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Information in stock prices: the case of the 2016 U.S. presidential election

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ABSTRACT

On the day before the 2016 U.S. presidential election, the odds of Hillary Clinton winning the presidency, according to political prediction markets, were above 90%. Surprisingly, Donald Trump won the Electoral College handily. In this study, we examine how movements in specific stock prices foreshadowed the eventual outcome. Specifically, we conduct a series of standard event-study tests focused on pharmaceutical companies, which became a focal point during the presidential campaign. Results show that while stocks of pharmaceutical companies significantly underperformed the market prior to the election, prices substantially increased beginning three days before the election outcome. This increase is both statistically significant and economically meaningful and robust to various event-study methodologies. These results suggest that some sectors of the stock market seemed to anticipate the election outcome.

KEYWORDS

Election; cumulative abnormal returns; market efficiency; stock prices

JEL CLASSIFICATION

G10; G12; G14

I. Introduction

One of the most important roles of capital markets is to ensure that information is efficiently impounded into asset prices. The speed at which prices incorporate information is one way to measure market efficiency (Hou and Moskowitz 2005). While examining the market's reaction to new information is important in the context of Fama's (1970) efficient market hypothesis, examining the flow of information into prices prior to the information's release seems to be equally important. Observing price movements prior to the release of information can indicate the ability of market participants to anticipate events or predict outcomes. Numerous examples of markets anticipating outcomes have been documented. One well-known example is the price movements of Morton-Thiokol after the Space Shuttle Challenger explosion. Within minutes, the market anticipated the outcome of months of investigation (Blose et al. 1996; Maloney and Harold Hulherin 2003). The literature identifying cases where markets seem to anticipate information about impending announcements during the pre-announcement period is broad and discussed in a number of different settings that range from merger and acquisition (M&A) announcements (Keown and Pinkerton 1981) to different types of accounting scandals (Agrawal and Cooper 2015).

Following this line of research, the objective of this study is to examine whether or not sectors of the stock market anticipated the 2016 U.S. presidential election outcome. This particular election is an interesting setting for several reasons. First, while information leakage might explain some of the stock price movements prior to corporate announcements, the election seems to rule out this explanation given that the outcome is determined after the votes are counted. Second, and perhaps more interestingly, a large majority of the election polls were incorrect, and the prediction markets placed the odds of a Hillary Clinton victory higher than 90% on the day of the election.

To determine whether the stock market anticipated the presidential election, we focus our analysis on a particular sector that was central to the political debate leading up to the election. In the fall of 2015, then Presidential Candidate, Hillary Clinton began discussing the potential problems with price gouging by pharmaceutical firms. As expected, the stock prices of publicly traded pharmaceutical companies decreased substantially in response to this discussion (see Table 6). These same companies generally

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underperformed in the months and weeks leading up to the election, as the polling and pundits predicted an eventual Clinton presidency. In our empirical tests, we estimate cumulative abnormal returns (CARs) for pharmaceutical stocks across various time-windows surrounding the election outcome.

Our results show that average CARs of pharmaceutical stocks during days *t*-10 to *t*-4 prior to the election outcome (November 9th, 2016), are significantly negative and range from −2.49% to −6.15% depending on the methodology employed. However, the average CARs during the three-day period prior to the election outcome (Friday, November 4th to Tuesday, November 8th), are significantly positive and continue to increase in the three days following the outcome. In economic terms, we find that the average three-day pre-election CARs are above 2%. As a means of robustness, we replicate our analysis using multifactor model CARs (Fama and French 1996; Carhart 1997) and find similar results. Admittedly, these multifactor CARs are statistically weaker, but the general pattern of returns around the election outcome are qualitatively similar.

Our results seem to suggest that the stock prices of pharmaceutical firms began to increase in the three days prior to the election outcome. This supports the notion that pharmaceutical stock prices anticipated the results of the most recent U.S. presidential election, as a democratic victory would have brought intense scrutiny upon the industry. It is possible, however, that the observed significance for our estimated CARs is spurious. To account for this possibility, we conduct a series of placebo tests where we randomly select 250 stocks and conduct the same event-study analysis around the election outcome.[1] After obtaining four different randomly selected placebo samples, we do not find any meaningful increase in the stock prices of these securities in the days prior to the election. We also estimate cross-sectional regressions where the dependent variable is the post-election CARs from day *t* to *t*+ 3, and the independent variable of interest is the pre-election CARs from day *t*-3 to *t*-1. Other factors held constant, we generally find that the average pre-election CARs are positively related to the average post-election CARs. These findings seem to suggest that our results are not driven by sample selection bias, or market momentum.

Our remaining analysis attempts to provide further evidence that some sectors of the U.S. stock market anticipated the election outcome. In particular, we attempt to identify pharmaceutical companies most sensitive to political intervention. To do so, we examine the stock prices most affected by Presidential Candidate Clinton's early discussions of price gouging more than a year prior to the election.[2] First, we conduct a series of event studies surrounding the first discussion of drug price gouging by Hillary Clinton, which, to our knowledge, was a tweet on September 21st, 2015. Event study tests reveal a significant and marked decline in the stock prices of pharmaceutical companies in the days following the initial tweet in September of 2015. In economic terms, two-day post-event CARs range from −2.37% to −3.63% depending on the event-study method. These results are robust to CARs obtained from multifactor models. Furthermore, we find that four placebo samples do not experience the same price decline.

