Master Thesis Behavioural Economics

Event studies in the prediction market: the case of overreaction among bettors during the 2016 US Presidential Election.

This thesis explains whether overreaction among bettors causes persistent mispricing of the odds. It provides insight into how bettors perform in the prediction market. Additionally to existing literature, I apply the methodology of event studies on the prediction market of the 2016 US Presidential elections to detect overreaction using 18 different betting markets and 12 surprising events. I hypothesized that surprising news events lead to an overreaction among bettors and that good news is more sensitive to changes than bad news. I provide evidence that overreaction could occur among bettors in the prediction market and that it leads to mispricing. Moreover, there is not enough evidence that bettors are more sensitive to surprising good news. This study contributes to the application of event studies on the prediction market. This thesis concludes with betting recommendations for long-term and short-term bettors to overcome overreaction for the next US Presidential Elections.

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1. Introduction

Fama (1969) examined how market prices in the financial market are formed based on the Efficient Market Hypothesis (EMH). This theory mainly posits that the price of an asset reflects all available information. Thus, when new information emerges, the news arrives at the investors and is immediately incorporated into the prices. Therefore, under many assumptions, it is difficult to make any profit from any trading strategy. In other words, anomalies do not exist since they are arbitraged away. Fama performed empirical tests to measure the efficiency of three different types of markets; weak, semi-strong, and strong.

This prominent hypothesis in the field of finance is often disputed both empirically and theoretically. Talented investors such as Warren Buffet frequently beat the market, and researchers identified anomalies and behavioral biases where one could generate excess returns. While Fama looked at the financial market at a rational approach, Kahneman and Riepe (1998) considered the market from a behavioral perspective. Behavioral biases such as overconfidence, optimism, and overreaction to news distort the efficiency of the financial market. Huberman and Regev (2001) found that a perception of optimism among investors can cause an increase in trading volumes and stock prices in the biotech industry. Daniel and Hirshleifer (2015) explained that overconfidence is a distortion in the financial market. This phenomenon could cause investors to trade aggressively, hence increasing the trading volumes. Malmendier and Tate (2005) found that overconfident CEOs, who are prone to the better-than-average effect or optimism, are more likely to overestimate the returns of their investment decisions and their company's value. This behavioral bias may explain the financial crisis of 2008 (Duncan, 2009).

Numerous studies have been performed to examine the effect of behavioral psychology on how the market responds. As a result, some behavioral biases do explain the presence of market anomalies in the stock market. The field of behavioral finance describes why investors make specific investment decisions and how it affects the stock market in turn.

A similar but relatively new market is the prediction market. Here, contracts for the expected outcome of events are traded, and the market price may indicate the crowd's sentiment of the probability of an event. As the financial market, supply and demand set the market price; their principles are roughly the same. The prediction market, however, is less liquid and is less researched than the financial market. The main focus of this paper is how the prediction market responds to behavioral biases among betters. Like investors, betters have their expectations and beliefs on the fair value of the market price. This dispersion of expectations may lead to an erroneous price. Barberis, Shleifer, and Vishny (1998) stated that the drivers of the degree of expectations are conservatism and representativeness heuristic. Besides, these two characteristics determine whether these market participants underreact or overreact.

Overreaction is an extreme response to (unexpected) news events. Investors who are subject to such reactions cause the security to divert from its intrinsic value by either overbuying or overselling: sudden drops or rises in market prices after news events are implications of overreaction. A salient news article that could illustrate overreaction among betters on the US Presidential Election is a heart attack that Bernie Sanders had in October 2019. This event led to discussions on whether presidential candidates prone to health risks, such as elderly candidates, are suitable candidates for the White House. Sanders' health risk led to doubts about whether such a person can perform one of the most challenging jobs in the world (Ember, 2019). Voters' behavior can also match betters who sell their odd stakes as a blind reaction due to this recent news event. The analysis of PredictIt (2019) pointed out, shortly after the heart attack, that the likelihood of Bernie Sanders winning the Democratic Nominee race has been restored quickly.

The goal of this paper is to clarify whether market prices in the prediction market are prone to the overreaction bias that has already been widely studied in the financial markets. Market participants in the prediction market learn from this paper to interpret forecasts and the price mechanics more accurately by gaining insights into overreaction. Thus, the research question is formulated as follows:

To what extent does overreaction of surprising news events on the US Presidential Election cause mispricing of market prices in the prediction market?

The literature review below will first discuss the concept of the prediction market, including its efficiency and accuracy based on existing empirical research. The next chapter consists of the hypothesis development for answering the research question. The methodology section will discuss the empirics behind event studies, followed by a justification for selecting the event windows and matching data derived from PredictIt. The results section states the findings. In the discussion, the results are interpreted. The final section answers the research question, as well as the implications of this study.

2. Literature Review

2.1 Concept of the Prediction Market

Berg and Rietz (2003) defined the prediction market as "those run for the primary purpose of using the information contained in market values to make predictions about specific future events." The origins of the prediction market can be traced back to the 16th century in the Papal States, where one could bet who would become the new successor as the head of the papacy. In the 18th century Great Britain, public betting was so popular among the British population that the state of the odds was regarded as an accurate benchmark of public opinion. Now, betting on political events is more popular due to the presence of the internet, which makes betting more accessible. The first online prediction market, Iowa Electronic Markets (IEM), started during the 1988 US Presidential Election, solely for research purposes. This market is currently seen as a more accurate predictor of the outcomes of political events than traditional polls (Berg, Nelson, & Rietz, 2008).

A prediction market, such as the IEM, has different characteristics than polls (Berg et al., 2008). First, the market has a self-selected pool of traders who are interested in betting in politics. The polls, on the other hand, has a randomly selected representative sample. Further, polls equally weigh the opinion of each subject on a specific period and aggregate the whole sample in a final result. The market, however, contains more information about its subjects; the probability does not only depend on one's belief but also on one's self-confidence, risk-aversion, status-quo, and aggressiveness, derived from one's trading pattern. Last, the market is more dynamic than the traditional polls; traders receive relevant information and incorporate it into their updated belief, while polls are fixed snapshots.

The mean square prediction error for the IEM forecasting is smaller than poll forecasting (Kou & Sobel, 2004). Another article, published by Berg et al. (2008), showed that in every US election (from 1998 to 2004), the markets always outperformed the polls when forecasting 100 days in advance. The authors compared 964 different polls with the market predictions derived from IEM with varying groups of time sorted from short to long term. Their results showed that on both absolute and relative levels, the markets outperformed the polls. The performance of the markets is relatively more robust in the long run than in the short run.

2.1.1 PredictIt

The intuition behind the prediction market will be explained through the trading platform PredictIt. PredictIt is a prediction market launched in 2014 by the Victoria University of Wellington as a research project, whether it can predict outcomes of certain events more accurately than public polling. Six years later, Predictit had roughly 100.000 active traders by March 2020. Now, this trading platform is a prominent place to bet on US politics. The site has numerous markets not only on who will win the

US Presidential Election in 2020 but also on how many Tweets president Donald Trump publishes on Twitter in Week 16, 2020. Most of the markets present 'Yes' or 'No' questions: "Trump wins the popular vote in 2020?".

The participants can either buy 'Yes' or 'No' shares (binary options) or shares with more than two possible outcomes on each market, ranging from 1 to 99 dollar cents. Like the stock market, demand and supply determine the price. For example, betters forecast a probability of 78%, based on the trading volume of market shares, that Hilary Clinton will win the popular vote in 2016. A buyer who is confident that Hillary Clinton will win can buy this share, stating 'Yes,' costing 78 dollar cents. When this event occurs, the value of the share jumps to one dollar, thus making a profit of 22 dollar cents. Otherwise, a buyer who was confident that Hillary Clinton would not have won the popular vote could have bought this share for 22 dollar cents, stating 'No.' When Hillary Clinton would not have won the popular vote, the buyer would make a profit of 78 dollar cents per share.

Nevertheless, the value of the shares changes over time. A share worth 78 dollar cents could decrease to 50 dollar cents after Hillary performed poorly during a public debate. The 'Yes'-holder can then sell one’s share with a loss of 28 cents.

2.2 Empirical research in the prediction market

The Efficient Market Hypothesis of Fama (1970), where all prices reflect all available information, can be applied to the prediction market. In PredictIt, the law of supply and demand determines the price of a share. Therefore, the participants develop the price by incorporating their information into making an individual prediction. In the financial market, rational investors assess carefully whether the market price reflects the fundamental price of an asset. Rational betters in the prediction market then should ask themselves whether the price of a binary option truly demonstrates the probability of an outcome. The rational better can only match the probability with the price when the prediction market is efficient. This section defines the efficiency of the prediction market by existing literature and examples, followed by empirical evidence on the accuracy of the prediction market.

2.2.1 Efficient prediction market

Two factors define an efficient market (Snowberg, Wolfers & Zitzewitz, 2012). First, the price incorporates all information (stated in the EMH), and second, there are no trading strategies possible to generate risk-adjusted excess returns. When new information appears, the advantage of having that information will be directly eliminated.

