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EPPS 6356: Data Visualization

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Market Prices, Volatility and the U.S. Presidential Election

Introduction

Presidential elections have always been a point of contention among the American public. Despite much debate, there is no doubt that elections have major consequences outside of the typical political sphere. One sector that is often less considered in that context is finance. Though many understand the finance sector to be heavily affected by policy changes throughout time, few scholars have sought to explore the relationship between elections themselves and financial market returns. Exploiting this relationship is not an easy feat, as it is imperative to have a lot of robust data. This data is not hard to come by, but it is extremely difficult to compile, clean, and present in a succinct way.

One interesting observation is that of stock prices alongside the COVID-19 pandemic. Our study is similar, though the scope is much larger. One study that focused on 2020 in particular looked at COVID-19 indicators alongside financial markets, and their findings reflected multiple slow-downs and difficult monetary transitions (Wójcik & Ioannou, 2020). The COVID-19 pandemic was a tremendous backdrop for market analysis, as those years not only yielded financial stress on individuals but the overall state of the global economy as a whole. The unpredictability and uniqueness of the event made COVID-19 a popular backdrop for study. However, despite the incredulous nature of the pandemic, its uniqueness does not offer much implication for events outside of it. Certainly, COVID-19 has lingering effects, but we believe that the scope of study within financial markets should be broadened. Instead, we focused on presidential elections as a backdrop for our analysis. Not only is the data on presidential elections abundant, but we did not have any concerns about incomplete or unreliable data. We were able to stay focused on trends rather than the impact of one specific, unpredictable event.

Uniqueness

Our study is unique because most studies in the US focus on presidential elections and market returns in general. However, market returns are simply an average of returns of different sectors, and may not represent the actual impact at the sector level. However, in our study, we consider returns from different sectors such as Technology, Finance, Defense & Aerospace, Healthcare, and Industrials. Moreover, we not only consider prices to understand the impact of elections on different sectors but also consider the impact on volatility by considering the volatility measure VIX. Thus, we measure the impact of elections in terms of prices and volatility.

Furthermore, we also contribute to the existing literature by creating a new time series panel dataset of daily returns of these sectors that can be used by future researchers. Also, in conjunction with looking at the sectors in isolation, we take a portfolio approach. Long-term investors generally invest in portfolios and not in single sectors/stocks to diversify their risk. So, we gauge the impact of elections by simulating 10,000 portfolios under different presidential regimes and creating an efficient frontier for long-term investors.

We also provide a unique dashboard of bar graphs to portfolio managers to gauge the short-term impact of elections. From a short-term perspective, for example, 15 days, 30 days, and 60 days before and after the relevant elections. The time series graphs with moving averages with a flexible moving average window further aid traders and investors in informing their investment decisions both from a long-term and short-term perspective.

Similarly, the sector correlations generated by heat maps provide correlations among sectors which can be helpful for traders who implement different trading strategies. For example, if two sectors are inversely correlated then a trader can short one sector and go long on the other. Thus, our project aids different participants (i.e. students, investors, and traders in the finance sector) in many different ways.

Hypotheses

H1: Proximity to the U.S. presidential election will increase sector volatility.

H2: Tech and Healthcare sectors will perform better if a Democratic president comes to power.

H3: Finance, Aerospace and Defense and Industrial sectors will perform better if a Republican president comes to power.

Data

The panel dataset consists of daily market prices and several economic measures between January 1st, 2011, and September 30th, 2024. Daily market prices for each sector and the VIX volatility and S&P 500 indices were pulled from the London Stock Exchange (LSEG) database. Data for the following U.S. economic variables: monthly CPI, quarterly GDP, and 10-year treasury bond yields, were collected from the FRED database. The monthly and quarterly variables were linearly interpolated over the respective periods to align the variables' date ranges with trading days in the U.S. market. From the parent dataset, three additional datasets were created for the Efficient Frontier visualizations.

It is important to mention the lack of analysis of the Aerospace and Defense sector for three of the four models introduced in the original proposal. An error occurred in the reported market prices from the LSEG data for the Aerospace & Defense sector, rendering the data unusable for the time-series, heatmap, and bar-graph analyses.

Chatgpt was used to assist with this project. While the members handled compiling the dataset and making the plots, the UI of the Shiny application was made with AI assistance, along with assistance in debugging. In particular, consolidating the many different visual types into a seamless application is where AI came into place.

Time Series

This section will focus on the analysis of data using time series with rolling statistics. Time series analysis is very useful for visualizing and organizing sequential data. In the finance industry, this is especially useful when it comes to identifying trends over time and allows experts to make predictions for future financial outcomes. For this analysis, we also utilize a 20-day "rolling window" or "rolling statistic." Essentially, rolling windows are used to assess the predictive viability of time series models, and in this case, the viability of the trends that were observed over time before and after the 2020 presidential election.

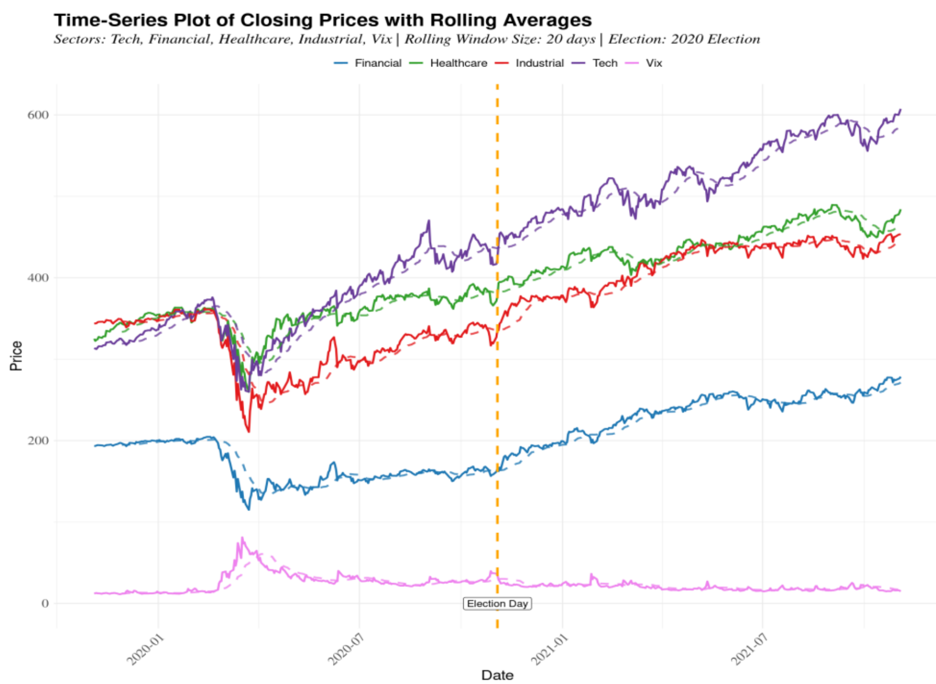
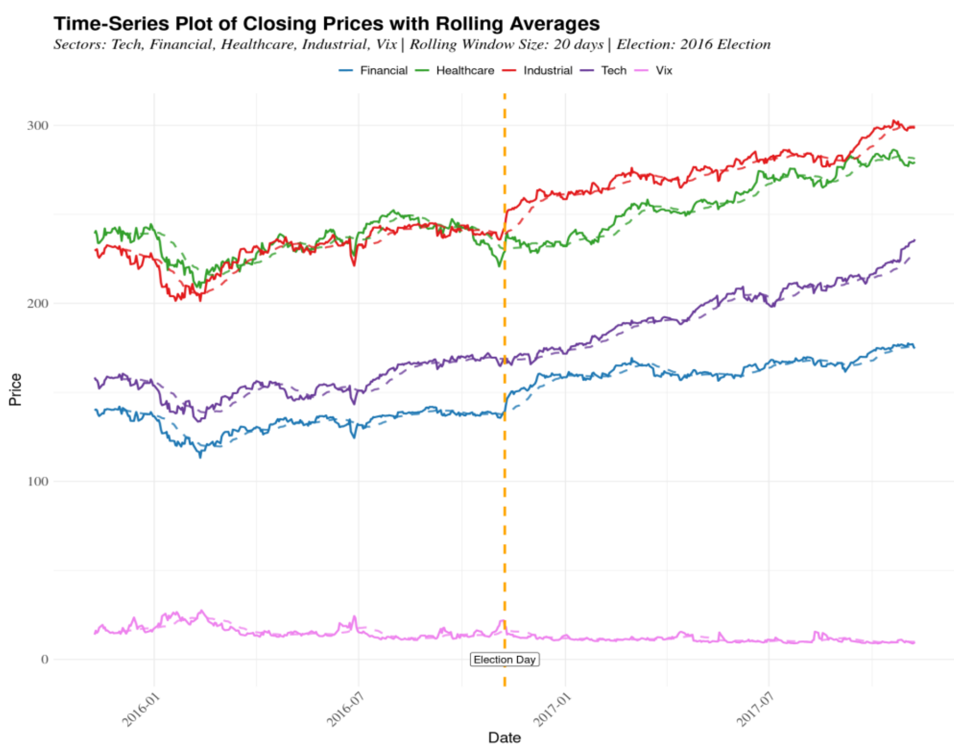


