data, since there are some public companies that primarily focus on agriculture.

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