Prediction markets can include new information rapidly. The prediction market, whether Osama Bin Laden will be captured by 31 December 2011, of Intrade is an excellent example of how quickly such a market incorporates information. A staff member of the Defense Ministry published on 11 May 2011, at 10:25 pm that he is told that Osama Bin Laden has been killed (Hudson, 2011). Within 25 minutes, the probability of that event rose from 7% to 99%. Eight minutes later, the first articles from mainstream media were published about this event.

Cao (2013) stated that a necessary condition for an efficient prediction market is the absence of arbitrage opportunities. For instance, when the probability of an election victory of a candidate rises, then the probability of winning for the other candidate, in turn, must decline in the same magnitude. Arbitrage traders find mispricing opportunities when it appears and bid the prices either up or down until this mispricing is removed. On how quick mispricing is eliminated hangs on four limitations: bad-model risk, fundamental risk, noise trader risk, and transaction costs (Lamont & Thaler, 2003). Not only those four limitations, but also the trader's characteristics affect the persistence of mispricing. The perception of one's risk, preferences on trading commodities, budget constraints, and rationality play a role. Cao (2013) found that the prediction market is less exposed to arbitrage than the financial market. An important distinguishing characteristic is that the prediction market not only has human traders as a counterparty but also the market maker. It functions as a stabilator of the price mechanism by taking losses and facilitating more liquidity by requiring the trader to deposit. Lastly, the financial market is more prone to persistent mispricing since commodities are not wholly identical in contrast to the prediction market that trades in identical shares across contracts.

What a prediction market further distincts from financial markets is that the prediction market has an end-date where the price of a contract ends with either 0 dollar cents and 100 dollar cents. The further away from the end date, the more uncertain what the exact outcome will be. Silver (2020), the founder of FiveThirtyEight, an opinion poll analysis, mentions that three months before the election day is still a long way. Uncertainty lies, for example, how economic factors (jobs, government spending, and manufacturing) develop over time and how the Presidential Nominees will perform during their campaign. Take the elections of Dukakis 1998, Bush 2000, and Kerry 2004; their probabilities in August of winning the popular vote had a positive lead of 5.6, 10, and 2.5 percentage points, respectively. The results of the election showed that none of them won the popular vote.

2.2.2 Accurate prediction market

Snowberg et al. (2012) list three features that enhance the ability for prediction markets to generate accurate forecasts. Often, traditional polling forecasts lack at least one of these factors. A combination of three makes the forecasting superior. First, the market is a collection of information; each better has its expectation on the outcome of an event that aggregates the heterogeneous belief. This feature is complementary with the 'Wisdom of the crowds' theory written by James Surowiecki (2004), where he implies that a group of individuals know more than one individual. Second, each better has an extrinsic motivation to predict the right outcome; that is, receiving a payoff after having correctly forecasted the result. Therefore, it provides an incentive to perform extensive research to predict as accurately as possible. Incentives test predictors on how strongly one believes in its view; to challenge one to put one's money where one's mouth is. Contrera (2016) wrote about the growing popularity of the prediction market during the 2016 US Presidential Election. What strikes from the interviews she conducted is that the majority assessed multiple polls and keeping itself informed about the candidate's strategies, rather than betting on one's favorite longshot. People tend to separate their views from their wagers. Third, it enables long-term incentives to specialize in finding new information and trading on it. When betters perform well, they win the game and may continue playing. The ones who do not will lose money and may drop out of the market. This pattern functions as a vehicle in making the prediction market more accurate (Oliven & Rietz, 2004).

These three characteristics define, in theory, the prediction markets such as PredictIt and the IEM as a trustworthy and reliable means of predicting the outcome. A general limitation of the prediction market is that it is often assumed that traders possess a standard information set (Kou & Sobel, 2004). Assumptions as these do not display an impeccable description of participating traders. To justify the theory of the prediction market, an exposure and elaboration on the descriptive behavior of the market participants are necessary. This subsection will further discuss existing empirical research that not only tested but also disputed the accuracy of the prediction market by including multiple (behavioral) factors that could influence the accuracy.

Although numerous studies have found that prediction markets are accurate, it does not mean that it is, by definition, a stylized fact. To start, Jacobsen et al. (2000) and Brüggelambert (2004) showed evidence that the prediction market failed to predict the outcomes of the Dutch and German National Elections, respectively. Figure 10 (Appendix A) shows the previous prediction of PredictIt's US Presidential Election 2016 market. On the day before the outcome, PredictIt estimated the probability of Donald Trump to win by 22%. After the unofficial election result, Donald Trump made an increase of 76 percentage points.

A prediction market, such as PredictIt, assumes that the current price of an event is equal to the current probability of that event happening. Wolfers & Zitzewitz (2012) studied whether market prices correspond with the subjective beliefs about the likelihood of an outcome. They created a model so that the market prices equal the aggregate belief. They assumed that there is heterogeneity in beliefs among traders, that traders are price-takers to maximize its subjective probability, and that one's belief and wealth are uncorrelated. When these assumptions hold, the mean belief is equal to the market price. After relaxing the assumptions, the price diverges. The concluding remark of this paper is that the efficacy of the forecast can be undermined when prices are close to 0 or 100%, traders' beliefs are divergent, numerous degrees of risk aversion are present, and trading volumes are constrained. Those factors can drive the market price away from the actual probability.

Gjerstad (2005) studied how to close the gap between the market price and the mean belief that an event will occur, focusing on the risk-attitude. To better understand the relationship between the market price and the traders' characteristics, he included risk aversion as a determinant. He assumed that every trader has a CRRA utility function, i.e., the higher the income, the lower the absolute risk aversion. A market, including risk-averse agents, has a market price relatively close to the mean belief of the participants, compared with risk-seeking people. They, on the other hand, react on average more aggressive when prices change predominantly from their belief. Those who are most confident in his prediction have the most significant effect on the change in prices. This results that the prices for the favorite shots move towards one and zero for longshots. In the mean-time, the price diverges from the mean beliefs.

Boulou-Reshef, Comeig, Donze & Weiss (2016) created a framed field experiment to measure the effect of the participant's risk-attitude on prediction market prices. After a risk-attitude test, the participants were divided into two groups: risk-averse and less risk-averse. In an artificial market, both groups were allowed to bet on the outcome of a basketball game in 2015. They found that the price set by the risk-averse participants were, on average, significantly lower than the less risk-averse participants. In other words, a risk-averse participant in this experiment was willing to pay less for the assets. This result implies that a pool of risk-averse traders may undervalue the market price.

2.2.3 Behavioral implication prediction market

The theory that a prediction market is efficient seems highly disputable (Grossman & Stiglitz, 1980); information is costly, and prices do not reflect the available information. The ones who spent time and effort to receive information will receive no net compensation. Therefore, there is no incentive for traders to trade. Moreover, according to Forsythe, Rietz, and Ross (1999), the pool of traders within a prediction market is a self-selected group that does not reflect the representativeness of the population. Besides that, traders are prone to the belief of other traders, which affects, in turn, their own belief.

There are two critical anomalies; first, false consensus effect, meaning that an individual perceives its opinion as a common opinion in the general population. Second, the cognitive dissonance theory states that when there is an inconsistency in one's behavior and attitude, people strive to reduce this dissonance by adapting their behavior. These two anomalies lead to wishful thinking bias, which could impact the market price of a tradeable event. This bias can cause an increase in prices, correlated with the beliefs of traders who like to make it happen. People who personally support the Democratic Party tend to be overly optimistic about the success of their preferred party leading to invest more in that party (Oliven & Rietz, 2004). Similar to that bias is the so-called longshot bias (Thaler & Ziemba, 1988), where betters often overvalue and undervalue longshots and favorites, respectively. The occurrence to ignore information that is contraceptive to one's belief, confirmation bias, leads market prices to be biased in the movie-box-office prediction market.

Even though Cao (2013) stated that the prediction market is less prone to arbitrage mispricing than the financial market, Rietz (2005) showed the limitation that arbitrageurs are not fully able to drive out the mispricing unless they have sufficient resources and are to an extend competitively. Furthermore, arbitrageurs increase the total volume and volatility while decreasing the relative price efficiency.

2.3 The concept of overreaction and underreaction

Several studies have empirically tested over and underreaction in the financial market. A prominent paper is the study of De Bondt & Thaler (1985). They tried to find evidence to contest the EMH. On the New York Stock Exchange, both authors separated the securities by the 35 best performing and 35 worst-performing stocks. Over five years, they measured the performance of all stocks, and according to the EMH, both portfolios would perform equally well. They found, however, that the worst-performing stocks consistently beat the market while the best-performing stocks underperformed. In short, the winners became losers and vice versa. Investors who hold loser stocks reacted to bad news by selling their stock, driving the price down. Over time, investors realized they overreacted, and those stock prices jumped to its fundamental value. Investors who hold the winner stocks understood they were too excited in the beginning. An explanation is the Availability Heuristic; most people weigh heavily on their decisions against the most recent information, neglecting important information from the past.