Figure 1- 20 day window of the 2020 Election

The first figure shows the time series analysis with a 20-day rolling window for the 2020 presidential election. This election yielded particularly interesting statistics since, as discussed previously, this election took place during the first year of the COVID-19 pandemic. This election also yielded a democratic victory. The analysis covers each of the specified sectors -- Tech, Financial, Healthcare, and Industrial -- as well as the VIX (an indicator of sector volatility). When considering H1, this analysis only offers partial support. It is clear that volatility was high at the beginning of the year (which was the onset of the pandemic), however, there is no spiking closer to the election. The VIX was quite low during that time, indicating low volatility in each sector. The spike closer to the beginning of the year could be attributable to the pandemic, but that was not explored in this analysis. Looking at each sector individually, the most notable is Tech, as the analysis indicates a stable upward trend during the period following the election. The other sectors did not yield particularly notable results, but there is a noticeable recovery for them post-election.

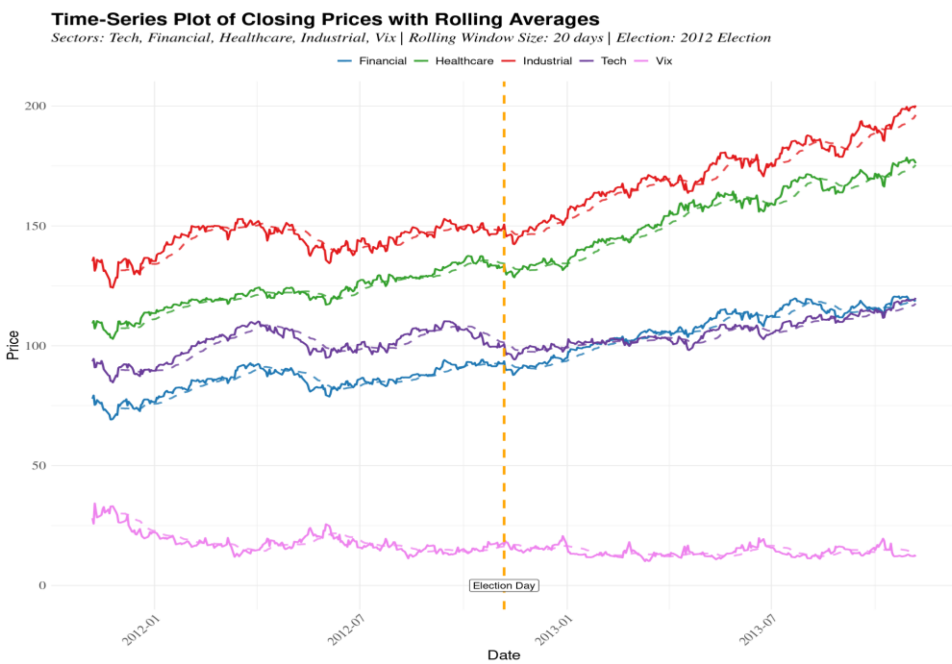
Figure 2- 20 day window of the 2016 election.



The second figure shows the time series analysis of the 2016 election with a 20-day rolling window. This election is particularly interesting, as many would view it to be one of the most influential in modern U.S. history. In 2016, Republican candidate Donald Trump secured the presidency, which went against most predictions in the months leading up to the election. This social backdrop makes for an interesting analysis.

The volatility trends in this analysis are intriguing, as the VIX indicates that each of these sectors responded to the election stably. This is a positive observation, as it suggests steadiness within the industry at large. Regarding H1, there are no indicators that market volatility experienced any kind of spike in the time leading up to and the time following the election. In this case, there is not much support for this hypothesis. When it comes to H2, things get dicey, as the winner of the election was a Republican, not a Democrat. All sectors experienced significant growth during the time following the election, according to the analysis, though the financial and industrial sectors experienced more growth than the healthcare and tech sectors. These findings do not justify the hypothesis, as the findings indicate that volatility is not dependent on a Democratic victory. There is also support for H3, as the financial and industrial sectors performed very well after the election.

Figure 3 – 20 day window of the 2012 election.



The third figure represents the time series analysis for the 2012 presidential election with a 20-day rolling window. 2012 yielded a Democratic victory, and this represented a large accomplishment in American politics. This period was not as influential as 2016, so the sector observations are not as noteworthy. Each of them was stable during the time leading up to and after the election. The results within the healthcare sector indicate that participants had a lot of confidence in their performance. This could be attributable to the implementation of the Affordable Care Act (ACA) in 2010. When it comes to H1, the results do not provide much support -- there were no noticeable changes in the VIX, which indicates that there was no improvement in volatility. Regarding H2, a Democrat did win, and both the healthcare and tech sectors performed quite well. Though there was no significant improvement, the results indicate stability in the election of a Democrat. There is not much support for H3 in this election -- the financial and industrial sectors experienced moderate growth before and after the election. However, these sectors did not perform as well as the healthcare and tech sectors. These findings indicate that growth within the financial and industrial sectors is not dependent on a Republican victory.

Bar Graph

The following horizontal bar graphs compare sector performance with four analytical measures for each election. The first is drawdown, which describes a fall in share or portfolio price as a percentage of the peak price for the specified time. The second is volatility, or the standard deviation of returns for the period multiplied by the square root of the number of trading days, estimated at 252 days each year. Multiplying the volatility by 100 allows the bar graphs to report them as percentages. Sectors with lower volatility experience fewer price fluctuations, and vice versa.

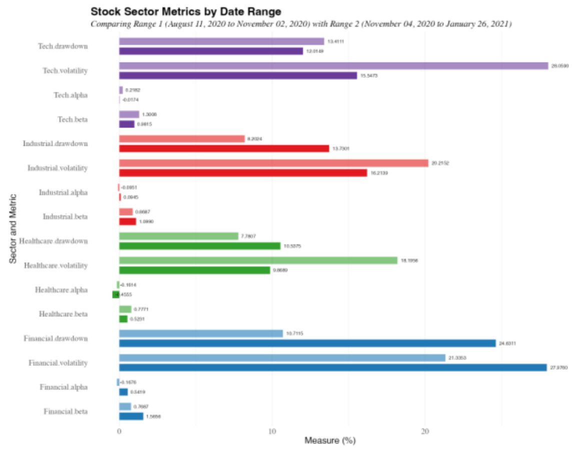
The last two metrics, alpha, and beta, compare sector performance to a benchmark index for the market. This paper uses the S&P 500 index. The alpha metric reports how much better or worse the sector did compared to the S&P 500. For example, if the alpha is 3%, this sector earned

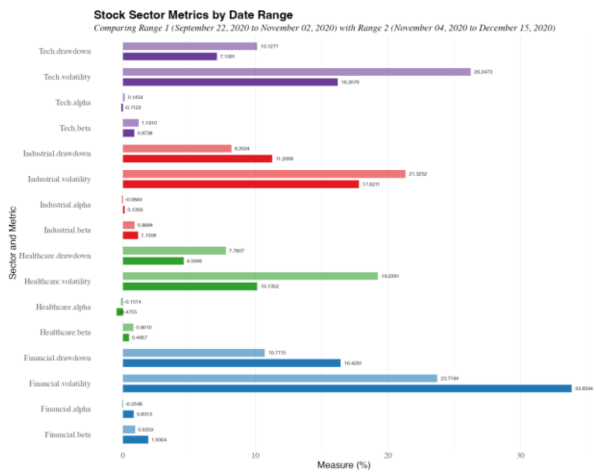
3% more than the S&P 500 did for the period, the opposite is true for negative alpha values. Beta, on the other hand, compares sector volatility to that of the benchmark index. With the index fixed at 1, betas greater than 1 are considered more volatile than the market, and those below 1 are less volatile than the benchmark for that period.