Second, we use cross-sectional regressions to determine whether the documented three-day pre-election CARs are affected by those stocks most responsive to the Clinton tweet. We estimate a series of cross-sectional regressions where we attempt to explain the three-day pre-election CARs with the post-Clinton CARs. After controlling for a number of stock characteristics, we find a significant, negative association between the post-event CARs (from the initial tweet about drug price gouging) and the pre-election CARs. Specifically, a 1% decrease in the post-tweet CARs is associated with a 9.31 basis point increase in pre-election CARs, other factors held constant. These results seem to indicate that the price increase in the stocks of pharmaceutical companies during the pre-election period was driven by the same stocks that experienced the most severe

[1]Simple random sampling is used as the sample selection method, where each stock has an equal probability of selection, and sampling is done without replacement.

[2]We are not attempting to link what Hillary Clinton said to the returns preceding the election, but rather to identify the pharmaceutical stocks most sensitive to political intervention.

price decline in response to the initial suggestion of price gouging.

In a number of robustness tests, we replicate our event-study analysis for health-care companies instead of pharmaceutical companies. Similar to the idea behind our initial analysis, the proposed policies between the presidential candidates differed greatly in how they would affect the health-care industry. Unreported results show that in the three days prior to the election, the prices of health-care stocks also began to increase. Admittedly, the results are weaker than those of pharmaceutical companies. However, at a minimum, these other unreported tests tend to support the results reported in this study.

Combined, our findings suggest that sectors of the stock market seemed to accurately forecast the election outcome – particularly in the days just before the election. These results contribute to the literature, which is discussed in the next section, on the interaction between stock markets, information, and political elections. It appears that investors in pharmaceutical stocks interpreted the information regarding the 2016 U.S. presidential election differently than participants in polls and prediction markets.

The rest of the paper is outlined as follows. Section 2 briefly discusses some of the relevant literature. Section 3 describes the data used throughout the analysis. Section 4 presents the results of our empirical tests. Section 5 provides some concluding remarks.

II. Related literature

There exists a broad literature that examines the interaction between political elections and stock markets. For instance, Roberts (1990) and Herron et al. (1999) examine the performance of the stock market in response to the 1980 and 1992 U.S. presidential elections, respectively. Gemmill (1992) and Herron (2000) examine the behaviour of financial markets in London in response to the 1987 election and the 1992 election. Leblang and Mukherjee (2005) conduct analysis from U.S. and British stock markets for a 70-year period surrounding a number of elections. In general, the results from these studies show that political elections influence the prices of stocks in financial markets. This is particularly true for industries that will be most affected by the election outcome. For example, when analysing the 1980 U.S. general election, Roberts (1990) explores the effect of the election on the defence industry. Similarly, Herron et al. (1999) identify 15 economic sectors that would have been most effected by the 1992 presidential election. Instead of examining the stock-market response, however, our tests differ from the existing research by examining prices in financial markets in the period just before the election to ascertain whether or not price movements can anticipate election outcomes.

A growing literature also examines how well prediction markets forecast election outcomes. Using the Iowa Electronic Market (IEM) for the 1988 election, Forsythe et al. (1993) show that the IEM outpredicted opinion polls and forecasted the election outcome remarkably well. In a more recent study of various elections, Berg et al. (2008) show that IEM has provided accurate election predictions and has generally outperformed polling organizations. However, the accuracy of such markets has not gone without debate and additional research questions the accuracy of these markets (Brüggelambert 2004; Erikson and Wlezien 2008). As an anecdote, on November 8th, 2016 – the day of the U.S. presidential election, the IEM winner-take-all contract for the Democrat Nominee, Hillary Clinton, was priced as high as \$0.963, indicating an implied probability of Clinton winning the election at 96%.

In addition, our results also speak to the efficiency of markets. The motivation for our tests is based on a large branch of literature in financial economics that discusses the informational efficiency of prices in securities markets. Beginning in Fama (1970), the theory of efficient markets predicts that prices in financial markets will incorporate existing information. Early studies suggest that financial markets are fairly efficient (Fama 1965; Fama et al. 1969; Ball and Brown 1968). Fama (1970) argues that financial markets seem to incorporate publicly available information into prices reasonably well. A few studies also suggest that financial markets incorporate both public and private information into prices. For instance, Keown and Pinkerton (1981) show that prices of target companies begin to increase in the days prior to an acquisition announcement. Busse and Clifton Green (2002) find that stocks prices begin to move in the direction of analyst recommendation announcements during the minutes prior to the announcement. However, the consensus, even in Fama (1970), is that private information is not usually incorporated into stock prices. Other studies document anomalies that question the efficiency of financial markets more generally (Lakonishok and Smidt 1988; Jegadeesh and Titman 1993). Our results seem to suggest that investors in pharmaceutical stocks more accurately interpreted the available information than polls and prediction markets.