Brooks et al. (2003) examined the effect of 21 surprising news events (such as a Factory plant explosion or unexpected death of a CEO) on stock prices. They found that unexpected events impact prices. The initial reaction among investors took place within 20 minutes and reversed in 2 hours.

Barberis et al. (1998) present in their model how investors' expectations are formed through conservatism and the representativeness heuristic. These heuristics describe that investors underreact or overreact to news, creating a not fully incorporated stock price, causing an inefficient market. Conservatism states that the processing of new information for investors is slow to the adaptation of his beliefs. They also might ignore the full information content since they expect that this is a temporary shock of which the effect reverts. Subsequently, their expectations on the value of a share are partially adjusted after a new event. Conservative beliefs may lead to an underreaction to new relevant information. The representativeness heuristic means that there is a tendency to perceive patterns in random sequences. Even though a company's valuation is continuously growing, it does not infer that this company will maintain the same pattern. Investors might perceive that past growth is representative of future growth. This heuristic is the fuel of overreaction.

Another determinant of overreaction could be 'surprise.' For humans, it is an update in belief to unexpected events that contradict its own belief (Meyer, Reisenzein, & Schutzwohl, 1997). Maguire, Maguire, and Keane (2011) stated that when a surprising event occurs, people bridge the gap between the observed and expected outcome, modeled in a sense-making process. Thus, when the higher the degree of surprise, the bigger the contrast between the observed and expected, resulting in more adaptive behavior. Tversky and Griffin (1997) created a framework to explain conservatism and the representativeness heuristic, where people adjust their expectations on the saliency and credibility of news. So, conservative-minded people focus on average more on credibility than saliency; they are unimpressed and react merely to the new situation. Also, 'surprise' can be incorporated in their model; the representativeness heuristic states that people outweigh the saliency of an event more than its credibility. Therefore, 'surprise' is consistent with this heuristic.

These behavioral biases are relevant in the prediction market since bettors continuously need to adjust their views based on news or new events. New beliefs are measured by the formula below, constructed by Choi and Hui (2014). This formula is suitable to analyze when comparing it with a contract from the prediction market.

$$New\ belief = w_1 * Prior\ belief + w_2 * New\ Information.$$

Conservatism implies underreaction to unsurprising news (Barberis et al. (1998). The weight on one's prior belief is higher than on new information. When translating the Availability Heuristic in this formula, the weight of new information surpasses prior belief. The magnitude of w2 is a function of credibility and strength.

3. Hypotheses

This section elaborates on the hypotheses. The key hypotheses state how conservatism and the representativeness heuristic are the drivers of under-and overreaction to new events in the prediction market.

The framework of Tversky and Griffin (1997) includes the representativeness heuristic. This heuristic causes people to overweigh the strength of news rather than the credibility. An unexpected event where people need to adjust their own beliefs could cause a significant adaptive behavior to narrow the expected and observed outcomes. This state of mind may trigger overreaction among bettors in the prediction market.

Hypothesis 1: Surprising news leads to an overreaction of bettors.

Optimism, confirmation bias, and the favorite longshot bias are anomalies in the betting market that cause mispricing. These anomalies solidify the beliefs of bettors. This paper tests whether surprising good news attracts more reaction than bad news.

Hypothesis 2: Surprising good news is more sensitive to changes in odds than surprising bad news.

4. Methodology

Event studies in the field of finance is a tool to describe the effect of an economic event on the value of firms. The underlying idea is that the effects of an event will be immediately incorporated into security prices. The event study methodology includes three critical assumptions set by Siegel and McWilliams (1997).

First, that markets are efficient, second that events are perceived to be unexpected, and third that the event has no confounding factors. The first assumption is related to the EMH, where information is quickly incorporated into the stock price. An event is the appearance of new relevant information. An event study finds events that could impact the stock price.

The second assumption is that only events reveal new relevant information. It is crucial to keep in mind that bettors could have prior knowledge from a news event due to leakages. This phenomenon makes it then difficult for researchers to know when market participants exactly received this information.

The third assumption is the most critical assumption that there must be no confounding effects from other events. Any other event occurring around the studied event might impact the share price and thus makes it difficult to gain an understanding of the effect of an event.

4.1 Steps to conduct an event study

4.1.1 Set Event and Estimation Window

An important consideration regarding the accuracy of event studies is the length of an event window. Researchers must be careful in assessing the optimal range; the longer the event window, the more plausible that the estimations of the full effect include other unrelated events. Snowberg, Wolfers, and Zitzewitz (2011) stated that prediction markets are not prone to this problem. These markets display an accurate estimation of the probability. Therefore, unrelated events do not correlate with changes in the price of a bet in the prediction market.

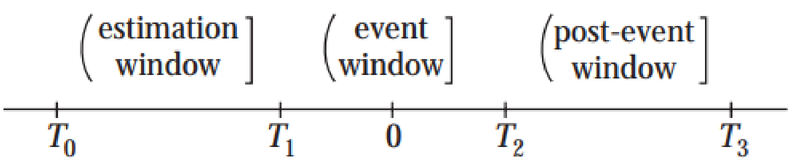

Figure 1 Overview of different event study windows

Figure 1 shows the event timeline in MacKinlay's methodology. The date of the publication of a news event as τ=0, or day 0. As seen in the figure above, the event window is the interval between T1 and T2. T1 – T0 depicts the estimation window and is used as a comparison to the event window to find any significant changes. One rule set by MacKinlay is that both windows must not overlap in order to ensure that the event does not influence the returns during the estimation period. A day between the estimation and event window can be left out to prevent this problem.

A shorter event window reduces the likelihood of confounding effects. These effects could be problematic for the analysis of the 2016 US presidential election. Any event occurring within the event window could have an impact on the contract price, which makes it difficult to claim for controlling confounding effects. There is existing empirical literature that proved that short event windows incorporate the effect of an event. A study by Dann, Mayers, and Raab (1977) showed that the market price of an asset updates within 15 minutes after the release of firm-relevant information. Hudson (2011), as written in the literature review, pointed out that the Osama Bin Laden contract was updated within 25 minutes after an informal death-announcement on Twitter.

However, PredictIt's dataset is a time-series model that measures the value of a contract per day. Even though the information is incorporated quickly, it is impossible to set an event window in minutes. I use time intervals on days. An empirical study such as Holler's (2012) suggests that short-term event studies' event windows typically range between 1 and 11 days, where day 0 centers within the window. Oler, Harrison, and Allen (2007) found that in 62 event-study papers from Management Journals, 76.3 percent of those include 0 to 5 days. This paper applies four different event windows t=[-2,2], t=[-1,1], t=[-1,0], t=[0,1], where t=[-1,0] presents the main result.

Existing empirical financial literature tries to find the optimal range of an estimation window. There is a tradeoff in selecting the optimal range between the availability of confounding effects and its accuracy. The longer the range, the more risk the model includes confounding effects, but the shorter the range, the less accurate the expected returns. Armitage (1995) and the CIBIF (2018) mention that the optimal range is 100 days, and is between 90 and 200 days. Silver, however, (2020) warns that the longer the estimation window, thus more further away from the expiration date, the more likely the expected returns include confounding effects and uncertainty.

Therefore, this paper uses two different estimation windows. The main window has a range of 100 days, as proposed by CIBIF (2018), and the other has a range of just ten days to check whether the estimations cancel out confounding effects and uncertainty.

Politico, a newspaper, published a list of events during the 2016 US Presidential Election that Politico perceived as surprising. This paper uses only these events mentioned by Politico since this platform is rated as 'least biased' according to Media Bias Fact Check, a website. It is a difficult question to define the degree of 'surprise' for each news event since every media source has its perception of surprisingness. For example, the leaked private interview of Donald Trump, stating that he can have sex with any woman since he is a star, sparked astonishment on CNN, a left-leaning news site, titling its article: *How the shocking hot mic tape of Trump was exposed* (Stelter, 2016). Whereas Fox News, a right-leaning news site, titled its article: *The left freaks out over Trump's tape but loves culturally lewd behavior* (MacDonald, 2016). The 'least biased' news site of Politico has a neutral view on events happening around the 2016 Election; they cover both sides to the story. Both sources use emotionally loaded words such as 'shocking' and 'freaks out.' This paper assumes that a 'least biased' news site reports' surprisingness' as the most accurate and the least emotionally loaded. Therefore, I use only news events published by Politico.

Table 4, Appendix B displays an overview of Politico's surprising news events during the 2016 Election.

To double-check Politico's claim that these news events are surprising, a simple search test on Google News will be conducted on whether media sources already predicted that one of these events were going to happen. Systematically, for each event, a maximum of five relatable keywords are used to generate search results for articles from the past to the day before the event. When the first three pages of Google do not mention any information related to an event, this paper confirms that it is surprising. The results of this assessment are in Table 5, Appendix B. Two surprising events, stated by Politico, were expected in other news sources. Therefore, this paper does not discuss events two and seven.