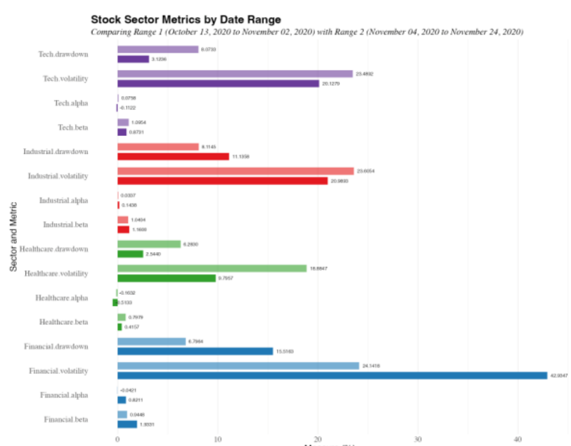
To implement the calculation of these variables in R, several packages are required. R package '*readxl*' imports the dataset. R packages *'dyplr'* and *'tidyr'* aid in data manipulation for panel data. *'quantmod'* is a package that digests the stock data and calculates useful metrics like daily and average returns, which are needed to calculate the above metrics. Finally, 'ggplot2' allowed for the final visualizations to be organized and customized for readability.

Figure 4 compares the variables over the same periods before and after the 2020 election, the start of the Biden administration. The lighter bars represent the metrics in the periods before the election, the darker bars represent the time after. The relationships between the time periods share similar patterns as the proximity to the election increases. Both the financial and industrial sectors experience increasing volatility as the time before the election shortens, but then they experience post-election declines. Volatility in the healthcare sector appears to be relatively stable, not experiencing much change both pre and post-election. Surprisingly, volatility in the tech sector declines as the election grows nearer and in the days following the election.

Figure 4 - Temporal Analysis for 2020 Election



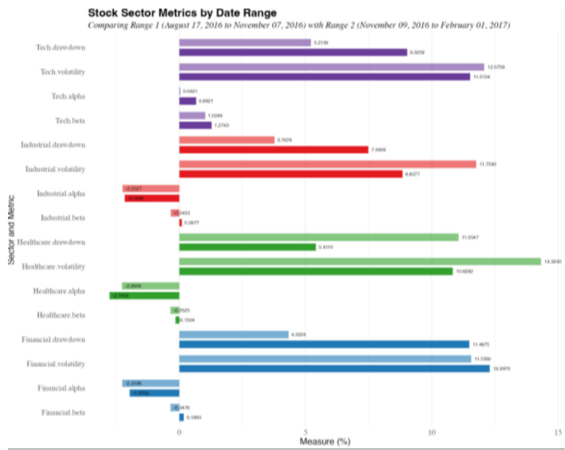




Per Hypothesis I, some sectors do experience increased volatility as proximity to the election increases, primarily the financial and industrial sectors, but this is not seen across the other sectors. Since Biden was the democratic nominee, the tech and healthcare sectors are expected to experience greater performance. The returns on the tech sector prices are greater than the benchmark's returns for the periods leading up to the election, however, afterwards the returns fall below the market. This is not true for the healthcare sector, whose returns are less than the benchmark for all periods before and after the election. Beta values for the tech sector indicate a decline in volatility compared to the market as the time before the election decreased, eventually resulting in the volatility of the sector falling below the benchmark's volatility. Along with the reduced drawdown before and after the election, these metrics indicate strong performance in the tech sector. The betas for the healthcare sector show slight increases in volatility before the election and clear increases in volatility after the election. Healthcare drawdown decreases closer to the election but then increases significantly after the election. This sector did not experience the same positive performance as the tech sector.

Using similar analytical interpretations for the other two sectors, the financial sector had large swings in volatility and drawdown after the election. The industrial sector's volatility peaked on election day but proceeded to decline steadily afterward. Tech had the greatest improvement in performance compared to the other sectors for this election.

Figure 5 - Temporal Analysis for the 2016 Election


Stock Sector Metrics by Date Range
Comparing Range 1 (August 17, 2016 to November 07, 2016) with Range 2 (November 09, 2016 to February 01, 2017)
Tech drawdown
Tech volatility
Tech alpha
Tech beta
Industrial drawdown
Industrial volatility
Industrial alpha
Industrial beta
Healthcare drawdown
Healthcare volatility
Healthcare alpha
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Financial drawdown
Financial volatility
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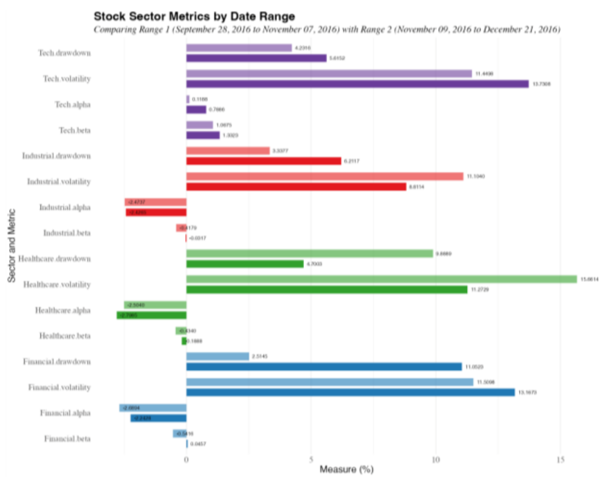
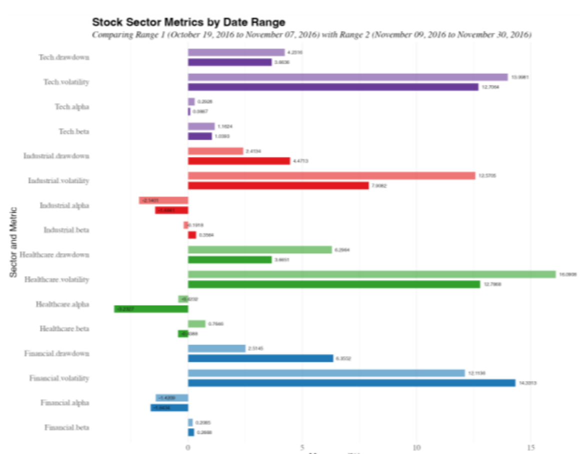
Sector and Metric
0
5
10
15
Measure (%)

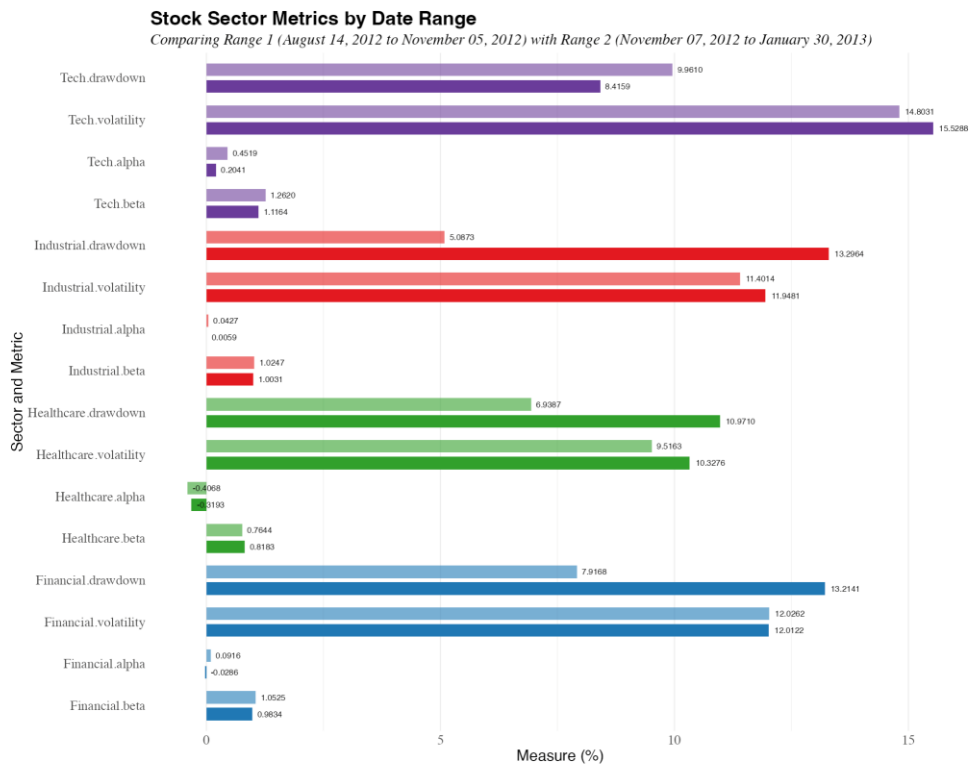

Stock Sector Metrics by Date Range
Comparing Range 1 (September 28, 2016 to November 07, 2016) with Range 2 (November 09, 2016 to December 21, 2016)
Tech drawdown
Tech volatility
Tech alpha
Tech beta
Industrial drawdown
Industrial volatility
Industrial alpha
Industrial beta
Healthcare drawdown
Healthcare volatility
Healthcare alpha
Healthcare beta
Financial drawdown
Financial volatility
Financial alpha
Financial beta
Sector and Metric
0
5
10
15
Measure (%)