III. Data description

To examine whether or not the stock market provided any information regarding the 2016 U.S. presidential election outcome ex-ante, we gather price and volume information from the Center for Research in Securities Prices (CRSP) database. We focus on securities within the pharmaceutical industry, four-digit SIC codes 2830 to 2836, as they received significant attention during the presidential campaign. In fact, Clinton's plan was to reform how drug companies spend federal grants and allow the U.S. government to negotiate down prescription drug prices and enforce a monthly cap on drug costs. At a campaign stop in Des Moines, Iowa, Clinton stated, 'we need to protect hard-working Americans here at home from excessive costs. Too often these drugs cost a fortune… bad actors are making a fortune off of people's misfortune.'[3]

Table 1 reports summary statistics for the 210 publicly traded pharmaceutical companies with non-zero volume days surrounding the 2016 U.S. presidential election outcome. The descriptive variables are calculated daily and averaged over the three business days prior to the election outcome (Friday, Nov. 4th to Tuesday, November 8th). The companies in the sample have market capitalizations ranging from $3.6 million to $318.1 billion. The average stock in the sample has a closing price of $23.90 and a market capitalization of $8.2673 billion. We find that these securities are actively traded, but with substantial variation, as the average daily share volume is 1.72 million with a standard deviation of 4.41 million. To estimate the average transaction cost on a trade for a security in the sample, we measure the difference in daily closing bid and ask prices divided by the midpoint price, which we denote as the spread (see Chung and Zhang 2014). We find that the average closing spread is 9.3 basis points. The average daily volatility, measured as the log difference in daily high and low prices (Alizadeh, Brandt, and Diebold 2002) is 0.0671. We also show that the average daily share turnover for a stock in the sample is 1.18%.

IV. Empirical results

To begin our empirical analysis, we examine both raw returns and CARs for the sample of 210 pharmaceutical stocks around the outcome of the 2016 U.S. presidential election on November 9th. We note that the election actually took place on November 8th, but that the outcome was not determined until later that night. In fact, when financial markets closed, prediction markets still

Table 1. This table reports descriptive statistics for 210 drug companies during the three days preceding the 2016 U.S. presidential election outcome on 9 November 2016. The closing price is the absolute value of the daily closing price on CRSP. Market Cap. is the closing price multiplied by the number of shares outstanding. Volume is average daily share volume. Closing Spread is the difference between the closing ask and bid prices, divided by the midpoint. Volatility is the log difference in the daily high and low prices. Turnover is share volume divided by shares outstanding.

	Mean	Median	Std. Dev.	Min	Max
Close Price	$23.90	$5.45	$44.03	$0.07	$358.18
Market Cap. ($ billions)	$8.2673	$0.2771	$31.7529	$0.0036	$318.1095
Share Volume (100,000s)	1,718,363	347,346	4,407,705	1,074	43,817,162
Closing Spread	0.0093	0.0038	0.0130	0.0001	0.0914
Volatility	0.0670	0.0606	0.0397	0.0062	0.2139
Turnover	0.0118	0.0064	0.0158	0.0002	0.1261

[3]See Reuters article 'Clinton proposes $250 monthly cap on prescription drug costs' by Amanda Becker for an overview of the campaign discussion available at: https://www.reuters.com/article/us-usa-election-clinton/clinton-proposes-250-monthly-cap-on-prescription-drug-costs-idUSKCN0RM08D20150922.

heavily favoured a Clinton Presidency. Table 2 reports raw returns and CARs for non-overlapping event windows that range from day t-10 to t+ 3.

Column [1] of Table 2 reports cumulative raw returns. We find that the average cumulative return from day t-10 to t-7 is −5.81%, which is significantly different from zero at the 0.01 level. Similarly, the average cumulative return from day t-6 to t-4 is −6.15%. Interestingly, the average cumulative return from day t-3 to t-1 is 4.63%, which is also significant at the 0.01 level. Although the majority of the news coverage preceding the election outcome was pointing towards a Clinton victory, investors in pharmaceutical stocks showed a dramatic change in sentiment. We continue to see a positive trend in pharmaceutical stock prices following the election outcome. For instance, the average return on the event day is 5.41%, and the average cumulative return from day t+ 1 to t+ 3 is 5.13%.

While the unadjusted raw returns look informative, it could be that the entire market was moving upward and that pharmaceutical stocks were merely part of market momentum. In columns [2] through [5] of Table 2, we report results for CARs that are adjusted using a variety of benchmarks. Columns [2] and [4] use an equal-weighted market portfolio as the benchmark. Column [2] subtracts the equal-weighted market return from the event return and column [4] takes the residual return from a market model regression where the event return is regressed on the equal-weighted market return. Columns [3] and [5] are analogous to columns [2] and [4] but use a value-weighted market return instead of an equal-weighted return. Similar to our results using unadjusted raw returns, we find a negative average CAR from day t-10 to t-4, and a positive average CAR from day t-3 to t-1. Even the lowest average CAR from day t-3 to t-1 in column [5] is statistically and economically significant. For instance, the three-day average CAR is 1.96%, which is significant at the 0.01 level.

Table 3 reports additional robustness results from three-factor and four-factor models, where CARs are estimated using the residuals from these multi-factor models.[4] We report the results for the three-factor model CARs in columns [1] and [2]. In column [1], we use an equal-weighted market portfolio and in column [2] we use a value-weighted market portfolio. In columns [3] and [4], we use returns that are cumulated from residuals from a four-factor model where the market index is either equal-weighted or value-weighted. While our results are not as strong as before, we still see the same general pattern with negative or insignificant, CARs in the window t-10 to t-4, and positive CARs in the window t-3 to t-1. We note that the average CARs in the period t-3 to t-1 are only significant when the market index is equal-weighted.