4.1.2 Choose an expected/normal return model

MacKinlay (1997) made a distinction between two types of models in the event study literature. First, the constant mean return model depicts only the nominal returns and does not associate with other market stocks. The Market model measures both nominal returns and the returns of other market stocks. In financial literature, it is common to apply the market model to measure expected returns in the event window to correct index movements during the news event. For event studies in the prediction market, it is more common to apply the constant mean return model. Slamka, Soukhoroukova, and Spann (2008) stated that prediction markets have a winner-takes-all scheme, implying that all stock prices amount to a predetermined sum, a zero-sum game. A 'Yes' stock and a 'No' stock in PredictIt is negatively correlated. Therefore, it is not possible to link such a market to an indexed market.

This paper will apply the steps of the constant mean return model denoted in the paper of MacKinlay (1997). The Constant Mean Return Model is

$$R_{it} = \mu_i + \zeta_{it}$$

where R_{it} is the period-t return on market contract i, μ_i the mean return of asset i, and ζ_{it} is the time-period disturbance term for market contract i. This model assumes that the average return of a given contract is constant over time.

4.1.3 Calculate Expected/ Normal and Abnormal Returns

When quantifying the effect of a surprising news event on the return of a bet, the abnormal return must be measured. The abnormal return is the difference between the actual return of an asset and the expected return. The expected return in the event studies literature is defined as the return had the event not been occurred. The following formula illustrates the abnormal returns (AR) with τ depicted as the event date.

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_{\tau})$$

Where $R_{i\tau}$ is the actual return of market i on day τ and $E(R_{i\tau}|X_{\tau})$ the estimated expected return of market i on day τ. The latter parameter is calculated using the Constant Mean Return Model of 100 days.

To gain insight into the effect of surprising news events, all abnormal returns from the studied events within a market are accumulated across time, the Cumulative Abnormal Return (CAR). The CAR is the sum of abnormal returns from all days within the event window. The CAR is defined as:

$$CAR_i[\tau_1, \tau_2] = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}$$

With multiple events and multiple markets, it is interesting to determine whether the reaction of surprising news events differs across the different markets. The Cumulative Average Abnormal Return (CAAR) measures the average effect of an event on the prediction market, where N is the number of contracts. For interpreting the results of the Patell test, this paper categorizes all markets (besides Woman) into four categories: Democratic (Democratic party, Clinton), Republican (Republican party, Trump), Landslide, and the Swing States.

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i[\tau_1, \tau_2]$$

Lastly, this paper assumes that each contract's abnormal returns are normally distributed. Therefore, to analyze whether CAAR is equal to zero, a Patell Z test will be performed. This test assumes cross-sectional independence and standard normal distribution. The Patell test calculates the significance of the CAAR per event, meaning that all three categories (Election, Swing States, Landslide) from event 6 to 12 are aggregated. The Election category splits into two groups: Democratic and Republican groups. Then it tests whether the CAAR is significant for each category separately.

To summarize, this paper performs 10 event studies on 18 different markets around ten different dates prior to Election night on 8 November 2016. Two different estimation windows of 10 and 100 days are applied for the Constant Mean Return Model, and four different event windows (t=[-2,2], t=[-1,1], t=[-1,0], t=[0,1]).

4.2 T-test good news vs. bad news

Finally, a t-test measures whether surprising good news events are more sensitive to changes than surprising bad news events. The CARs of each event are in either the good news column or in the bad news column. Each column includes a mean, and I test whether the mean of good news CARs is higher than the mean of bad news CARs.

5. Data

This paper examines 18 markets published by PredictIt that were all related to the 2016 Presidential Election. There are multiple markets since PredictIt signed a no-action letter to eliminate the risk of being accused of illegal online gambling. As a result, each market has a cap of 5,000 active traders with a limitation of 850 USD per investor per market. To let as much as betters participate in forecasting the outcome of the Election, PredictIt added markets similar to the main market: "Who will win the 2016 US Presidential Election?". Some markets include: "Will a woman be elected US President in 2016" or "Which party will win the 2016 US Presidential Election?" The latter is a non-binary market. The selected markets are directly related to the 2016 Election and thus exposed to the surprising news events listed above.

Each market provides five values of each contract each day: Open, Low, High, Close, and Volume. This paper will use the 'Close' values as units of measurement. There are four categories between the different markets; these are Nomination, US Presidential Election, 370 Majority, and the Swing States. The nomination market is an early-phase market of the 2016 election, where both parties are required to select its Nominee for the Presidential Election. Those markets ended when the Republican and Democratic conventions in July 2016 formally nominated both candidates. From that period, the betting continued on all other markets until November 2016.

Another group of markets is the Swing States Markets. Swing States are states where either a Democrat or a Republican nominee could win the most votes. Florida, for example, was Republican favored in 2016, but Democratic favored in 2012 and 2008. Contrary to safe states, those are the states that were either Republican or Democratic favored for at least the consecutive past five elections. Mahtesian (2016) has identified 11 swing states with equal chances to vote either Democratic or Republican. Those were Colorado, Florida, Iowa, Michigan, Minnesota, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, and Virginia. These markets also include a binary question of whether which party will win the 2016 US Presidential Election (Democratic or Republican).

The final group is the 370 majority. Two markets ask whether either the Republican or Democratic party will win at least 370 electoral college votes. What this category distincts from the other three is that this occurrence may not happen. Therefore, the probabilities of both parties winning the vast majority do not usually add up to 100 percent. For example, the probability of the Democratic and Republican party was on 23 October 2016 31 and 10 percent, respectively.

Table 6 (Appendix B) summarizes all 18 markets.

6. Results

This section comprises three categories. First, descriptive evidence will present visual information on the effect of surprising news events on the odds. Then, the econometric output of the CAR regressions accurately describes the effect. Finally, robustness checks will determine whether the main results are different after changing the lengths of both event and estimation windows.

To estimate the effect of surprising news events on the odds for the Presidential Election, the CARs of 10 surprising events for 18 markets are estimated. The main results are calculated by applying a 100-day estimation window and an [-1,0] event window. All CARs of the Swing States markets need to be derived from the Democratic Party perspective. The odds for the Democratic Party and the Republican Party are perfectly negatively correlated. A negative CAR for a Swing State is disadvantageous for the odds of the Democratic Party but beneficial for the Republican party.

Table 1 below shows the CARs of the Nomination Market, whereas Table 2 shows all CARs of the Election Markets. The latter table has four groups (Democratic, Republican, Landslide, and the Swing States), and each of them has a CAAR Patell that accumulates the abnormal average return. In all tables, the asterixis of ***, **, * mean a significance of one, five, and ten percent, respectively. I consider CAARs when it is at least five percent significant.

For the discussion of each event, there is a short description of the event, followed by describing trends in the graphs, then the CA(A)Rs.

6.1 Main Results

Below, Tables 1 and 2 display the main results. Table 3 the results of the t-test. The robustness results are in Appendix C.

Table 1 Cumulative Abnormal Returns of Nomination Market. Event window [-1,0], Estimation window 100 days

Nomination Markets CAR [-1,0]				
	Events			
Contracts	**Event 1**	**Event 3**	**Event 4**	**Event 5**
Clinton	-	-	-3.35%	-
			(0.422)	
Kasich	54.14%	-46.70%	-	44.52%
	(0.241)	(0.488)		(0.261)
Rubio	-11.82%	0.21%	-	-
	(0.100)	(0.9877)		
Sanders	-	-	41.19%***	-
			(0.006)	
Trump	22.32***	-1.49%	-	5.76%
	(0.005)	(0.903)		(0.617)

Table 2 Cumulative Abnormal Returns of Election Markets. Event window [-1,0], Estimation window 100 days