Stock Sector Metrics by Date Range
Comparing Range 1 (October 19, 2016 to November 07, 2016) with Range 2 (November 09, 2016 to November 30, 2016)
Tech drawdown
Tech volatility
Tech alpha
Tech beta
Industrial drawdown
Industrial volatility
Industrial alpha
Industrial beta
Healthcare drawdown
Healthcare volatility
Healthcare alpha
Healthcare beta
Financial drawdown
Financial volatility
Financial alpha
Financial beta
Sector and Metric
0
5
10
15
Measure (%)

Similarly to the 2020 election, the relational patterns between the 2016 time periods remain consistent from 60 to 15 days. Trump was the republican president-elect in 2016, so this study hypothesizes stronger performance in the industrial and financial sectors. Volatility for the industrial sector fluctuates, ending at a peak before the election. The financial sector experiences a slow rise in volatility before the election, an increase immediately after the election, and then a gradual decline after. Additionally, there is a drop in industrial volatility after the election but then a steady increase from 15 to 60 days. Drawdowns in the industrial and financial sectors decline as the election approaches but then rise dramatically afterward, indicating increasing losses for the sectors' market prices.

The industrial and finance alphas both underperform compared to the benchmark for all periods. Immediately following the election, the healthcare 15 days after alpha drops below the 15 days before alpha, canceling out the improvements made prior. Both sectors' betas remain less than one for all periods, this indicates that they are less volatile than the benchmark on average. While these results do not indicate terrible performance, these sectors do not experience the same performance benefits that we saw in the tech sector during the 2020 election. The healthcare sector is less volatile than the benchmark for all periods, but the returns are also less than the benchmark's. Tech remains volatile across all periods, and the drastic increase in its drawdown means it performed worse than other sectors. Overall, these metrics reflect the negative impacts of a republican president-elect on the industrial and financial sectors in 2016.

Figure 6 - Temporal Analysis for the 2012 Election



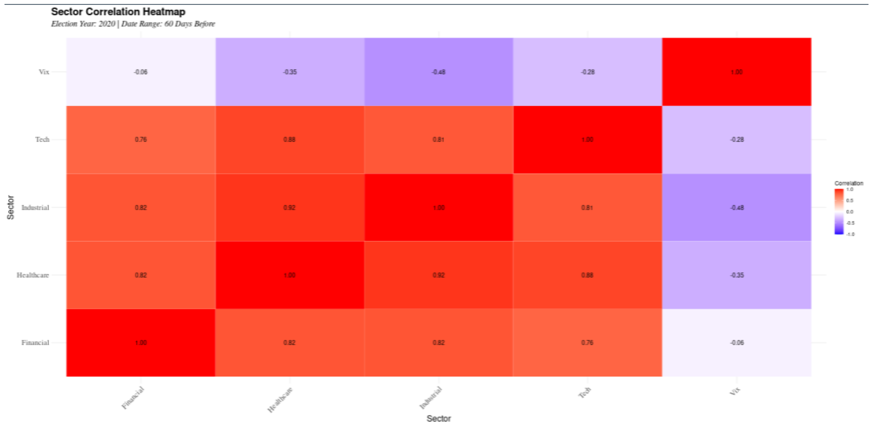
Compared to the other periods, the 2012 election has much less variation when comparing periods before and after the election. The relationships within each sector's variables remain close to the same regardless of the number of days in the period; the 30-Day and 15-Day plots are almost identical to the 60-Day graph. From initial impressions, it appears that the Obama administration has the weakest effect on these four market sectors when compared to the Trump and Biden administrations.

Surprisingly, the tech and industrials share similar patterns. Both volatilities increase as the number of days before the election decreases, and then they both decline gradually post-election. They also have slightly greater risk than the benchmark, which explains the higher returns. The drawdowns also decrease heading into the election and then increase afterward. Healthcare's variables remain relatively constant. Volatility doesn't change much and this is supported by the beta remaining less than one for all periods. For the financial sector, volatility and drawdown decrease before the election. Afterwards, volatility spikes and then gradually declines, but the drawdown increases significantly. These results indicate that the relationships between the political parties and the stock market sectors may change for each election.

Heat Map

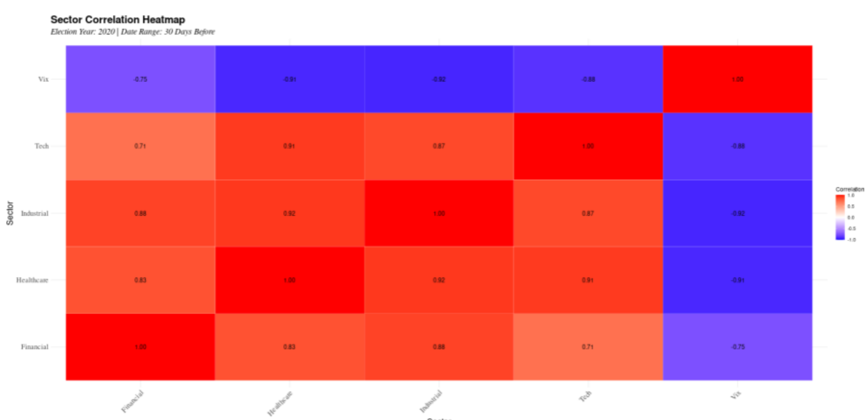
The following section explores several heat maps of the various sectors at different times and how they interact. The heatmaps display the four sectors we have explored thus far in addition to the Volatility Index, over three separate election years: 2012, 2016, and 2020. It accounts for time frames ranging from 15-60 days both before and after the relevant election day. The correlations between the economic sectors reflect how correlated their movements were at the time; more highly correlated values mean they were moving in much the same direction. The VIX correlation shows how strongly the volatility is influencing the direction of the prices. This provides retrospective insight as to how the impending election and results can impact the immediate economic environment. The *'tidyr'* and *'dplyr'* packages were used to streamline the filtering and reshaping the data. The *'ggplot2'* package was used to create the heatmaps themselves, and *'reshape2'* further aided in melting the filtered data into a format suitable for visualization.

Figure 7 - 60 days before the 2020 election



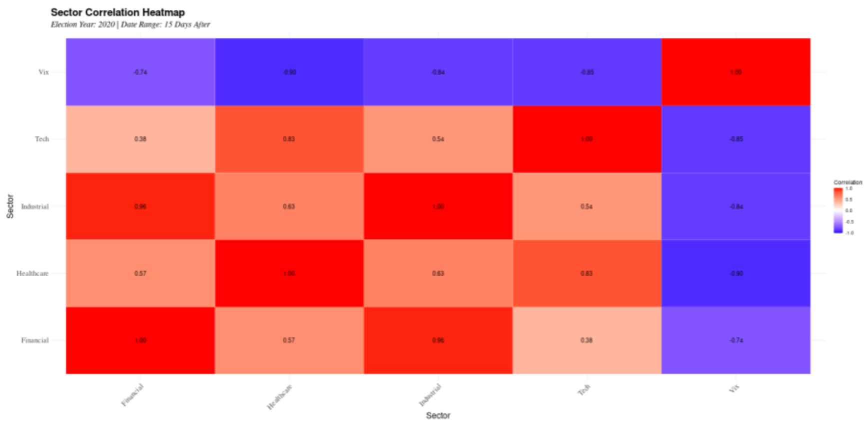
Starting with the 2020 election, Biden's first and only term, we see consistently negative correlations among the volatility among each sector, though the financial sector seems to only have been very minorly correlated. This negative correlation indicates that as volatility increased, prices in the healthcare, tech, and industrial sectors decreased during this time frame. In addition, the high degree of positive correlation among the sector prices themselves indicates a considerable level of synchronization. Even the financial sector, which had a low correlation with the VIX, still followed this trend, implying that this sector was still beholden to general market trends, even if the volatility was a non-factor.

