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The Impact of the 2016 Election on the Financial Performance of Major Healthcare Companies

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THE IMPACT OF THE 2016 ELECTION ON THE FINANCIAL PERFORMANCE OF
MAJOR HEALTHCARE COMPANIES

by

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A thesis submitted in partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in Financial Economics

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Logan, Utah

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Abstract

Healthcare reform was a significant political issue during the November 2016 US general elections, and played an important role in campaigning and political discourse leading to the election. Donald Trump, the Republican presidential candidate, and Republicans running for congressional office, campaigned on a platform advocating for the repeal and replacement of the Patient Protection and Affordable Care Act of 2010 (ACA), among other changes. Hillary Clinton, the Democratic presidential candidate, and Democrats running for congressional office, campaigned on a platform that included support for the ACA, as well as increased regulations on the pharmaceutical industry and health insurers, among various other policies. Republicans achieved unexpectedly large electoral victories. In order to determine the impact of the election results on the financial health of key firms operating in health care industries, event study techniques and multivariate regressions are used to calculate and analyze cumulative abnormal returns (CARS) surrounding different event windows surrounding the election for the various relevant firms (N=402). Abnormal returns are also calculated by industry, including pharmaceutical companies, health insurers, health care providers, and medical device manufacturers. Statistically and economically significant CARs are observed for the entire sample, as well as for drug companies, health insurers, and health care providers in the short term. Firms in the pharmaceutical industry, who faced more stringent regulation under a Clinton administration, were affected the most by the election results and generated the largest positive abnormal returns in every event window considered.
Introduction

Political Background

Healthcare system reform was one of the most controversial political issues of the first decade of the twenty-first century in American politics, as healthcare reform became a consistent subject of research and legislative debate. Ballooning healthcare costs both in terms of dollars spent and as a portion of GDP, ethical concerns surrounding the difficulty of those with pre-existing conditions to obtain health insurance, and the difficulties facing millions of other uninsured Americans facing difficulties obtaining insurance inspired a push that resulted in dramatic legislation. Despite significant opposition, the Patient Protection and Affordable Care Act, colloquially referred to as the Affordable Care Act or Obamacare (ACA), was signed into law in March 2010.

Passage of the ACA did not eliminate the vocal opposition to the policies it enacted. Republicans in Congress voted to repeal or undermine the ACA 56 times between its enactment and the beginning of the 2016 election cycle in 2015. The political climate leading up to the November 2016 general elections was marked by vitriolic partisan conflict. Virtually all Republican candidates for the presidency promised to “repeal and replace” the ACA, along with the vast majority of Republican candidates for Congress. Donald Trump, the presidential candidate who ultimately achieved an upset electoral victory, claimed one week before his election that, if elected, he would immediately hold a “special session” to repeal and replace Obamacare. The platform published by the Republican Party asserted that “Any honest agenda for improving healthcare must start with repeal of the dishonestly named Affordable Care Act.” Thus, in the time period surrounding the 2016 election, Republican electoral victories
could be perceived as a referendum on the ACA and a potential first step to its eventual repeal. The objective of this study is to determine the effect of the surprise 2016 election results influenced the stock prices of certain health care companies.

Democratic candidates participating in the 2016 elections proposed a fundamentally different platform in terms of health care. Unsurprisingly, the Democratic Party supported the continued existence of the ACA, which was passed under a Democratic administration. Hillary Clinton, the democratic candidate, actively supported the ACA, and generally advocated for expansions of coverage and ACA-participation-related tax credits. She also accused pharmaceutical manufacturers of price gouging and consistently supported dramatic increases on regulations for pharmaceutical companies, including demanding higher rebates for prescription drugs through Medicare, allowing Medicare to negotiate drug prices, increased allowances for imported pharmaceuticals, prohibit “pay for delay” arrangements that allowed drug companies to delay the entrance of generic drugs into the market, and increased regulations for pharmaceutical advertising and profits of drug companies that receive government funding. In the months preceding the election, when a Clinton victory seemed probable, observers noted drops in pharmaceutical stock prices if Clinton so much as tweeted about pharmaceuticals.