	Election Markets CAR [-1,0]				
	Events				
Contracts	**Event 6**	**Event 8**	**Event 9**	**Event 10/11**	**Event 12**
Woman	1.36%	0.98%	-7.42%***	10.71%***	-5.58%
	(0.796)	(0.747)	(0.001)	(0.002)	(0.111)
Clinton	-1.71%	6.75%**	-10.10%***	10.78%***	-9.12%**
	(0.565)	(0.022)	(0.000)	(0.001)	(0.011)
Democratic	3.10%	3.99%*	-5.85%***	12.07%***	-7.85%**
	(0.262)	(0.091)	(0.001)	(0.000)	(0.020)
CAAR Patell	0.70%	5.37%***	-7.97%***	11.42%***	-8.48%***
	(0.670)	(0.005)	(0.000)	(0.000)	(0.001)
Republican	-3.20%	-2.67%	9.91%**	-25.08%***	22.65%***
	(0.543)	(0.655)	(0.021)	(0.000)	(0.008)
Trump	-1.31%	-5.83%	9.88%**	-37.86%***	36.92%***
	(0.864)	(0.353)	(0.027)	(0.000)	(0.000)
CAAR Patell	-2.25%	-4.25%	9.89%***	-31.47%***	29.78%***
	(0.582)	(0.331)	(0.002)	(0.000)	(0.000)
370 Democrat	15.01%	17.22%	-8.00%	60.69%***	-34.11%**
	(0.137)	(0.116)	(0.298)	(0.000)	(0.040)
370 Republican	7.46%	-16.54%	40.14%***	-11.69%	22.81%
	(0.549)	(0.273)	(0.000)	(0.468)	(0.219)
CAAR Patell	11.24%	0.34%	16.07%*	24.50%***	-5.65%
	(0.140)	(0.737)	(0.057)	(0.007)	(0.560)
Colorado	3.57%	-2.83%	-1.47%	8.54%**	-7.21%*
	(0.466)	(0.477)	(0.599)	(0.034)	(0.064)
Florida	1.26%	-0.34%	-3.34%	16.12%***	-6.76%
	(0.793)	(0.944)	(0.310)	(0.003)	(0.242)
Iowa	-1.50%	-3.80%	5.68%*	45.19%***	-7.95%
	(0.740)	(0.394)	(0.074)	(0.000)	(0.499)
Michigan	0.96%	-1.36%	1.07%	8.06%**	-3.55%
	(0.802)	(0.664)	(0.650)	(0.023)	(0.328)
Minnesota	3.89%**	0.10%	1.19%	3.39%	-3.52%
	(0.017)	(0.961)	(0.425)	(0.110)	(0.180)
Nevada	1.12%	-3.29%	-9.31%***	14.83%***	-8.36%
	(0.774)	(0.447)	(0.003)	(0.008)	(0.169)
New Hampshire	0.06%	2.11%	-4.17%	5.80%	-10.07%**
	(0.990)	(0.624)	(0.176)	(0.222)	(0.037)
North Carolina	-2.24%	3.22%	-3.88%	23.07%***	-0.32%
	(0.735)	(0.590)	(0.366)	(0.001)	(0.964)
Ohio	1.33%	1.42%	-0.08%	38.09%***	-14.24%*
	(0.781)	(0.748)	(0.979)	(0.000)	(0.087)
Pennsylvania	-2.98%	-3.14%	-4.15%*	5.73%	-7.44%*
	(0.368)	(0.346)	(0.083)	(0.135)	(0.062)
Virginia	1.16%	-0.48%	-5.03%***	4.29%	-3.78%
	(0.815)	(0.864)	(0.009)	(0.151)	(0.223)
CAAR Patell	0.60%	-0.76%	-2.13%**	15.74%***	-6.65%***
	(0.380)	(0.443)	(0.015)	(0.000)	(0.000)

Table 3 Absolute CA(A)Rs of all events

Event	Absolute CA(A)Rs Good	Bad
Event 1	*Trump* 22.32%***	*Rubio* 11.82%
Event 3	*Trump* 1.49%	*Rubio* 0.21%
Event 4	*Sanders* 41.19%***	*Clinton* 3.35%
Event 6	*Democratic* 0.70%	*Republican* 2.25%
Event 8	*Republican* 4.25%	*Democratic* 5.37%***
Event 9	*Republican* 9.89%	*Democratic* 7.97%
Event 10/11	*Democratic* 11.42%***	*Republican* 31.47%***
Event 12	*Republican* 29.78%***	*Democratic* 8.48%***
Mean	15.13	8.865
Ha: diff > 0	0.1662	

6.1.1 Discussion by events

Event 1 – 6 February

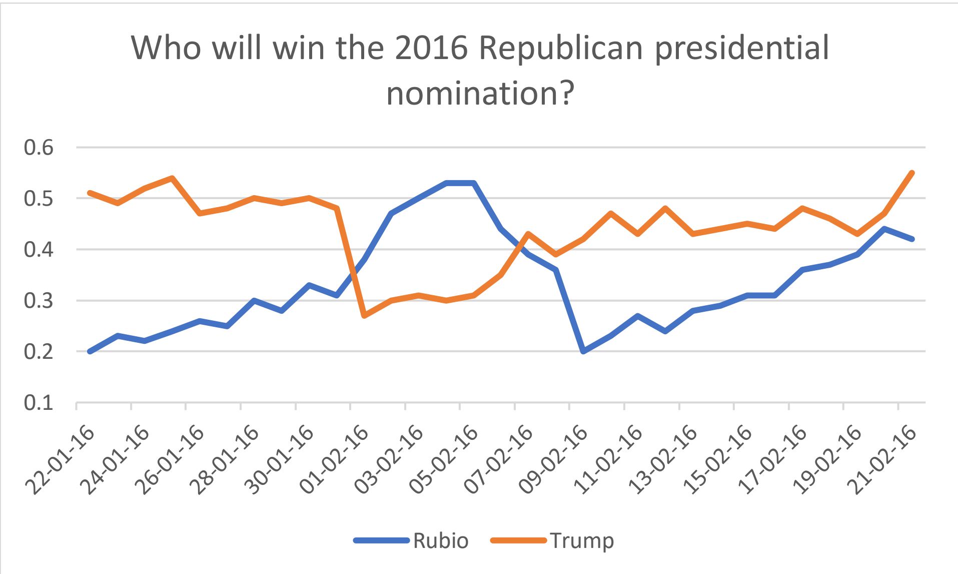

Figure 2 Odds of Rubio and Trump around Event 1

Rubio had for some days an increasing momentum during the Republican nomination race, until Christie, another Republican candidate, mocked Rubio for being a robot during a debate. This event led to a decrease of nine percentage points the following day. Trump, Christie, and Kasich gained increased confidence from betters by closing with an increase of 4, 2, and 2 percentage points, respectively.

When looking at the results, there is no effect on Rubio's odds; bettors did not lose confidence in him. However, only Trump gained significantly more confidence (22.32%) in winning the nomination, while the odds for Kasich remained unchanged.

Event 3 – 26 February

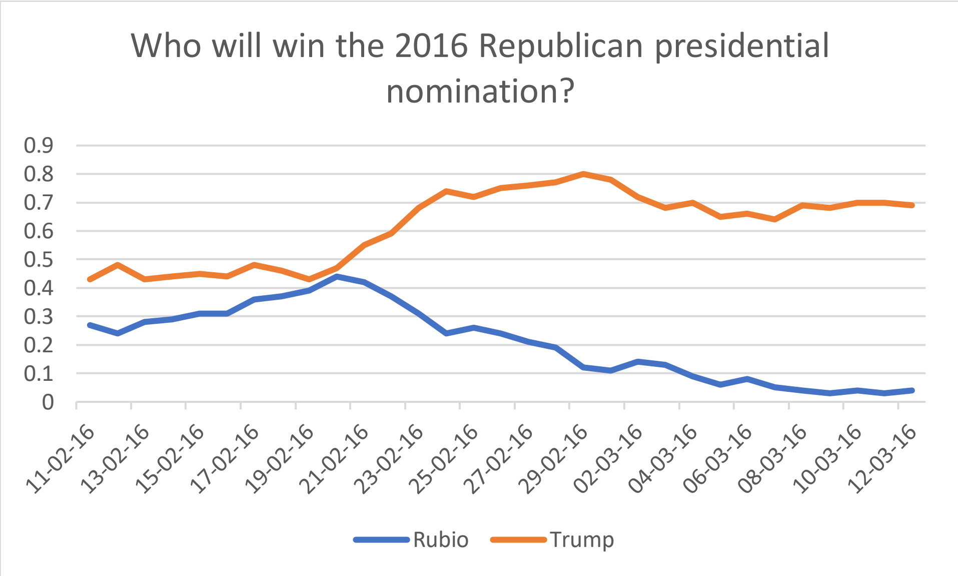

Figure 3 Odds of Rubio and Trump around Event 3

Chris Christie was once a fierce rival of Trump during the Republican Nomination race but unexpectedly endorsed Trump's nomination to combat against Clinton. Trump's odds increased on that day by three percentage points on winning the Republican nomination. Rubio's decreased by 2; however, he already had a decreasing momentum.

The endorsement, however, did not cause a significant change of odds by bettors for Trump winning the nomination. Besides, there was no reaction to Kasich and Rubio.