Figure 8 - 30 days before the 2020 election



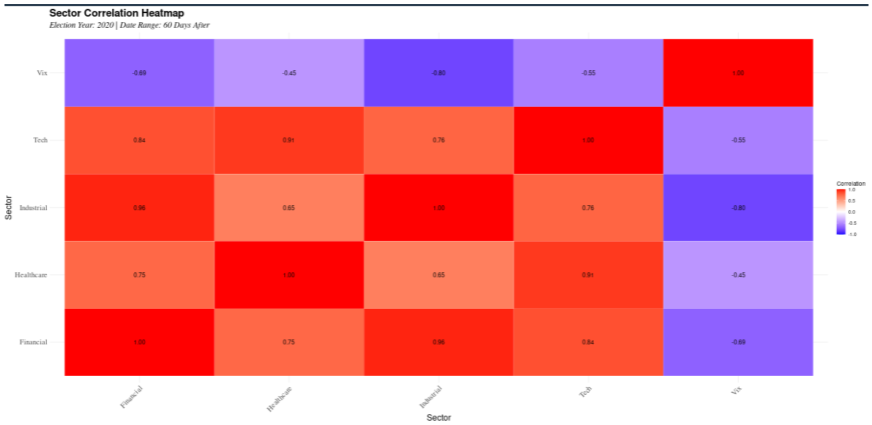
We see a similar heatmap, this time only 30 days before the 2020 election. We see a similar story of the degrees of positive correlation among the four sectors, suggesting they were in sync in the face of the coming election. No significant change has occurred thus far. No significant change occurred in the 15 days leading up either, so this model will be omitted for brevity.

Figure 9 - 15 days after the 2020 election



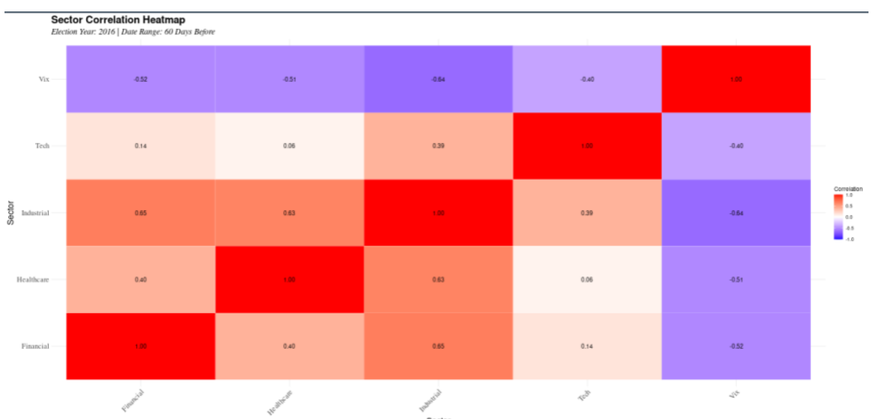
15 days after the 2020 election, we see a fair bit of change compared to pre-election data. While the Vix is still negatively correlated, telling a similar story as the prior heatmaps. However, the correlation between the sectors has changed greatly. While all the correlations are still considerably positive, many are not as strongly correlated as before. Tech and healthcare are still correlated strongly, as are financial and industrial, but all other correlations have decreased significantly. This implies that soon after the results of the election were made known, sector prices began to fall somewhat out of sync, likely as they all tried to adjust for the new president and what this might mean for the economy at large. No notable changes had occurred during the 30 day period after the election, thus this section will be omitted for brevity.

Figure 10 - 60 days after 2020 election



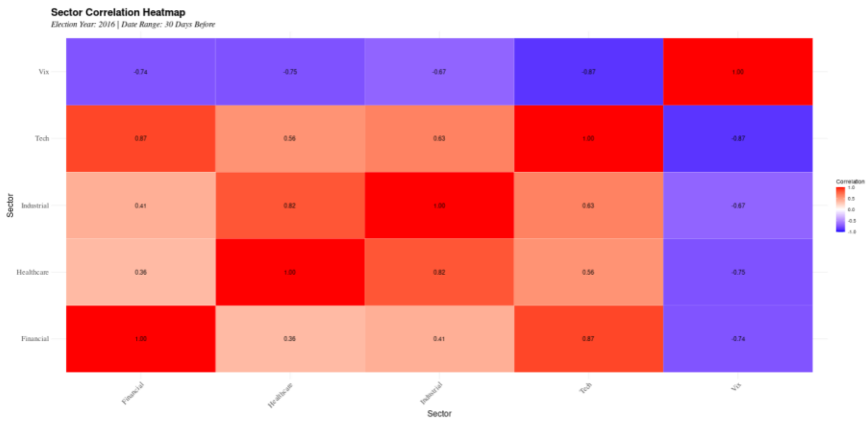
Finally, 60 days after the 2020 election, we see a fair number of changes. The correlation for the VIX is lower than before but is still fairly high. As for the four sectors, they all have seen a general increase in their correlation levels, akin to how they were before the election, meaning that the prices are in higher sync again. One possible explanation for this would be that 60 days was enough time for the sectors to become more stable and gain a relative grasp of the direction of the economy.

Figure 11 - 60 days before the 2016 election



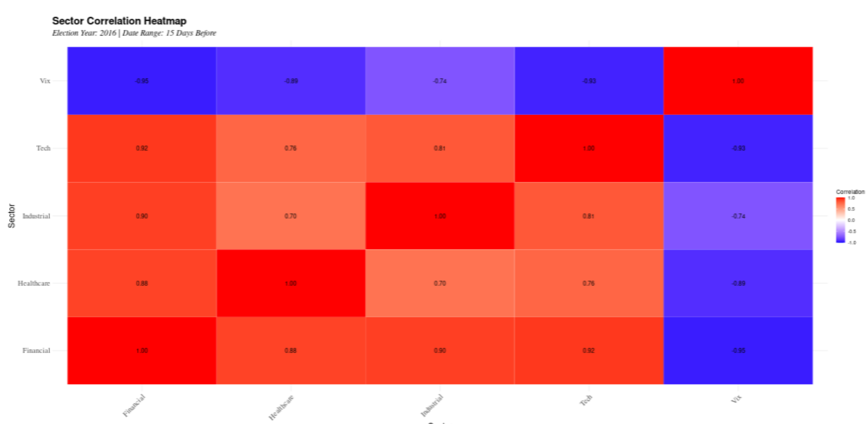
Moving on to the 2016 data, Trump's first term, we see a vastly different landscape. 60 days before election day, while the VIX correlation values are all still negative, they are much lower than normal, more similar to that of the 60 days before the 2020 election. Not only that, but during this time frame correlation between the sectors was not as high as it was compared to the 2020 election overall, meaning the sector prices were often out of sync.

Figure 12 - 30 days before the 2016 election



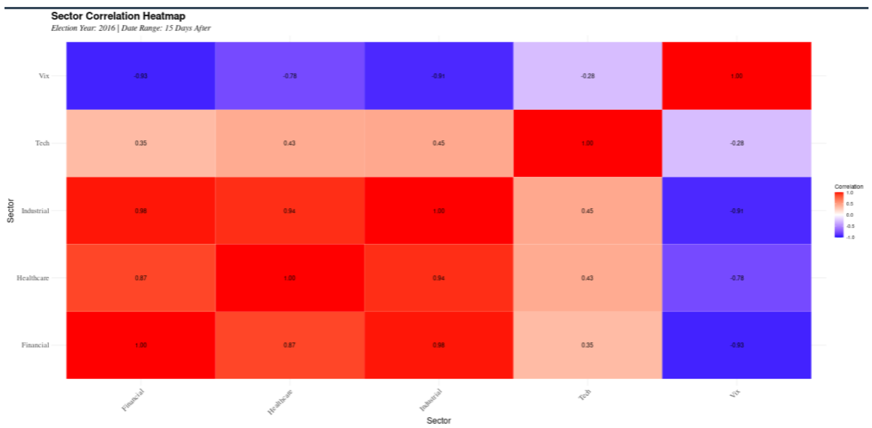
As we move on to 30 days before, we see that the VIX increases overall in each sector compared to the 60-day mark, meaning that uncertainty has yet again begun to set in, meaning sector prices are once again going down. There is a notable increase in correlation between the healthcare and industrial sectors, as well as between the tech and financial sectors. Otherwise, there are no substantial changes among the sectors.