The 2010 legislation was of intense interest to the industries involved with supporting or providing health care. This was evidenced by companies such as health insurers and pharmaceutical companies spending record amounts in lobbying efforts during the formation process of the ACA, with the healthcare industry spending more on lobbying endeavors than any other sector of the economy in the three years leading to the passage of the ACA. These
firms also exhibited unusual behavior, such as providing more funding to Democratic politicians than Republican ones for the first time since the last time a Democratic-controlled government was planning healthcare reform under the Clinton administration. The health and success of these industries is essential for long-term improvements in the quality and quantity of the supply of health care in the United States, and the results of the 2016 election cast considerable doubt on the continued existence of the most significant regulations, including but not limited to the ACA, that govern the environment in which they operate. Given this, it is worthwhile to consider the impact of the 2016 elections on the financial performance of companies in the healthcare industry.

Several researchers have used event study techniques have been used to evaluate the impact of the implementation of the ACA, with mixed findings surrounding the impact of the ACA on healthcare financial performance. This report models the event study analysis conducted by Blau et. al (2016). They evaluated both the impact the signing of the Affordable Care Act into law, and its validation in the Supreme Court, had on the financial performance of health care companies. They observed general decreased stock price reactions to its passage, particularly amongst insurers. After a brief consideration of how ACA policies impact healthcare industries, this report will use event study techniques to evaluate the impact of the 2016 elections on the financial performance of the healthcare industry. Examining abnormal returns of various healthcare stocks surrounding the electoral success of the Republican party and Donald Trump will provide insight in the market’s opinion of the policies almost seven years following their implementation.

*Brief Summary of Policy Implications of the ACA on Healthcare Industries*
Because the incoming administration and legislators elected by the 2016 would have a large impact on the continued implementation of the ACA, a very brief overview of the implications of the ACA on the health care industries studied is relevant here. The ACA was a complex piece of legislation with broad goals. Some of the changes broadly affected all participants in the healthcare industry. One of the most pronounced effects of the ACA on the healthcare industry was the introduction of uncertainty for companies with no experience in the new market conditions. The ACA placed excise taxes on health insurers and pharmaceutical companies. Research has also implied that some of the costs of the changes of the ACA were offset by government transfer payments in the form of subsidies, and benefits of increased volume of customers resulting from the legislation. The Affordable Care Act has also fueled market concentration in health care industries, with mergers of health plans, hospitals, and medical groups. This may account for the fact that although using the same data collection methodology, the sample size is ten percent smaller relative to the sample used by Blau et. al.

Some policies specifically impact health insurers: In order to address high rates of Americans without insurance, the ACA implemented an “individual mandate” requiring individuals and small businesses to obtain insurance or face punitive fines. In order to facilitate the transition, the ACA also mandated the creation of marketplaces for individuals to shop for different government-approved insurance plans, and increased subsidies (in the forms of federal refundable tax credits and incentives for businesses) available to fund the plans. While insurers benefit from additional Americans purchasing insurance, the ACA also implemented policies that increased burdens on insurers. The ACA implemented a guaranteed
issue policy, which prohibits insurers from denying coverage to individuals due to any pre-existing conditions, and prevents insurers from dropping individuals when they develop a condition.\textsuperscript{26} The ACA also increases regulatory burdens in requiring the approval of new plans, regulating risk management programs, regulating the use of premium dollars and co-payments, and similar policies.\textsuperscript{27}

**Data Description**

*Data*

Financial performance data used in this analysis includes metrics such as closing daily share prices, market capitalization, volume, shares outstanding, and bid-ask spread. Data was collected from the Center for Research on Security Prices (CRSP). Firms were sampled based on their Standardized Industry Codes (SICs) used by CRSP to identify types of firms. The firms sampled in this analysis were restricted to four different subsets: those with SIC codes that identify as pharmaceutical companies, health care providers, health insurers, or medical device producers. This data was used to conduct standard event studies surrounding the first day of market operation after the 2016 general election results were announced, November 9\textsuperscript{th}, 2016. As the results of the election were unexpected, this day uniquely illustrates how the market surrounding the health care industry responds to an information shock unfavorable to the ACA.

Table 5, in the appendix, lists the stock tickers of the companies included in this analysis, delineated by company type. The sample includes 402 firms total, with 59 firms listed as pharmaceutical companies (*DRUG*), 378 firms listed as health care providers (*HEALTHCARE*), 14 firms listed as insurers (*INSURER*), and 51 firms listed as medical product manufacturers
Some firms fit into multiple categories and are listed as such, so the components do not sum to 402.