Event 4 – 8 March

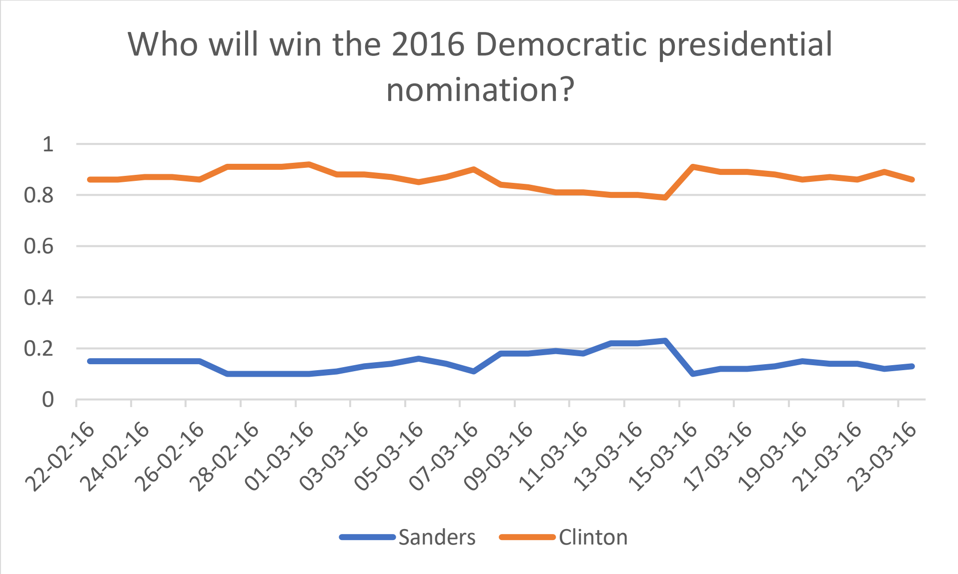

Figure 4 Odds of Sanders and Clinton around Event 4

On the day that Bernie Sanders had won the Michigan primaries, confidence in Clinton decreased by six percentage points, and Sanders increased by seven percentage points.

Polls suggested that Clinton will win Michigan on the Democratic Primaries. This state, however, actually narrowly favored Sanders. His victory in this state led to a significant increase (41.19%) in his odds of winning the nomination. Bettors did not feel anything on Clinton's odds.

Event 5 – 3 May

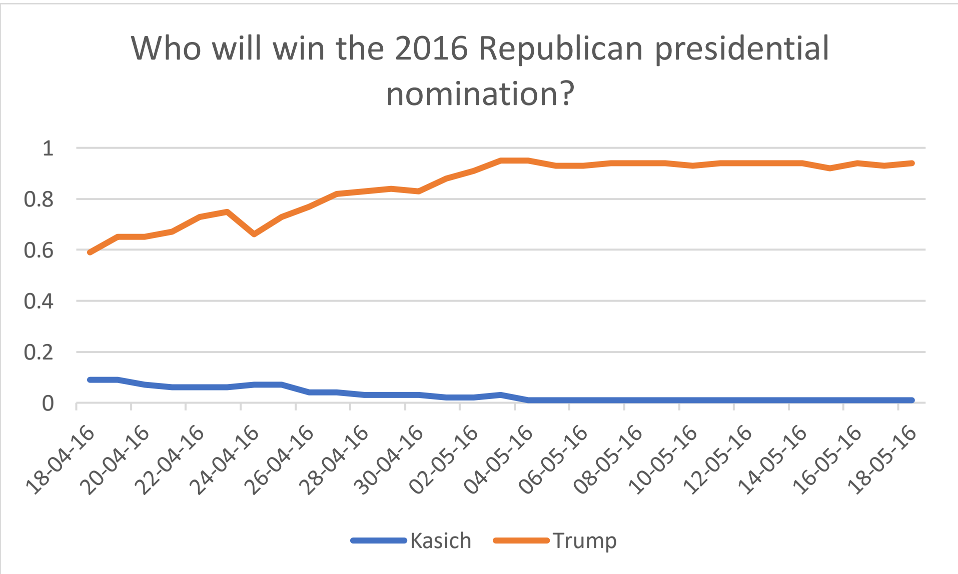

Figure 5 Odds of Kasich and Trump around Event 5

Ted Cruz dropped out of the Republican nomination race, which led to a four percentage point increase in odds for Trump and a one percentage point increase for Kasich. A day later, Kasich dropped out of the race, and Trump remained the last Republican nominee for the presidential race.

Trump drove Cruz out of the race after crushing Cruz in Indiana. Only Kasich and Trump remained for the nomination, but both did not enjoy increased confidence by bettors.

Event 6 – 20 July

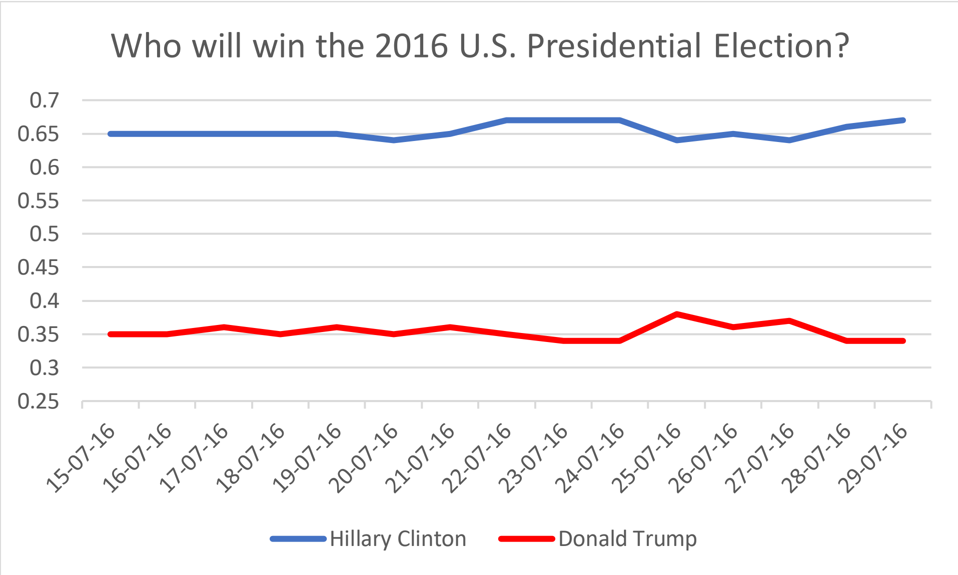

Figure 6 Odds of Clinton and Trump around Event 6

When Ted Cruz refused to endorse Trump's nomination, Politico (2016) stated that this action led to a division within the Republican party. When translating this event to the odds of Donald Trump and the Republican party, there was only a one percentage point decrease on that day. This event, however, did not translate in an increase to the odds of Clinton; her odds fell by one percentage point as well. The sentiment of betters in the Swing States remained somewhat unchanged, except for Florida, where betters obtained more confidence (+3) for the Democratic party to win.

On the day that Cruz refused to endorse Trump for his nomination, it signaled that the Republican Party is divided (Politico, 2016). However, when calculating the CAR of all 18 markets, it seems there was no effect among all markets. No market, except Minnesota, displayed a significant change (3.89%) in odds. The average effect for all markets of this event is, according to the Patell Test, not different from zero. This event caused a little effect on the prediction market

Event 8 – 9 September

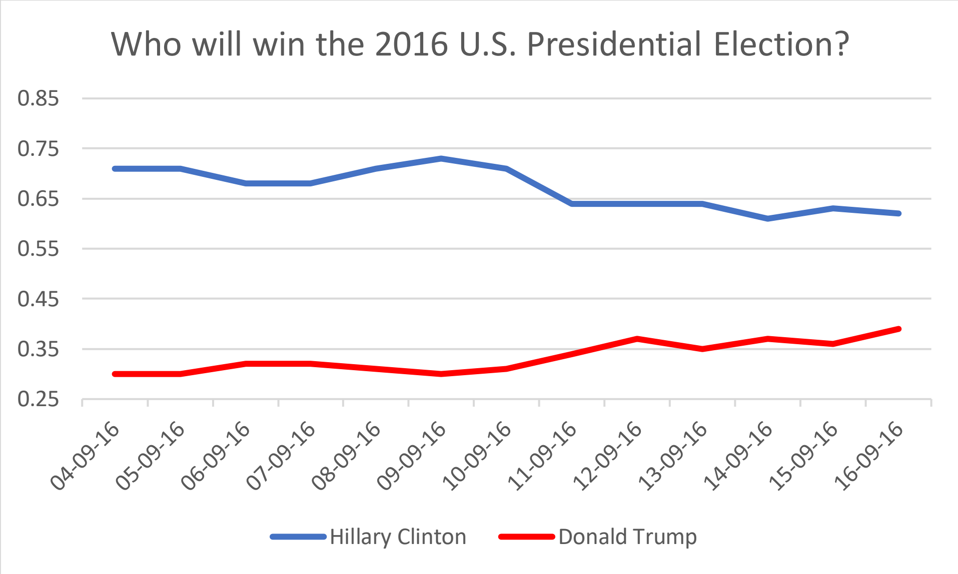

Figure 7 Odds of Clinton and Trump around Event 8

On 9 September, Hillary Clinton generalized Trump's supporters as 'deplorables.' The closing odds of Hillary Clinton, compared to the day before, increased by two percentage points, whereas Trump's odds decreased by one percentage point. The sentiment of traders in the party market remained unchanged. Michigan experienced an increase of 4 percentage points after this event occurred.

The confidence of bettors for Clinton significantly increased (6.75%), whereas confidence for the Democratic party remained unchanged. The Patell test displays an increase of confidence for the Democratic Group (5.37%). However, the statement of Clinton did not affect the sentiment among bettors for the Republican, 370, and Swing States groups. To summarize, there is a light effect of this event on the prediction market.