Given how surprising the election results were and how contrasting the CARs from pharmaceutical securities are, we think it is important to rule out the possibility that the result is merely spurious. It could

Table 2. This table reports cumulative abnormal returns (CARs) for various event windows around the 2016 U.S. presidential election outcome on 9 November 2016. We report unadjusted raw returns, equal-weighted and value-weighted market adjusted returns, and equal-weighted and value-weighted market model returns. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

2016 U.S. Presidential Election – Standard Event Study Methods

	Unadjusted Raw Returns	E-W Adjusted Returns	V-W Adjusted Returns	E-W Market Model	V-W Market Model
CAR(−10,-7)	−5.81%***	−3.70%***	−4.90%***	−2.49%***	−4.29%***
	(−8.94)	(−5.70)	(−7.55)	(−3.85)	(−6.59)
CAR(−6,-4)	−6.15%***	−3.33%***	−4.27%***	−1.99%***	−3.54%***
	(−11.53)	(−6.25)	(−8.00)	(−3.80)	(−6.73)
CAR(−3,-1)	4.63%***	2.49%***	2.21%***	2.09%***	1.96%***
	(7.96)	(4.28)	(3.81)	(3.66)	(3.45)
CAR(0,0)	5.41%***	3.50%***	4.14%***	2.94%***	3.95%***
	(12.46)	(8.06)	(9.53)	(7.17)	(9.48)
CAR(+1,+3)	5.13%***	2.39%***	4.60%***	1.77%**	4.78%***
	(7.28)	(3.39)	(6.53)	(2.57)	(6.78)

[4]We note that the three risk factors include SMB (the small-minus-big) risk factor, HML (the high-minus-low) risk factor, and the market risk premium (returns on the market less the risk-free rate – or the yield on short-term government bonds). In the four-factor model, we include these first three factors as well as the UMD (the up-minus-down) risk factor. Each of these risk factors is carefully explained in Fama and French (1996) and Carhart (1997).

Table 3. This table reports both Fama-French three-factor model and Fama-French-Carhart four-factor model cumulative abnormal returns (CARs) for various event windows around the 2016 U.S. presidential election outcome on 9 November 2016. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

2016 U.S. Presidential Election – Multi-Factor Event Study Methods				
	Fama-French Three-Factor Residuals		Fama-French-Carhart Four-Factor Residuals	
	E-W	V-W	E-W	V-W
CAR(−10,-7)	−0.26%	−0.81%	−0.30%	−0.82%
	(−0.39)	(−1.22)	(−0.45)	(−1.23)
CAR(−6,-4)	0.08%	−0.65%	0.07%	−0.52%
	(0.15)	(−1.21)	(0.13)	(−0.97)
CAR(−3,-1)	0.93%*	0.28%	1.01%*	0.53%
	(1.65)	(0.51)	(1.78)	(0.95)
CAR(0,0)	3.49%***	2.69%***	3.55%***	2.95%***
	(7.99)	(6.25)	(8.08)	(6.82)
CAR(+1,+3)	4.02%***	2.44%***	4.27%***	3.50%***
	(5.70)	(3.49)	(5.98)	(4.91)

be the case that the increased market volatility around the election resulted in large movements for numerous stocks, and our sample of pharmaceutical stocks is correlated with that volatility. If that were true, then a similar result might be found in a random sample of stocks around the election. To alleviate these concerns, we perform a series of placebo tests, where we randomly draw a similar number of stocks from the population of stocks (excluding pharmaceutical firms) and then run the identical event study. Table 4 reports the results from these pseudo-event studies. Although we do see a similar pattern of negative value-weighted returns turning positive as the election nears, the majority of the coefficients are insignificantly different from zero. In fact, five of the eight coefficients for the −3 to −1 window are zero or negative and none of them is significant. This allays some of our concerns that the results are spurious and merely a statistical artefact of the increased volatility around the election.

To further examine whether investors of pharmaceutical stocks anticipated the election outcome, we estimate the following cross-sectional regression equation:

Table 4. This table reports equal weighted and value-weighted cumulative abnormal returns (CARs) for four random samples of 250 securities around the 2016 U.S. presidential election outcome on 9 November 2016. We estimate the market model for various event windows. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

2016 U.S. Presidential Election – Placebo Tests				
	Random Sample 1		*Random Sample 2*	
	E-W Market Model	V-W Market Model	E-W Market Model	V-W Market Model
CAR(−10,-7)	−0.04%	−1.25%***	0.30%	−0.79%***
	(−0.14)	(−4.10)	(1.18)	(−3.12)
CAR(−6,-4)	−0.07%	−1.01%***	0.40%	−0.44%
	(−0.22)	(−3.35)	(1.36)	(−1.55)
CAR(−3,-1)	0.30%	0.00%	−0.11%	−0.39%
	(1.17)	(0.02)	(−0.44)	(−1.50)
CAR(0,0)	−0.52%**	0.10%	0.00%	0.54%**
	(−2.07)	(0.38)	(−0.02)	(2.40)
CAR(+1,+3)	−1.16%**	0.97%**	0.12%	2.04%***
	(−2.54)	(2.12)	(0.27)	(4.45)
	Random Sample 3		*Random Sample 4*	
	E-W Market Model	V-W Market Model	E-W Market Model	V-W Market Model
CAR(−10,-7)	0.29%	−0.87%**	0.02%	−1.05%***
	(0.80)	(−2.41)	(0.08)	(−3.31)
CAR(−6,-4)	0.10%	−0.80%**	−0.19%	−1.01%***
	(0.33)	(−2.64)	(−0.53)	(−2.84)
CAR(−3,-1)	−0.02%	−0.30%	0.38%	0.07%
	(−0.05)	(−0.88)	(1.22)	(0.23)
CAR(0,0)	0.05%	0.64%**	−0.45%**	0.08%
	(0.16)	(2.05)	(−2.09)	(0.37)
CAR(+1,+3)	−0.42%	1.63%***	−0.18%	1.74%***
	(−0.99)	(3.81)	(−0.33)	(3.23)