**Summary Statistics**

Table 1 reports statistics that describe the sample of healthcare related firms for November 9\(^{th}\), 2016, the day the information conveyed by the results of the previous days’ election could be internalized by the market. *Price* is the closing price at the end of the day according to CRSP. *MktCap* is the firm’s market capitalization. *Turn* is the share turnover or the daily volume scaled by shares outstanding. *Spread* is the bid-ask spread using closing bid and ask prices from CRSP. *Pvolt* is a measure of price volatility, which is the difference between the daily high price and the daily low price scaled by the daily high price. The remaining four variables are indicator variables that equal one if any specific firm is meets the classification of the variable, but is equal to zero otherwise. Firms are identified according to their standard industry codes (SICs). *DRUG* is equal to one if a firm is considered a pharmaceutical company – zero otherwise; *HEALTHCARE* is a broader, dummy variable capturing health care companies; *INSURER* is an indicator variable that represents health insurers; *DEVICE* is an indicator variable that equals one for companies that produce medical products – zero otherwise. The average stock price in the sample was $34.84, and the median stock price was $12.70. The largest category considered in this analysis are health care providers, which constitute 94.26% of the sample. Pharmaceutical companies and medical device manufacturers constitute a similar and much smaller portion of the sample at 14.93% and 12.72%, respectively. Health insurers form the smallest component of the analysis at 3.49% of the firms in the sample. Note that the four
indicator variables do not sum to one given that some of these companies may belong to two categories.

**Table 1**


<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std. Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>34.84</td>
<td>12.70</td>
<td>60.2209</td>
<td>0.0515</td>
<td>651.46</td>
</tr>
<tr>
<td>MktCap</td>
<td>7,704,286.96</td>
<td>472,223.77</td>
<td>26,797352.25</td>
<td>2,290.61</td>
<td>329,153,361.97</td>
</tr>
<tr>
<td>Turn</td>
<td>18.6245</td>
<td>11.0858</td>
<td>26.1708</td>
<td>0.04842</td>
<td>297.9262</td>
</tr>
<tr>
<td>Spread</td>
<td>0.0673</td>
<td>0.0100</td>
<td>0.4390</td>
<td>0.0001</td>
<td>7.8999</td>
</tr>
<tr>
<td>Pvolt</td>
<td>0.0774</td>
<td>0.0686</td>
<td>0.0436</td>
<td>0.0000</td>
<td>0.3120</td>
</tr>
<tr>
<td>DRUG</td>
<td>0.1493</td>
<td>0.0000</td>
<td>0.3543</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>HEALTHCARE</td>
<td>0.9426</td>
<td>1.0000</td>
<td>0.2328</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>INSURER</td>
<td>0.0349</td>
<td>0.0000</td>
<td>0.1838</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>DEVICE</td>
<td>0.1272</td>
<td>0.0000</td>
<td>0.3336</td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

**Results**

*Cumulative Abnormal Returns – Entire Sample*

Table 2 summarizes the Cumulative Abnormal Returns (CARs) for selected event windows, as well as the z-statistics calculated using the Patell test (reported in parentheses) and the Jackknife test (reported in brackets) used to determine the statistical significance of the results. The returns were estimated by summing the residuals generated by simulating a market model over the event windows listed. The first day of market operation with the election results, $t$, is considered day 0. The first window described evaluates CARs over the course of the day before the election, $t-1$, to the day after, $t+1$, which will here be denoted as $CAR(-1,1)$. The second window evaluates CARS for only the day of the election, $t$, to the day after the election, $t+1$, and will be denoted here as $CAR(0,1)$. The following three event windows in this analysis
evaluate the periods 5, 10, and 30 days following the day of the election \((CAR(0,5), CAR(0,10),\) and \(CAR(0,30)\) respectively).

### Table 2
Statistical significance is at the 0.10, 0.05, and 0.01 levels is denoted with *, **, and *** respectively.

<table>
<thead>
<tr>
<th>Election Result Night – Entire Sample</th>
<th>CAR(-1,1)</th>
<th>CAR(0,1)</th>
<th>CAR(0,5)</th>
<th>CAR(0,10)</th>
<th>CAR(0,30)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0357***</td>
<td>0.0376***</td>
<td>0.0561***</td>
<td>0.0460***</td>
<td>-0.0061</td>
</tr>
<tr>
<td>Jackknife Z</td>
<td>[9.117]</td>
<td>[9.398]</td>
<td>[9.218]</td>
<td>[5.819]</td>
<td>[-0.986]</td>
</tr>
</tbody>
</table>