Figure 13 - 15 days before the 2016 election



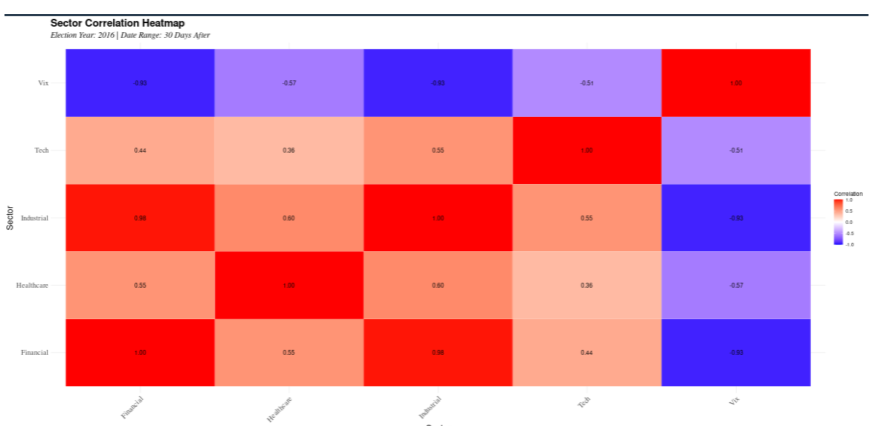
15 days before the 2016 election, we see that correlation values are much higher overall, akin to the corresponding figure in 2020. As the election came closer and closer fear over the future became greater and greater, thus the sector prices fell all in unison.

Figure 14 - 15 days after the 2016 election



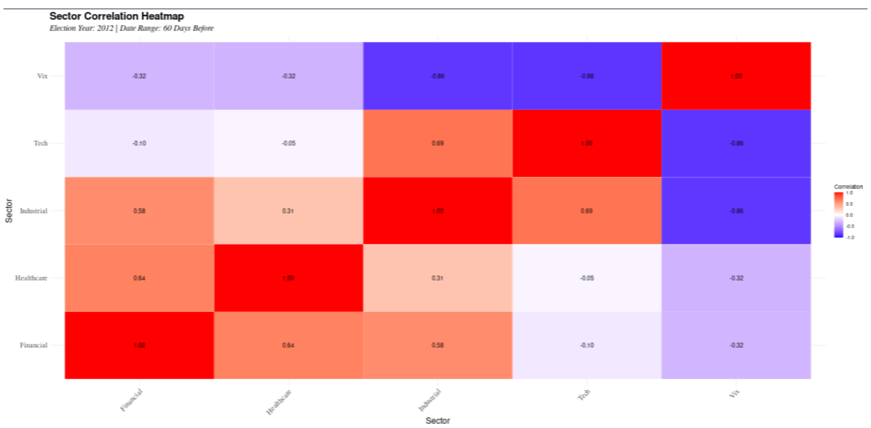
15 days after Trump's victory in 2016, we have rather curious results. Most sectors have a high degree of correlation on all fronts, reflecting a high degree of uncertainty even after the next president has been declared. Tech, however, deviates greatly from this trend, having a much lower correlation both among prices and VIX. That said, the actual amounts are still moderately strong, but a far cry from every other sector.

Figure 15 - 30 days after the 2016 election



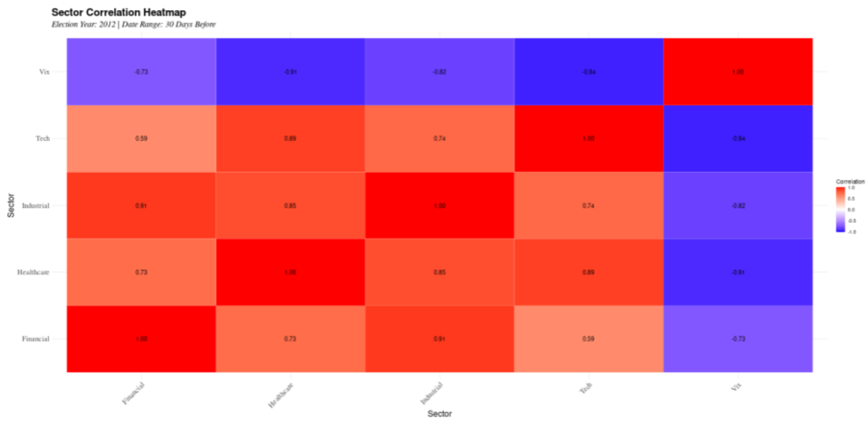
30 days after the 2016 election, we have an interesting blend of high and moderate correlations. The financial and industrial sectors have a nearly one-to-one correlation, and each has a very high correlation with the Vix, meaning both these sectors had a high degree of volatility and their prices were shifting in much the same direction. Aside from those notable examples, all other correlations are fairly moderate. 60 days after the 2016 election held no significant changes, thus is omitted.

Figure 16 - 60 days before the 2012 election



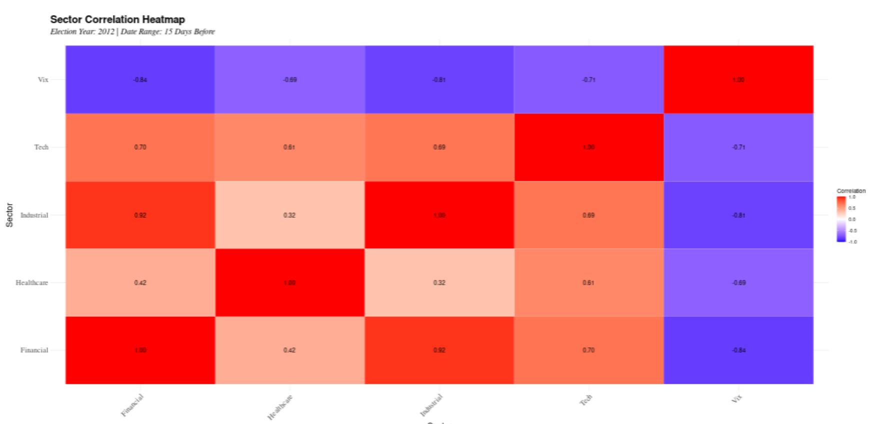
Finally, we reach the 2012 election. 60 days before the election, we see that the industrial and tech sectors have significantly higher Vix levels than the financial and healthcare sectors. The moderate correlations between sectors are not surprising, though what sticks out most is the tech sector's negative correlations between the financial and healthcare sectors. While weak, this is the first instance of any negative correlations between sector prices. This implies that the prices between tech and healthcare and tech and financial may be prone to moving in opposite directions, albeit not strongly or consistently.

Figure 17 - 30 days before the 2012 election



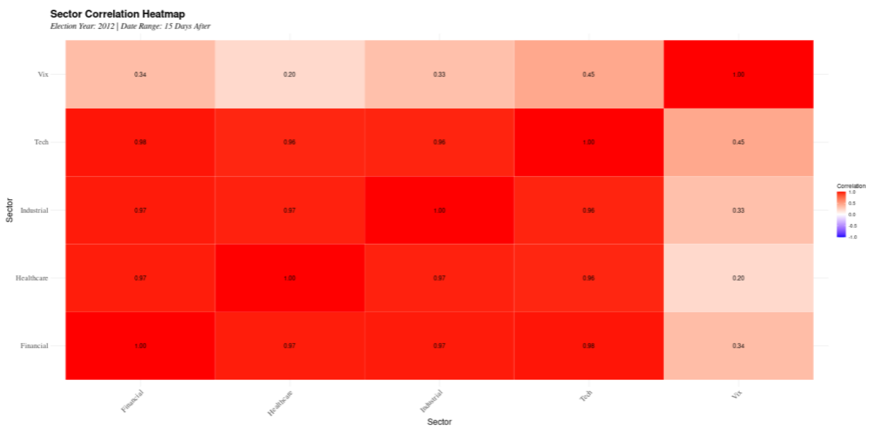
Closer to the election, we see that the correlation becomes much stronger between sector prices overall, with no weak correlations. What's more, there are no more negative correlations between any of the sector prices after just 30 days. The VIX values for the financial and healthcare sectors have increased in strength, while the VIX correlations for industrial and tech are approximately the same in their strength.

Figure 18 - 15 days before the 2012 election



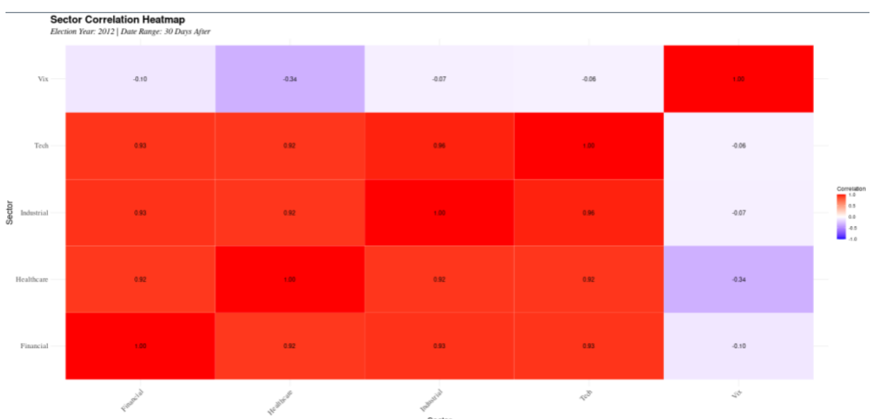
15 days before the 2012 election, we see results that differ greatly compared to the same timeframes from future election years. While the Vix correlation variables are comparable, the sector prices are noticeably different. Aside from the correlation between the industrial and financial sectors, which is quite strong, all the other correlations are weak to moderate.