$$\begin{aligned} Trump\ CAR(0,+3)_i = {} & \beta_1 Trump\ CAR(-3,-1)_i \\ & + \beta_2 Market\ Cap._i \\ & + \beta_3 Volume_i \\ & + \beta_4 Spread_i \\ & + \beta_5 Volatility_i + \alpha \\ & + \varepsilon_i, \end{aligned} \tag{1}$$

where the dependent variable is the cumulative abnormal return (CAR) for stock i during the t to $t+3$ event window around the 2016 U.S. presidential election outcome on November 9th.[5] The independent variable of interest is the CAR for stock i during the t-3 to t-1 pre-election window (Friday, Nov. 4th – Tuesday, Nov. 8th).[6] We include the following as control variables: *Market Cap.* is the closing price times the number of shares outstanding (in $ billions); *Volume* is the number of shares traded; *Spread* is the closing ask price minus the closing bid price, divided by the bid-ask midpoint, and *Volatility* is the log difference between the daily high and low prices. The control variables are measured at the daily level and then averaged over the three-day period preceding the election outcome.[7] Due to potential collinearity issues, we introduce the control variables independently into the regression model.

We estimate Equation (1) for the sample of 210 pharmaceutical stocks and report the regression coefficients in Table 5, with t-statistics in parentheses. In Panel A, we report cumulative returns that are adjusted using a value-weighted market index. In column [1], we find that the average CAR from day t-3 to t-1 is positively associated with the average CAR from day t to $t+3$. Specifically, the regression coefficient on the pre-election CAR variable is 0.2447, which is significant at the 0.01 level. In economic terms, a 1% increase in the average pre-election CAR is associated with a 24.47 basis point increase in the average post-election CAR. The results are similar after controlling for firm size, trading volume, bid-ask spreads, and volatility. For instance, in column [6] we find that a 1% increase in the average pre-election CAR is associated with a 21.69 basis point increase in the average post-election CAR, other things held constant. These results suggest that the positive run-up in pharmaceutical stock prices began prior to the election outcome.

In Panel B of Table 5, we report value-weighted CARs estimated from market model regressions. In the unconditional model specification in column [1], we find that a 1% increase in the average pre-election CAR is associated with a 17.59 basis point increase in the average post-election CAR, albeit the regression coefficient is only significant at the 0.10 level. We find similar results when controlling for firm size, trading volume, and bid-ask spreads. We note that the coefficient on the pre-election CAR is insignificant in the model specifications that include volatility as a control variable. While the market model returns are less significant, we continue to find a positive relation between pre-election CARs and post-election CARs in the sample of pharmaceutical stocks.

In unreported tests, we estimate Equation (1) for the placebo samples and find insignificant regression coefficients on the pre-election variable. The results from Table 5, and from the pseudo-event studies, seem to suggest that the pharmaceutical stocks began to rally prior to the election outcome. We believe that our results provide compelling evidence that some investors in the pharmaceutical industry anticipated the election outcome.

However, it could still be the case that the returns of the pharmaceutical stocks examined in our study are not the result of political changes or the election. To more fully understand what is driving our findings, we first examine CARs around a previous event initiated by the Clinton campaign. On 21 September 2015, Hillary Clinton tweeted the following, 'Price gouging like this in the specialty drug market is outrageous. Tomorrow I'll lay out a plan to take it on.'[8] As might be expected, pharmaceutical and biotech stocks experienced a significant negative market

[5]We have also performed cross-sectional regression analyses on longer post-event windows, such as t to $t+5$ and t to $t+10$, and we do not find that the pre-election CARs have predictive power over these longer time horizons. We believe that this provides further evidence of anticipatory trading rather than momentum trading.
[6]We have estimated Equation (1) using an equal-weighted market index and the results are qualitatively similar.
[7]We have log-transformed the control variables and the results are robust. We have also substituted share turnover for volume and the results are similar.
[8]See also CNN's article, Hillary Clinton's tweet crushes Biotech stocks, available at: http://money.cnn.com/2015/09/21/investing/hillary-clinton-biotech-price-gouging/index.html.