The results in the table imply statistically significant abnormal returns over the event windows surrounding the election. These abnormal returns continue in all the event windows included in the analysis up to the window 10 days following the election, as evidenced by the results presented in columns [1]-[4] of Table 2. These results imply massive abnormal returns to shareholders, as well. The two-day event window immediately after the election, \(CAR(0,1)\), reports an abnormal return of 3.76%, which annualizes to a return of about 474%. Even increasing the scope of the analysis to the eleven-day event window, \(CAR(0,10)\), reports annualized CARs in excess of 100%. There are no statistically significant CARs observed for the 30-day window in column [5]. This implies that although the surprise results of the election generated abnormal returns in the immediate aftermath, the market incorporated the information after the short term. It also may be that it became apparent to investors in the weeks following the election that quick and dramatic overhauls of the ACA would not likely be politically feasible.
Cumulative Abnormal Return – By Firm Type

Cumulative Abnormal Returns are again reported in the following table, this time the results are delineated by company type. As with the results presented in Table 2, CARs for five event windows are obtained from estimating a daily market model and summing the residual returns. $CAR(-1,1)$ measures the cumulative abnormal return from day $t-1$ to $t+1$, where day $t$ is the event day, November 9th, 2016. Similarly, $CAR(0,1)$ is the cumulative abnormal return from day $t$ to $t+1$. $CAR(0,3)$, $CAR(0,5)$, and $CAR(0,10)$ similarly cover increasing time windows surrounding the election. The mean CARs are presented along with two corresponding Z-test statistics generated using Patell tests (denoted using parentheses) and Jackknife tests (denoted using brackets). Furthermore, we estimate mean CARs for each of the four types of firms used in the sample. Listed in column [1], DRUG identifies firms that are classified as a pharmaceutical company according to standard industry codes. HEALTHCARE in column [2] captures health care companies. INSURER in column [3] specifies companies that are considered a health insurer. DEVICE in column [4] identifies companies classified as Medical Products manufacturers.
Table 3
Statistical significance is at the 0.10, 0.05, and 0.01 levels is denoted with *, **, and *** respectively. Z-statistics are reported in parenthesis.

<table>
<thead>
<tr>
<th></th>
<th>DRUG (N = 59)</th>
<th>HEALTHCARE (N = 378)</th>
<th>INSURER (N=14)</th>
<th>DEVICE (N = 58)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CAR(-1,1)</strong></td>
<td>0.0729***</td>
<td>0.0368***</td>
<td>0.0277***</td>
<td>0.0034</td>
</tr>
<tr>
<td></td>
<td>(9.393)</td>
<td>(11.953)</td>
<td>(4.270)</td>
<td>(-0.319)</td>
</tr>
<tr>
<td></td>
<td>[7.251]</td>
<td>[8.969]</td>
<td>[2.322]</td>
<td>[0.575]</td>
</tr>
<tr>
<td><strong>CAR(0,1)</strong></td>
<td>0.0769***</td>
<td>0.0271***</td>
<td>0.0195***</td>
<td>0.0160</td>
</tr>
<tr>
<td></td>
<td>(11.788)</td>
<td>(14.637)</td>
<td>(3.915)</td>
<td>(0.904)</td>
</tr>
<tr>
<td></td>
<td>[8.172]</td>
<td>[9.200]</td>
<td>[1.880]</td>
<td>[1.326]</td>
</tr>
<tr>
<td><strong>CAR(0,5)</strong></td>
<td>0.0873***</td>
<td>0.0460***</td>
<td>0.0424***</td>
<td>0.0282</td>
</tr>
<tr>
<td></td>
<td>(7.350)</td>
<td>(9.396)</td>
<td>(4.317)</td>
<td>(0.841)</td>
</tr>
<tr>
<td></td>
<td>[8.247]</td>
<td>[8.781]</td>
<td>[3.011]</td>
<td>[1.357]</td>
</tr>
<tr>
<td><strong>CAR(0,10)</strong></td>
<td>0.0808***</td>
<td>0.0390***</td>
<td>0.0650***</td>
<td>0.0354</td>
</tr>
<tr>
<td></td>
<td>(4.985)</td>
<td>(4.960)</td>
<td>(4.376)</td>
<td>(0.599)</td>
</tr>
<tr>
<td></td>
<td>[6.038]</td>
<td>[5.349]</td>
<td>[3.259]</td>
<td>[1.147]</td>
</tr>
<tr>
<td><strong>CAR(0,30)</strong></td>
<td>0.0362*</td>
<td>0.0072</td>
<td>0.0577***</td>
<td>0.0050</td>
</tr>
<tr>
<td></td>
<td>(1.293)</td>
<td>(-1.079)</td>
<td>(2.363)</td>
<td>(-0.934)</td>
</tr>
<tr>
<td></td>
<td>[1.275]</td>
<td>[-1.222]</td>
<td>[3.006]</td>
<td>[-0.773]</td>
</tr>
</tbody>
</table>
The results in the table suggest that, for the most part, statistically significant CARs are observed through most event windows in all of the industries considered in this analysis, with the exception of companies operating in the medical products and devices industry.