Figure 19- 15 days after the 2012 election



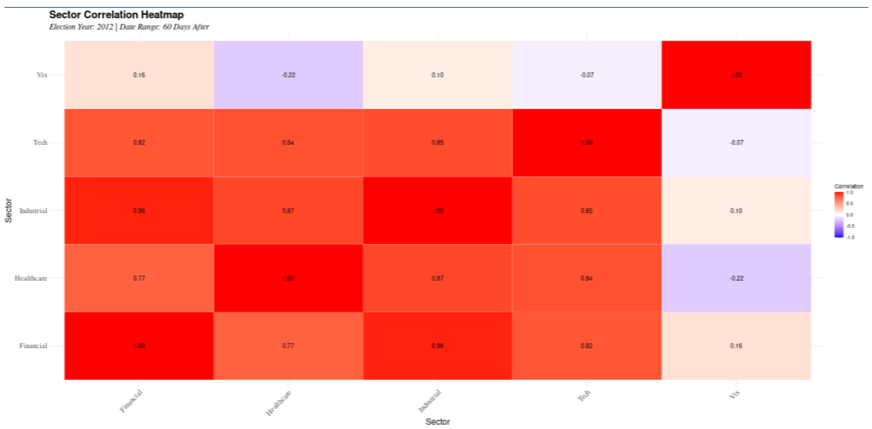
15 days after the 2012 election, we have by far the most standout heatmap as of yet. First of all, the sector prices are all extremely highly correlated. Even more curious, every single VIX correlation is positive, if only weakly so. This implies that the direction of the sector prices and the volatility of the market were moving in the same direction. This is not only unusual due to defying the trend that has been displayed thus far in every other heatmap but also goes against common economic theory, which posits that stock prices and volatility are inversely related.

Figure 20 - 30 days after the 2012 election



Moving on to 30 days afterward, we see a similar heatmap. Once again, sector prices are all highly correlated across the board. The main difference is that the VIX correlation is once again negative, albeit fairly weak, in contrast to how strong correlations typically are. This implies that all the relevant sectors were moving in unison and that the volatility of the market was unlikely to be a primary factor at the time.

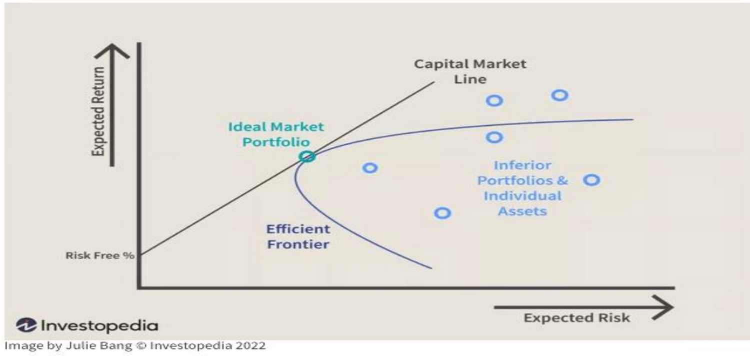
Figure 21 - 60 days after the 2012 election



Finally, 60 days after the 2012 election, we have the final timeframe. The sectors are once again all strongly positively correlated as usual. The VIX correlations, they are a curious mix of weakly negative and positive. The financial and industrial sectors are both very weakly positive, and the tech and healthcare sectors are both very weakly negative. This implies, once again, that the volatility of the market was likely not a primary factor driving this synchronization between the sector prices during this time frame.

Efficient Frontier

In the previous sections, we saw different graphs of sector prices plotted in the form of a bar graph, a heat map, and a time series graph. It is now time to combine all these sectors from a portfolio perspective. The efficient frontier allows us to view these sectors from a portfolio perspective. It is important to view these sectors from a portfolio perspective because investors usually invest in multiple sectors to hedge the risk they may face by investing in a single sector. The efficient frontier helps explain this more formally.



Source: Investopedia

The above figure shows the efficient frontier for hypothetical portfolios consisting of stocks belonging to different sectors. These different portfolios are mapped on a risk-return profile, where the portfolio's risk is plotted on the x-axis, and the portfolio's return is plotted on the y-axis. We generally expect a linear relationship between risk and return. i.e., as we take on more risk, we may expect more return.

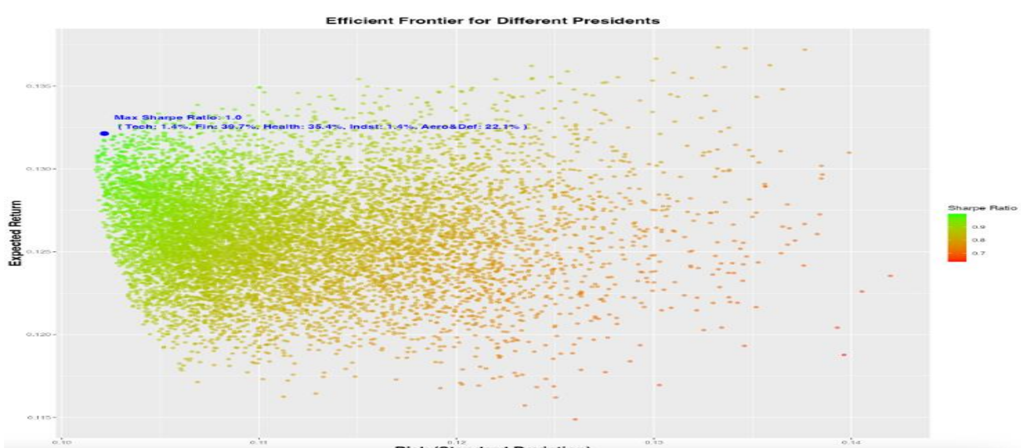
However, we do not see a linear relationship from a portfolio perspective. As shown above, as we take on less risk in the portfolio, the returns will increase up to a point, and then both risk and return will increase to give a parabola-shaped curve. After we cross the ideal market portfolio point, we see that as we take on more Risk (standard deviation of the portfolio) the returns also increase.

$Sharpe\ Ratio\ =\ (Expected\ Return$ - Risk Free RoR) / (Standard Deviation/ volatility)

To put it more formally, the Sharpe Ratio measures the returns per unit risk a portfolio takes. Here, we see that Rx-Rf is the excess returns generated by the portfolio over the risk-free rate divided by the portfolio's SD. In plain language, the Sharpe Ratio measures the excess returns per unit risk taken by the portfolio created by the investor. A portfolio that maximizes the Sharpe ratio is considered the best in the efficient frontier, denoted by the Ideal Market Portfolio, denoted by the above figure. The portfolios with blue rings are inefficient portfolios that do not maximize the Sharpe ratio.

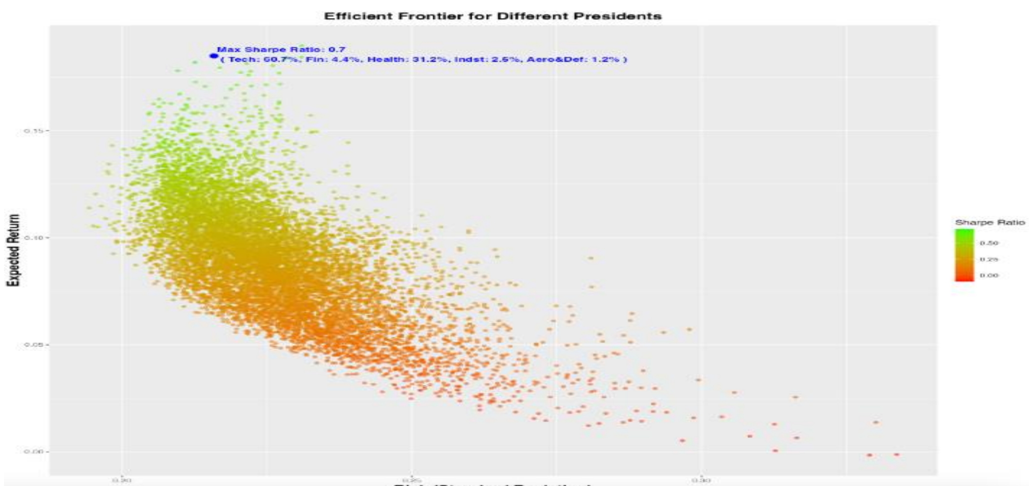
In this project, we take five sectors, namely Healthcare, Tech, Aerospace & Defense, Industrials, and finance, and create 10,000 portfolios consisting of different combinations of weights of each sector. For example, a portfolio can be constructed, giving each sector a 20% weight; likewise, different combinations of weights can be created to create different portfolios. After constructing these 10,000 hypothetical portfolios, we calculate the risk (Std Deviation) and return of these portfolios and plot it on a risk-return profile shown in the above figure. We also calculate the Sharpe ratio for each of these portfolios and find out the portfolio that maximizes the Sharpe Ratio with what weights of each sector maximized the Sharpe ratio. We do this for three regimes, taking daily data from 2012 to 2016 for the Obama administration, then from 2016 to 2020 for the Trump administration, and finally for the Biden Administration from 2020 to 2024.