Table 5. This table reports the results from estimating the following cross-sectional regression equation on a sample of 210 drug companies:
$Trump\ CAR(0,+3)_i = \beta_1 Trump\ CAR(-3,-1)_i + \beta_2 Market\ Cap._i + \beta_3 Volume_i + \beta_4 Spread_i + \beta_5 Volatility_i + \alpha + \varepsilon_i$. The dependent variable is the cumulative abnormal return (CAR) from day *t* to *t*+ 3 around the U.S. presidential election outcome on November 9th, 2016. The independent variable of interest is the CAR in the three days preceding the election outcome (Nov. 4th, 2016 to Nov. 8th, 2016). Panel A reports value-weighted market adjusted CARs, while Panel B reports value-weighted market model CARs. *Market Cap*. is the closing price times the number of shares outstanding (in $ billions). *Volume* is defined as the average daily share volume. *Spread* equals the closing ask price minus the closing bid price, divided by the midpoint. *Volatility* is the log difference between the daily high and low prices. The control variables are calculated at the daily level and then averaged over the three-day period preceding the election outcome. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Panel A. V-W Market Adjusted						
Trump CAR(−3,-1)	0.2447**	0.2379**	0.2459**	0.2233**	0.2037**	0.2169**
	(2.48)	(2.42)	(2.46)	(2.26)	(2.06)	(2.17)
Market Cap. ($ billions)		−0.0004				−0.0004
		(−1.58)				(−1.26)
Volume			0.0000			0.0000
			(0.08)			(0.88)
Spread				−1.1886*		
				(−1.86)		
Volatility					0.5105**	0.4476**
					(2.43)	(2.04)
Constant	0.0819***	0.0855***	0.0817***	0.0934***	0.0486***	0.0525***
	(9.55)	(9.67)	(8.76)	(8.87)	(3.02)	(3.00)
R^2	0.0288	0.0403	0.0288	0.0447	0.0557	0.0634
Panel B. V-W Market Model						
Trump CAR(−3,-1)	0.1759*	0.1710*	0.1756*	0.1686*	0.1313	0.1456
	(1.77)	(1.72)	(1.74)	(1.70)	(1.32)	(1.44)
Market Cap. ($ billions)		−0.0004				−0.0003
		(−1.59)				(−1.16)
Volume			−0.0000			0.0000
			(−0.02)			(0.77)
Spread				−0.9459		
				(−1.50)		
Volatility					0.5563***	0.4976**
					(2.69)	(2.31)
Constant	0.0838***	0.0873***	0.0839***	0.0927***	0.0474***	0.0511***
	(9.96)	(10.07)	(9.16)	(9.03)	(2.99)	(2.97)
R^2	0.0148	0.0267	0.0148	0.0254	0.0481	0.0546

reaction. Table 6 reports raw returns and CARs for our sample of 210 pharmaceutical stocks around that tweet. We report CARs for windows ranging from the event day *t* to *t*+ 25 and find a sharp negative reaction to the tweet. One-day CARs range from a low of −2.37% for the equal-weighted market model in column [4], to −4.53% for raw returns in column [1]. Within a month, a portfolio of pharmaceutical stocks would have lost more than 10% of its market value, regardless of the benchmark and method of adjustment. Table 7 confirms the robustness of these results by examining CARs using three-factor and four-factor models – all of the CARs are negative and significant.

For completeness, we also perform placebo-like tests for the Clinton tweet and report the results from four random samples of 250 securities (excluding pharmaceutical firms). Table 8 details the results from the random samples around the Clinton tweet. While there are some event windows that the average CARs are significantly different from zero, half of them are positive (wrong sign) and there does not appear to be a discernible pattern associated with the CARs.

The next step in our analysis is to determine if there are any other factors that are driving the relation between the CARs of pharmaceutical stocks in our sample and the election. To do this, we estimate the following cross-sectional regression on pre-election CARs from day *t*-3 to *t*-1 for our sample of 210 pharmaceutical stocks:

Table 6. This table reports cumulative abnormal returns (CARs) for various event windows around Hillary Clinton's drug company tweet (price gouging) on 21 September 2015. We report unadjusted raw returns, equal-weighted and value-weighted adjusted returns, and market model returns. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

21 September 2015 Clinton Tweet – Standard Event Study Methods					
	Unadjusted Raw Returns	Equal-Weighted Adjusted Returns	Value-Weighted Adjusted Returns	Equal-Weighted Market Model	Value-Weighted Market Model
CAR(0,+1)	−4.53%***	−2.73%***	−3.50%***	−2.37%***	−3.63%***
	(−10.72)	(−6.46)	(−8.28)	(−5.58)	(−8.54)
CAR(0,+5)	−16.31%***	−9.64%***	−11.56%***	−8.15%***	−11.91%***
	(−20.89)	(−12.35)	(−14.81)	(−10.50)	(−15.17)
CAR(0,+10)	−12.89%***	−10.63%***	−13.66%***	−11.03%***	−14.60%***
	(−12.05)	(−9.94)	(−12.76)	(−9.97)	(−12.99)
CAR(0,+15)	−12.93%***	−13.25%***	−15.34%***	−14.95%***	−16.76%***
	(−11.85)	(−12.14)	(−14.06)	(−12.47)	(−13.82)
CAR(0,+20)	−11.13%***	−11.53%***	−14.08%***	−13.76%***	−15.94%***
	(−9.57)	(−9.92)	(−12.11)	(−10.71)	(−12.27)
CAR(0,+25)	−14.93%***	−14.76%***	−19.05%***	−17.31%***	−21.36%***
	(−10.87)	(−10.74)	(−13.86)	(−11.44)	(−13.90)

Table 7. This table reports both the Fama-French three-factor model and Fama-French-Carhart four-factor model cumulative abnormal returns (CARs) for various event windows around Hillary Clinton's drug company tweet (price gouging) on 21 September 2015. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