Considering returns of the two-day event window including the day of the election and the day following, \( CAR(0,1) \), pharmaceutical companies (column [1]) exhibit CARs with the largest magnitude by a wide margin, with annualized CAR of approximately 969%. They are followed by the broadest subsection of the sample, health care providers (column [2]), with an annualized CAR of 341.46%. Health insurers (column [3]) also achieved relatively high CARs of 245.70%.

Healthcare providers, the subsection perhaps most representative of the industry as a whole, loses statistical significance after the eleven-day event window, \( CAR(0,10) \). However, the smaller pharmaceutical and insurance subsections continue to report statistically significant CARS event 30 days following the election results, with annualized returns of 29.4% and 46.90%, respectively. Although pharmaceutical companies report significantly larger CARS during the two-day event window, \( CAR(0,1) \), health insurers report larger CARs during the 31-day event window, \( CAR(0,30) \).
Cross-Sectional Regressions

Table 4 reports the results from estimating the following equation using cross-sectional data obtained from CRSP:

\[
CAR(0,1)_i = \alpha + \gamma_1 DRUG_i + \gamma_2 HEALTHCARE_i + \gamma_3 INSURER_i + \beta_1 Ln(size_i) + \beta_2 Turn_i + \beta_3 Ln(price_i) + \beta_4 Spread_i + \beta_5 Volt_i + \epsilon_i
\]