Figure 22- Obama Administration (2012 - 2016)



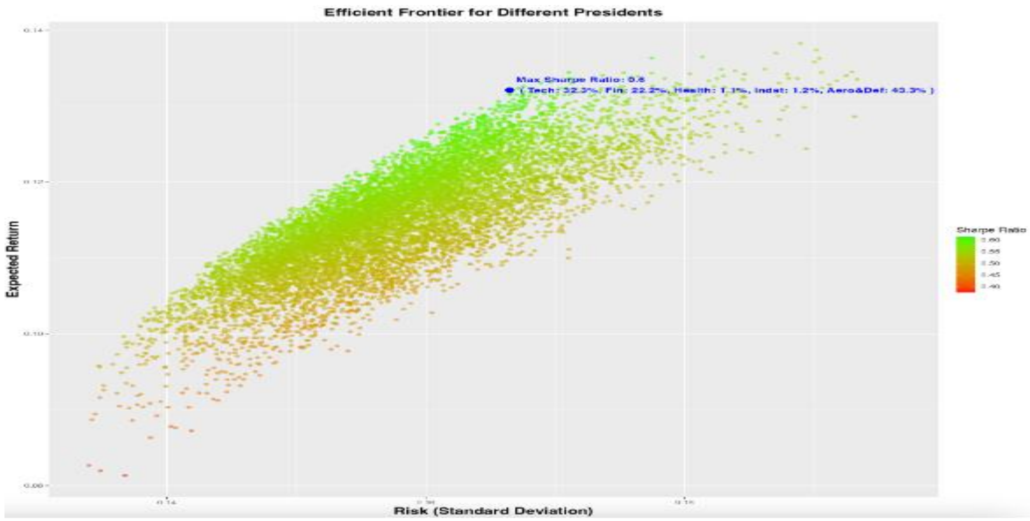
For the Obama administration, in the above figure, we plot 10,000 portfolios on a risk-return profile and find that the Sharpe ratio is 1 for the ideal portfolio, meaning that we get 100% returns for the risk we take in the ideal portfolio. The investor must invest 1.4% of his money in Tech, 39.7% in Finance, 35.4% in Healthcare, 1.4% in Industrials, and 22.1% in Aerospace and Defense to achieve this ideal portfolio. The inefficient portfolios(lower Sharpe ratio) are shown in red, and the efficient portfolios(higher Sharpe Ratio) are shown in green.

Figure 23- Trump Administration (2016 - 2020)



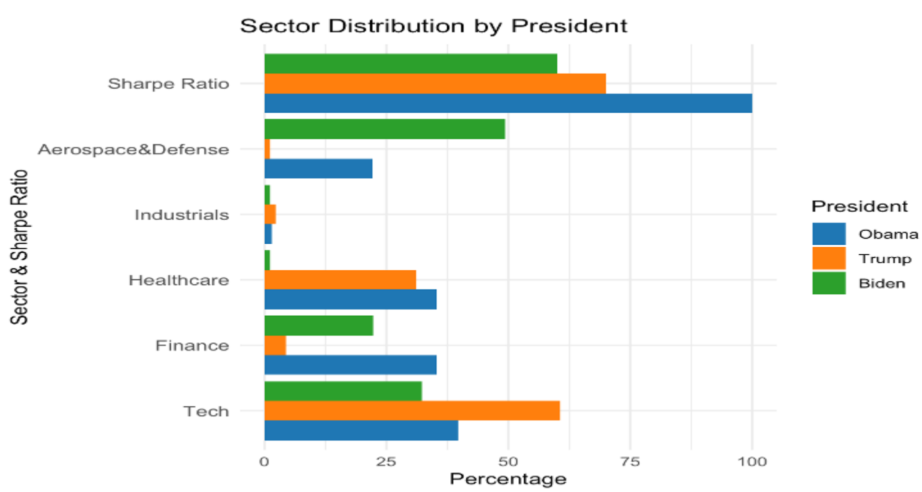
Again, we do the same thing for the Trump Administration and find that the Sharpe ratio is 0.7 for the ideal portfolio(Max Sharpe Ratio), meaning that we get 70% returns for the unit risk we take in the ideal portfolio. The investor must invest 60.7% of his money in Tech, 4.4% in Finance, 31.2% in Healthcare, 2.3% in Industrials, and 1.2% in Aerospace and Defense to achieve this ideal portfolio. The inefficient portfolios (lower Sharpe ratio) are shown in red, and the efficient portfolios(higher Sharpe Ratio) are shown in green.

Figure 24- Biden Administration (2020 - 2024)



For the Biden Administration, we find that the Sharpe ratio is 0.6 for the ideal portfolio(Max Sharpe Ratio), meaning that we get 60% returns for the unit risk we take in the ideal portfolio. The investor must invest 32.3% of his money in Tech, 22.2% in Finance, 1.1% in Healthcare, 1.2% in Industrials, and 49.3% in Aerospace and Defense to achieve this ideal portfolio. The inefficient portfolios (lower Sharpe ratio) are shown in red, and the efficient portfolios (higher Sharpe Ratio) are shown in green.

Figure 25- Summary



Overall, we see that the Sharpe ratio was maximized during the Obama administration. All the administrations resulted in very low portfolio weights for the industrial sector. The weight of the Tech sector for the ideal portfolio was the highest during the Trump administration. The weight for the Healthcare sector was the lowest during the Biden administration. The weight of the Finance sector was the highest during the Obama administration. Finally, for Aerospace and Defense, the weight was highest for the Biden administration.

Conclusions

H1: We see mixed results from the data we gathered. In the heat maps for 2016 and 2020, we see a steady increase in volatility leading up to the election, and similar findings are found in the 2020 bar chart within the financial and industrial sectors. However, within the time series data, we see the VIX does not consistently spike around election dates, instead primarily remaining stable. This inconsistency between sectors and elections means we cannot fully corroborate or oppose our initial hypothesis.

H2: Once again, the evidence in our data is mixed. The tech sector performed well during the Biden and Obama administrations, but healthcare was shakier. In the 2020 bar chart healthcare underperformed relative to the benchmark, while the efficient frontier model shows the sector had lower portfolio weighting during the Biden administration compared to Obama. Overall, findings are inconsistent between elections and thus are not wholly conclusive.

H3: For the third hypothesis, we see modest support from our data. The time series model for 2016 shows significant growth for both the financial and industrial sectors and the same two sectors contributed considerably to portfolio performance during Trump's tenure. That said, the 2016 bar chart shows both sectors with negative alphas, indicating a negative performance. For the efficient frontier model for the Trump era, aerospace and defense failed to make much of an impact, though this may have less to do with the sector and is more reflective of data limitations. Overall, the data seems to lean toward supporting the hypothesis, with a few notable caveats.

Limits, scalability, and possible expansions

Due to a degree of missingness in the Aerospace and Defense sector, it became impractical to use the data for that sector in all model types and was only compatible with the Efficient Frontier model. As such, most of the data visualizations lack a thorough investigation of this sector. If more data had been available, then it may have been possible to include this sector more robustly in every model. Not only that, we only explored data as far back as 2011 and up to September 2024, due to practical limitations with our sources. If we had a larger amount of data to explore, we may be able to come to a more nuanced and definitive conclusion.

As for the application itself, we were limited largely by the time frame to implement more robust features. The most direct way this could be improved would be by implementing more visualization types. Referencing the matter of the dataset mentioned previously, this would allow for including more filtering options for every election year accounted for. In addition, more sector data could be added in, allowing for an even greater picture of how the entire market is affected by the election.

Works Cited

Wójcik, D., & Ioannou, S. (2020). COVID-19 and Finance: Market Developments So Far and Potential Impacts on the Financial Sector and Centres. Tijdschrift Voor Economische En Sociale Geografie, 111(3), 387–400. https://doi.org/10.1111/tesg.12434