21 September 2015 Clinton Tweet – Multi-Factor Event Study Methods				
	Fama-French Three-Factor Residuals		Fama-French-Carhart Four-Factor Residuals	
	Equal-Weighted	Value-Weighted	Equal-Weighted	Value-Weighted
CAR(0,+1)	−0.72%***	−1.23%***	−0.94%**	−1.29%***
	(−1.70)	(−2.93)	(−2.19)	(−3.03)
CAR(0,+5)	−2.77%***	−4.64%***	−3.57%***	−4.87%***
	(−3.62)	(−6.14)	(−4.50)	(−6.17)
CAR(0,+10)	−4.13%***	−5.67%***	−4.19%***	−5.70%***
	(−3.82)	(−5.27)	(−3.90)	(−5.32)
CAR(0,+15)	−6.16%***	−6.68%***	−5.85%***	−6.60%***
	(−5.41)	(−5.87)	(−5.17)	(−5.85)
CAR(0,+20)	−5.07%***	−5.49%***	−5.02%***	−5.48%***
	(−3.99)	(−4.33)	(−3.96)	(−4.33)
CAR(0,+25)	−7.63%***	−8.57%***	−7.81%***	−8.61%***
	(−4.97)	(−5.61)	(−5.09)	(−5.64)

$$\begin{aligned} Trump\ CAR(-3,-1)_i = {} & \beta_1 Clinton\ CAR(0,+15)_i \\ & + \beta_2 Market\ Cap._i \\ & + \beta_3 Volume_i + \beta_4 Spread_i \\ & + \beta_5 Volatility_i + \alpha + \varepsilon_i, \end{aligned} \tag{2}$$

where the independent variable of interest, $Clinton\ CAR(0,+15)$, is the post-Clinton tweet CAR[9]; $Market\ Cap_i$ equals the stock's market capitalization or price times shares outstanding; $Volume_i$ is the average daily share volume; $Spread_i$ equals the difference between the closing bid and ask prices, divided by the spread mid-point; and $Volatility_i$ equals the log difference between the CRSP daily high and low prices. The control variables are measured at the daily level and then averaged over the three-day period preceding the election outcome.

We report the results from estimating Equation (2) in Table 9, with t-statistics in parentheses.[10] Panel A reports the results for cumulative returns adjusted using a value-weighted market index, while Panel B reports the results for value-weighted CARs from market model regressions. We find nearly identical results between the model specifications, so we focus our discussion on the market model CARs in Panel B.

Column [1] reports the results from a simple regression that only includes the CARs from the

[9]The results are similar when shorter and longer post-Clinton tweet CARs are used as the independent variable of interest.
[10]We estimate variance inflation factors (VIF) in the full model specification and find no evidence of multicollinearity.

Table 8. This table reports equal weighted and value-weighted cumulative abnormal returns (CARs) for four random samples of 250 securities around Hillary Clinton's drug company tweet (price gouging) on 21 September 2015. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

21 September 2015 Clinton Tweet – Placebo Tests				
	Random Sample 1		*Random Sample 2*	
	Equal-Weighted Market Model	Value-Weighted Market Model	Equal-Weighted Market Model	Value-Weighted Market Model
CAR(0,+1)	−0.17%	−1.02%***	0.01%	−0.73%***
	(−0.392)	(−2.433)	(0.023)	(−3.149)
CAR(0,+5)	−0.45%	−2.91%**	0.79%	−1.26%*
	(−0.346)	(−2.206)	(0.859)	(−1.374)
CAR(0,+10)	0.02%	−2.65%**	1.38%*	−0.94%
	(0.015)	(−2.203)	(1.540)	(−1.056)
CAR(0,+15)	−0.35%	−2.02%*	1.28%*	−0.01%
	(−0.256)	(−1.301)	(1.365)	(−0.007)
CAR(0,+20)	−0.33%	−2.39%	1.25%*	−0.28%
	(−0.184)	(−1.137)	(1.288)	(−0.291)
CAR(0,+25)	−0.35%	−3.81%*	1.00%	−1.81%**
	(−0.153)	(−1.516)	(0.946)	(−1.734)
	Random Sample 3		*Random Sample 4*	
	Equal-Weighted Market Model	Value-Weighted Market Model	Equal-Weighted Market Model	Value-Weighted Market Model
CAR(0,+1)	−0.20%	0.95%**	−0.06%	−0.82%***
	(−0.454)	(2.134)	(−0.221)	(−3.256)
CAR(0,+5)	0.15%	3.20%***	−0.45%	−2.60%***
	(0.217)	(4.597	(−0.763)	(−4.240)
CAR(0,+10)	0.00%	3.40%***	0.29%	−2.10%***
	(−0.001)	(4.831)	(0.408)	(−2.979)
CAR(0,+15)	−0.25%	2.61%***	0.43%	−0.87%
	(−0.299)	(3.144)	(0.508)	(−1.015)
CAR(0,+20)	0.04%	3.79%***	0.04%	−1.52%*
	(0.038)	(3.449	(0.038)	(−1.626)
CAR(0,+25)	−0.03%	2.48%**	0.18%	−2.68%***
	(−0.022)	(2.255	(0.169)	(−2.564)

Clinton tweet event study as an independent variable. We find a negative and significant relation between the negative returns of pharmaceutical stocks after the Clinton tweet and the three-day returns of those same companies prior to the election. In economic terms, a percentage point decrease in the Clinton CAR increases the pre-election CAR by approximately 9%. The results in Column [1] support the hypothesis that pharmaceutical company stock prices increased prior to the election in anticipation of a Trump victory and that the increase in prices is driven by those stocks that experience the most negative price decrease a year earlier in response to the Clinton 'price-gouging' tweet.