Event 9 – 11 September

However, on the day (9/11) that Clinton's collapsed due to overheating, there was a steep decrease of 8, 4, and 5 percentage points for Clinton's Democrat's and Woman's contracts, respectively. Some swing states experienced a drop in odds, but with a lower magnitude than Clinton's contract. This trader skepticism did not translate to increased confidence in Donald Trump, who only gained three percentage points.

Results showed that bettors sparked more reaction to these markets than the 'deplorables' event two days ago. For both Woman, Clinton, and Democratic, the CARs of the odds were significantly negative by at least -5.85 percent during this event window. Confidence in Trump, the Republican party, and its likelihood to win at least 370 electoral votes, in turn, increased significantly with a CAR of at least 9.88

percent. A negative CAAR of the Democrat group indicates that the collapse of Clinton had a substantial negative effect on the odds of the Democratic group and a positive CAAR a positive effect on the Republican group. Among the swing states, only Nevada and Virginia showed significant changes in the sentiment of bettors with negative CARs. Overall, the CAAR of all Swing States for the Democratic party was significantly negative, indicating that skepticism grew among betters for the Democratic party to win the Swing States. The collapse of Clinton was disadvantageous in odds for the Democrats but beneficial for the Republican party.

Event 10/11 – 7 October

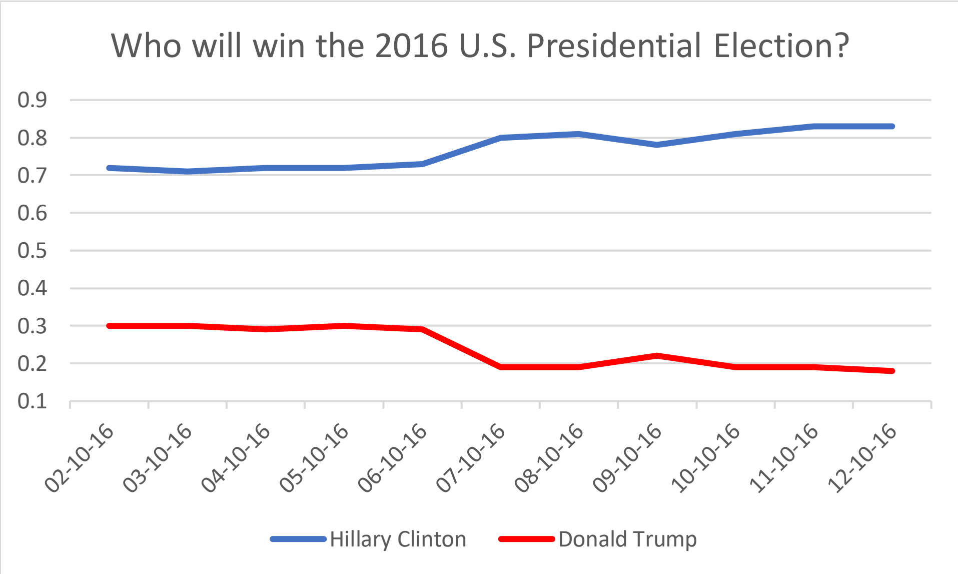

Figure 8 Odds of Clinton and Trump around Event 10/11

The day that Clinton's speeches and Trump's private interview were leaked caused more skepticism towards Trump than Clinton. Confidence in Clinton increased by seven percentage points, while Trump's confidence decreased by ten percentage points. The values of both contracts remained unchanged for two weeks after the event. Confidence in the democratic party increased dramatically in most swing states such as Ohio (+19), Florida (+10), Iowa(+20), and North Carolina (+11). It seemed that Trump's interview overshadowed the effect of Clinton's speeches.

The two events that Trump's private interview and Clinton's emails were leaked caused an overall positive sentiment towards the Democratic Group (11.42%) and a negative to the Republican Group (-31.47%). Here, the bad news for Trump provoked more reaction than the good news for Clinton. This result indicates that the odds of the Republican group were significantly worse off than the Democratic group due to the leaked emails and the interview. There was no additional skepticism that the Republican party wins at least 370 electoral votes, but there was more confidence for the Democratic party (60.69%). 7 out of 11 Swing States experienced a significant increase in odds for the Democratic party winning its state. These two events caused the odds of the Democrats to rise on average. Again, the interview of Trump sparked more unrest than the emails of Clinton. Therefore, this day brought the Democrats to rise in odds and the Republicans to fall.

Event 12 – 28 October

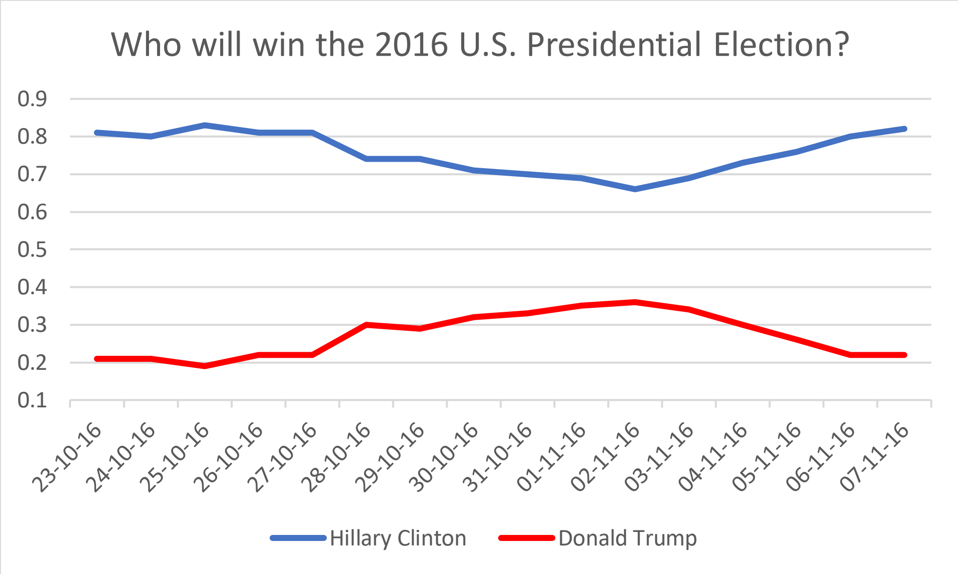

Figure 9 Odds of Clinton and Trump around Event 12

On the day that James Comey announced that he continues his FBI investigation of Hillary's emails, traders lost confidence in her by seven percentage points, whereas Donald Trump gained confidence by eight percentage points. What strikes from this graph is that, after the event, Clinton experienced a continuous loss of confidence until 2 November and gained momentum back to the pre-event value one day before Election Day. The Democrat and Woman market experienced the same trends. Trump and the Republican party had the opposite effect.

The general sentiment of traders in Swing States markets for the Democratic party was negative. All markets experienced a loss in odds, while most states gained a positive momentum as well afterward.

On that day, betters of the Democratic Group lost confidence in this party winning the election with a CAAR of -8.48%. At the same time, bettors gained significantly more confidence in the Republican party with a CAAR of +29.78%. It seems that, regarding these magnitudes of both CAARs, bad news for Clinton sparked less reaction on her odds, but the good news for Trump sparked more reaction to his odds. James Comey's announcement led to an increased skepticism on the odds for the Democratic Party winning the Swing States (-6.65%) and winning at least 370 electoral votes (-34.11%).

6.1.2 Asymmetric reaction

Table 3 compares the CA(A)Rs between surprising good and bad news events. Events 1, 3, and 4 display the CAR values of each candidate, whereas events 6, 8, 9, 10, 11, and 12 the CAAR values of either the Republican or Democratic group. This table omits Event 5 since the withdrawal of Cruz is good news for the remaining Republican candidate. What strikes from the table is that the mean of good news CARs is higher than the bad news CARs. The t-test, however, shows that this positive difference is not significantly different from zero.

6.2 Robustness checks

Some extra analysis makes it possible to check the robustness of the main results: First, the addition of three event windows, from which the length of two windows is extended. Second, the estimation window of 100 days is compressed to just ten days to see whether this test eliminates uncertainty from the preceding period during the election. Each window elaborates first on the Nomination events, then on the Election events.