The dependent variable is the two-day cumulative abnormal return, \(CAR(0,1)\), for each health care stock from the sample \(i\) from day \(t\) to \(t+1\), where day \(t\) is November 9\textsuperscript{th}, the first day of market operations with the election results. The independent variables that are the focus of this regression are the three indicator variables, which are the dummy variables that identify the industry the stocks belong in. As before, \(DRUG\) is an indicator variable equal to one if the stock belongs to a pharmaceutical company according to standard industry codes. \(HEALTHCARE\) is an indicator variable representing health care providers, \(INSURER\) is an indicator variable, which identifies whether the company is considered a health insurer. We omit the indicator variable \(DEVICE\) in order to avoid violating the full rank condition required for consistent estimates. Five different variables have been included to serve as controls. \(Ln(size)\) is the natural log of the firm’s market capitalization. \(Turn\) is the share turnover for each stock, which is defined as the volume of shares traded divided by shares outstanding, while \(Ln(price)\) is the natural log of the firm’s share price. \(Spread\) is the bid-ask spread and \(Volt\) is the price volatility, which again is defined as the share’s high price minus its low price, scaled by its high price. Statistical significance is indicated with asterisks. Robust standard errors that account for clustering across firms are reported in parentheses.
Table 4
Statistical significance is at the 0.10, 0.05, and 0.01 levels is denoted with *, **, and *** respectively.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.00563*</td>
<td>0.01203*</td>
<td>0.01020</td>
<td>0.01680</td>
<td>0.00786</td>
<td>-0.02581**</td>
<td>-0.08355**</td>
</tr>
<tr>
<td></td>
<td>(0.00952)</td>
<td>(0.02323)</td>
<td>(0.01010)</td>
<td>(0.01197)</td>
<td>(0.00978)</td>
<td>(0.01208)</td>
<td>(0.03293)</td>
</tr>
<tr>
<td>DRUG</td>
<td>0.05321***</td>
<td>0.05267***</td>
<td>0.05501***</td>
<td>0.04893***</td>
<td>0.05419***</td>
<td>0.04313***</td>
<td>0.04629***</td>
</tr>
<tr>
<td></td>
<td>(0.01422)</td>
<td>(0.01436)</td>
<td>(0.01465)</td>
<td>(0.01460)</td>
<td>(0.01417)</td>
<td>(0.01339)</td>
<td>(0.01410)</td>
</tr>
<tr>
<td>HEALTHCARE</td>
<td>0.01657</td>
<td>0.01634</td>
<td>0.01818*</td>
<td>0.01398</td>
<td>0.01667</td>
<td>0.00988</td>
<td>0.01027</td>
</tr>
<tr>
<td></td>
<td>(0.01056)</td>
<td>(0.01053)</td>
<td>(0.01049)</td>
<td>(0.01049)</td>
<td>(0.01070)</td>
<td>(0.00988)</td>
<td>(0.01027)</td>
</tr>
<tr>
<td>INSURER</td>
<td>0.00451</td>
<td>0.00566</td>
<td>0.00846</td>
<td>0.00908</td>
<td>0.00239</td>
<td>0.00067</td>
<td>-0.00380</td>
</tr>
<tr>
<td></td>
<td>(0.02758)</td>
<td>(0.02794)</td>
<td>(0.02588)</td>
<td>(0.02762)</td>
<td>(0.02767)</td>
<td>(0.02797)</td>
<td>(0.02526)</td>
</tr>
<tr>
<td>Ln(size)</td>
<td>0.00047</td>
<td>0.01650</td>
<td>0.00033</td>
<td>0.000072***</td>
<td>-0.00612</td>
<td>(0.00024)</td>
<td>-0.00026</td>
</tr>
<tr>
<td>ln(price)</td>
<td>-0.00033</td>
<td>-0.00026</td>
<td>0.00342*</td>
<td>(0.00219)</td>
<td>-0.00612</td>
<td>(0.00024)</td>
<td>-0.00026</td>
</tr>
<tr>
<td>Spread</td>
<td>-0.29673</td>
<td>0.00219</td>
<td>0.029673</td>
<td>(0.21345)</td>
<td>-0.65786***</td>
<td>(0.20504)</td>
<td>-0.65786***</td>
</tr>
<tr>
<td>Volt</td>
<td>0.48696***</td>
<td>0.62607***</td>
<td>0.48696***</td>
<td>0.62607***</td>
<td>0.12966</td>
<td>0.13621</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.0184</td>
<td>0.00164</td>
<td>0.0257</td>
<td>0.0217</td>
<td>0.0192</td>
<td>0.0727</td>
<td>0.11143</td>
</tr>
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The results of the multivariate regression generate mixed results in terms of confirming the results of the event study technique. The indicator variable for DRUG produces estimates that are statistically significant from zero beyond the 0.01 level, and economically significant, across the models in all seven columns, confirming that the pharmaceutical industry experienced positive CARs across the two-day event window. The statistically significant annualized abnormal return in the model used in column [7] is approximately 583%. The indicator variable for the broader healthcare providing section, HEALTHCARE, produced p-values close to statistical significance in many columns, but only demonstrated statistical significance in column [3]. The annualized CAR associated with health care providers in column [3] is approximately 229%. No statistically significant results were observed for health insurers across any of the columns. Examining the results in column [7], in addition to the statistically significant CARs in the pharmaceutical industry, in the full specification of the model, larger firms and firms with higher price volatility report statistically significant positive CARs, and firms with higher amounts of share turnover and larger bid-ask spreads reported statistically significant negative CARs.

Conclusion

The policy implications of health care reform are important, because changes can have significant impacts on the firms that provide health care, either directly or through medication and medical products. These impacts are evidenced by cumulative abnormal returns measured in the financial performance of firms operating in the health care industry. The success of the Republican party in the 2016 elections, which implied likely changes to health care policies such as the Affordable Care Act, resulted in economically and statistically significant positive
abnormal returns observed in the pharmaceutical, health care, and medical product industries, although the statistical significance is particularly pronounced and consistent in the abnormal returns in the pharmaceutical industry, where different methods of statistical testing found returns in the two-day event window surrounding the 2016 elections found abnormal returns in excess of an annualized rate of 500%. Event study techniques indicate no statistically significant abnormal returns for the entire sample when considering the 31-day window after the election, however, implying that the market incorporated the new information into share prices within the month.
## Appendix

### Table 5
Stock Tickers by Category - Day of Election Results – Listed Alphabetically (N = 402)

**DRUG (N=59)**

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**HEALTHCARE (N=378)**

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References


17 Ibid.


27 Hall, M. A., & McCue, M. J. op cit.