Column [2] of Table 9 reports the relation between election CARs and market capitalization and reports a coefficient that is not significantly different from zero. Columns [3] and [4] examine measures of liquidity. Illiquid stocks can see large price jumps when confronted with large orders, so making sure that our results are not driven by liquidity is important. Column [3] includes average daily share volume, which is negatively related to the election CARs but not economically meaningful. Column [4] includes the bid-ask spread of the stock, which appears negative but not significantly different from zero. Last, column [5] of Table 8 includes volatility as a control variable, measured as the log difference between daily high and low prices, and demonstrates that the more volatile the pharmaceutical stock, the more pronounced the event returns are in the pre-election period. After including the additional control variables, the CARs around the Clinton tweet remain significantly related to the returns prior to the election. Firms that had lower returns around the Clinton tweet experienced higher returns in the three days prior to the election outcome with a coefficient of −0.0931, which is both statistically significant and economically meaningful.

V. Concluding remarks

On the day before the 2016 U.S. presidential election, various political prediction markets provided the odds of Hillary Clinton winning the presidency above 90%. Surprisingly, Donald Trump

Table 9. This table reports the results from estimating the following cross-sectional regression equation on a sample of 210 drug companies:
$Trump\ CAR(-3,-1)_i = \beta_1 Clinton\ CAR(0,15)_i + \beta_2 Market\ Cap._i + \beta_3 Volume_i + \beta_4 Spread_i + \beta_5 Volatility_i + \alpha + \varepsilon_i$, The dependent variable is the cumulative abnormal return (CAR) in the three days leading up to the 2016 U.S. presidential election outcome on 9 November 2016. The independent variable of interest is the CAR in the 15 days following Hillary Clinton's drug company tweet (price gouging) on 21 September 2015. Panel A reports value-weighted market adjusted CARs, while Panel B reports value-weighted market model CARs. *Market Cap.* is the closing price times the number of shares outstanding (in $ billions). *Volume* is defined as the average daily share volume. *Spread* equals the closing ask price minus the closing bid price, divided by the midpoint. *Volatility* is the log difference between the daily high and low prices. The control variables are calculated at the daily level and then averaged over the three-day period preceding the election outcome. Test-statistics are reported in parentheses. *, **, *** denote significance at the 0.10, 0.05, and 0.01 level, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Panel A. V-W Market Adjusted						
Clinton CAR(0,+15)	−0.1040***	−0.1027***	−0.1047***	−0.1103***	−0.0826**	−0.0912**
	(−2.87)	(−2.80)	(−2.91)	(−3.05)	(−2.15)	(−2.38)
Market Cap. ($ billions)		−0.0000				0.0003
		(−0.24)				(1.24)
Volume			−0.0000**			−0.0000**
			(−2.22)			(−2.36)
Spread				−0.8748**		
				(−1.99)		
Volatility					0.2517	0.2487
					(1.65)	(1.59)
Constant	0.0062	0.0067	0.0110	0.0133	−0.0074	−0.0047
	(0.78)	(0.81)	(1.34)	(1.53)	(−0.65)	(−0.39)
R^2	0.0380	0.0383	0.0604	0.0562	0.0505	0.0757
Panel B. V-W Market Model						
Clinton CAR(0,+15)	−0.0987***	−0.0985***	−0.1011***	−0.0990***	−0.0821**	−0.0931***
	(−3.10)	(−3.06)	(−3.22)	(−3.11)	(−2.46)	(−2.80)
Market Cap. ($ billions)		−0.0000				0.0003
		(−0.04)				(1.59)
Volume			−0.0000**			−0.0000***
			(−2.45)			(−2.74)
Spread				−0.3242		
				(−0.75)		
Volatility					0.2303	0.2314
					(1.55)	(1.53)
Constant	0.0031	0.0032	0.0080	0.0060	−0.0096	−0.0075
	(0.40)	(0.39)	(1.01)	(0.70)	(−0.86)	(−0.63)
R^2	0.0443	0.0443	0.0712	0.0469	0.0553	0.0892

won the Electoral College handily. We examine whether or not the stock market provided any insight into the election outcome, ex-ante. Pharmaceutical firms became a focal point during the year prior to the election as Hillary Clinton began discussing policies to combat price gouging in that sector. We find that prices of pharmaceutical companies were quite prescient.

Our results show that the average cumulative abnormal returns (CARs) for 210 pharmaceutical stocks during the period t-10 to t-4 prior to election outcome, which was the day after the election (November 9th, 2016), are significantly negative and range from −2.49% to −6.15% depending on the event method and time horizon. However, when examining the three-day period from Friday, November 4th to Tuesday, November 8th, we find that average CARs become significantly positive and continue to increase in the few days following the election outcome. This increase is both statistically significant and economically meaningful, and robust to various event-study methods. Multivariate tests show that the positive pre-election CARs are driven by those stocks that experience the most negative price reaction to Hillary Clinton's initial tweet about her plan to combat pervasive price gouging within the pharmaceutical industry. Despite the lack of predictive ability in both the polls and prediction markets, our results seem to suggest that some sectors of the stock market anticipated the election outcome during the pre-election period.

Data availability statement

The data that support the findings of this study are publicly available from the Center for Research and Securities Prices

(CRSP). Restrictions apply to the availability of these data, which were used under license for this study.

Disclosure statement

No potential conflict of interest was reported by the authors.

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