6.2.1 Different Event Windows

[-2,2]

Only event five remained unchanged, whereas the other Nomination events experienced equivocal changes in significance. The odds of Rubio during event one and three became significant, meaning that bettors here lost their confidence. Referring to Figure 2, Rubio's odds experienced a momentous decline after his debate; this could explain why his odds became significant after adding two days post-event. Sanders enjoyed a significant increase in his odds when referring to the main results, but became insignificant because his odds remained constant right after winning the Michigan primaries. The results between the main and the extended event window show ambiguous differences. (Table 7, Appendix C)

Among all 22 changes in significance, most markets switched to an insignificant effect of surprising news events on the odds. For example, when expanding the event window to three more days, it switched to an insignificant change in odds for both the Republican Party and Donald Trump after Trump's private interview was leaked. However, the aggregate effect of the Republican Group during this event remained unchanged. Most significances of the CAARs did not change; only the Democratic Group and Swing States group became insignificant for events 8 and 9, respectively. (Table 8, Appendix C)

[-1,1]

Adding one day after the Event window did not lead to many changes in significance. Only when Christie mocked Rubio (event 1), it did not benefit the odds of Trump. (Table 9, Appendix C)

The election markets showed a few ambiguous changes in significance. It is striking that all CAARs have the same significance. Adding a post-event day to the main event window does not alter the results significantly. (Table 10, Appendix C)

[0,1]

This event window examines whether the changes in odds persist one day after the event. The results from this event window are similar to the [-1,1] window. (Table 11, Appendix C)

Some markets became insignificant by shifting this event window one day forward. Compared with the main results, this event window shows similar estimations. In the Swing States, Democratic and Republican Groups, the effects of events 10, 11, and 12 maintained its momentum. The change in odds for those groups during event 9 ceased after one day. (Table 12, Appendix C)

6.2.2 Different Estimation Windows

This section compares the results between a ten-day and a 100-day estimation window.

The 'Nomination' events do not display any changes in odds for all candidates during events 1 to 5 compared with the main results. Only Kasich's odds experienced a significant increase on the day that Trump trampled Cruz. Sanders' confidence still significantly increased after winning the Michigan primaries. (Table 13, Appendix C)

The shortened length of the estimation window showed ambiguous changes in the significances of all different markets during the election period. Among all markets and events, thirteen alterations occurred on significance, excluding the CAARs. Considering the latter, the change in odds for the Republican Group after Clinton's 'deplorables' statement became significantly negative. The aggregate confidence in the Democratic party winning all Swing States became unchanged after Clinton collapsed. The significance of all CAARs for both Democratic and Republican Group did not change. Shortening the estimation window does not alter the results significantly for both the nomination and election period. (Table 14, Appendix C)

7. Discussion

7.1 Answering Hypotheses

Hypothesis 1: Surprising news leads to an overreaction of bettors.

Since it is difficult to quantify the degree of surprisingness, this paper assumed that all events classified as surprising by Politico are equally surprising. In hindsight, it may be attractive to perceive Clinton's collapse as more surprising than Sanders winning the Michigan primaries. The results mention that four out of ten events sparked none to a meager reaction among bettors. There was no reaction in three events that were related to the Republican party; when Christie endorsed Trump, Cruz dropped from the race and refused to endorse Trump led to no reaction. For the Democratic party, Clinton's deplorables statement sparked no reaction. The remaining events sparked a significant reaction to the confidence in both parties. Here, there is a pattern that bad news leads to negative CARs and good news to positive CARs. Also, the results confirm that bad news for one party is inversely good news for the other, as can be seen from the Democratic and Republican CAARs from events 9 to 12 in Table 2. The majority of the events from this paper triggered significant changes in odds; still, some events sparked no reaction. **These observations provide some support for the hypothesis that surprising news leads to an overreaction of bettors.**

Hypothesis 2: Surprising good news is more sensitive to changes in odds than surprising bad news.

It is hypothesized that bettors tend to stick with their own beliefs and react more heavily on benefitting news for a party. The results showed that the mean of the good news CA(A)Rs is not significantly higher than the bad news CA(A)Rs. **Therefore, there is not enough proof that surprising good news is more sensitive to changes in odds than surprising bad news.**

7.2 Implications

This paper has found evidence that overreaction occurs in PredictIt's prediction market, which means that odds alter towards another direction rather than its initial price movement. For bettors, there is a risk of buying overvalued contracts after the odds rose due to surprising good news. The same applies to selling undervalued contracts. There are recommendations for two types of bettors: short-term bettors and long-term bettors. Short-term bettors continuously buy and sell contracts before the election ends. Long-term bettors place a bet and wait until the expiration date.

The former group of bettors should keep in mind that overreaction occurs in the prediction market and that their returns depend on the sentiment of other bettors. A surprising news event could cause contracts to divert from its fundamental probability. This paper did not study; however, the price reversal of contracts to its fundamental value. When considering the study of De Bondt and Thaler (1985), there is an occurrence that worst-performing stocks consistently beaten the market, whereas best-performing stocks performed poorly. Knowing this fact, bettors should adopt a strategy to sell recent winners and buy recent losers. Nevertheless, one needs to consider that price reversals within the prediction market have not been studied yet.

The latter group should assess the severity of consequences of each surprising news event to the real probability of winning the US election by asking themselves: does this make a difference? People tend to update their beliefs on the availability bias, thus underweighting information from the past. Clinton blamed Comey's action as the main reason for her defeat, but Ball (2016) mentioned underlying reasons why Clinton lost. It might be true that bettors were more hesitant to vote for Clinton after Comey's announcement, but the main reason was Clinton's weak campaign. Her focus was mainly on suburbian swing states voters and neglected other groups such as millennials and African Americans because she assumed they would show up for her since they are afraid for Trump (a sign of overconfidence). Clinton is also punished for her focus on social issues rather than economic developments. She discussed redistributing wealth by taxing the rich and creating welfare benefits but did not develop any plans to create jobs for the working class; her America was already great (Schneider, 2016). Long term bettors should assess the strengths, weaknesses, opportunities, and threats of each candidate's campaign and the current economic indicators to make an as accurate as possible prediction. Bettors should then find out whether surprising news events occurred could have been expected based on the SWOT-analysis on the candidates. When having assessed Clinton as an overconfident candidate, her remark about Trump supporters as 'deplorables' should not be surprising enough to update one's belief. Alternatively, Comey's announcement, in combination with Clinton's weak campaign, could be a reason to worry.

7.3 Limitations

One significant limitation to take into account is that 'surprise' is difficult to measure. Therefore, this paper cannot rank each event on its surprisingness. Everyone has its perception of the surprisingness of an event. For the doctor of Hillary Clinton, it might not have been a surprise that she collapsed during the 9/11 memorial ceremony. It is certainly possible to measure the aggregate degree of surprisingness among the general population. Here one could rank or score each event on how one perceives the surprisingness of an event. However, the hindsight bias might be an obstacle since recipients might be overconfident in their prediction abilities.

PredictIt does not provide hourly data, so it is impossible to assess the sentiment of bettors on the exact moment the event occurred. Bettors are very responsive to surprising news events, where they translate their updated beliefs to their bets. It could be the case that only in three hours, that bettors overreacted to a news event, realized the bets are undervalued/overvalued, and adjusted their beliefs again. Using only closing values each day might neglect the overreaction effect. When having a more detailed dataset, overreaction might be more present. This paper stumbled upon the problem that Clinton's leaked emails and Trump's leaked interview happened on the same day. Hourly data might have separated the effects of these events.

This paper assumed that Politico is a neutral leaning news-website based on the Media Bias Fact Check. However, this platform is an amateuristic attempt to review news sources on its media bias based on an assessment of biased wording and headlines. This website does not apply a scientific method to rate news sources (Funke, 2019). Like surprise, the definition of neutral is hard to define.

The third assumption that there must be no confounding effects is the hardest to maintain. Around the listed events, there could have been other unidentified events that affected the sentiment of bettors. For example, when Rubio refused to endorse Trump, only the odds for the Democratic party winning the State Minnesota significantly increased (20 July 2016). But during that day, in Philando Castile, an unarmed African American man was lethally shot by a police officer during a traffic check (Smith, 2017). This incident sparked public outrage, which led to demonstrations in Minnesota. It could have been the case that this event affected the odds of the Democratic party. Therefore, confounding events such as these make it difficult for this paper to hold this assumption.

The external validity might not be accurate since this paper only examined the behavior of bettors of PredictIt. Another available prediction market is the Iowa Electronic Market (IEM) that has the same concept as PredictIt.

7.4 Further Research

There is limited research on event studies applied in the betting market. This paper applied MacKinlay's financial markets methodology on the betting platform of PredictIt in 2016. Results showed that overreaction among bettors during the 2016 election occurred, proving that it is possible to apply event studies on the prediction market, new doors open for further research.

A limitation of this paper was that the only possibility of measuring the effect of an event relied on the Constant Mean Return Model. The Fama-French model is impossible to apply for such prediction markets. Unlike the financial market, PredictIt's prediction market is not backed by an indexed market. It does not include a benchmark where betters can inform themselves whether they have beaten the market. A market model does not work.

Nevertheless, there are dozens of daily-updated polls on the average attitude of American Voters. Websites like the Economist, FiveThirtyEight, and RealClearPolitics (RCP) have models that predict the outcome of the winner of the Presidential Election. RCP averages daily polls into the 'RCP Average' (RCPA) with values ranging from 0 to 100.

To illustrate, one takes the RCPA as a benchmark for the contract prices. For example, when the RCPA mentions that there is a 70 percent chance that Hillary Clinton wins (70 as the fair price), while PredictIt a 60 percent chance, then the current price of 60 dollars represents a 10 dollar discount to the intrinsic value—using polls as a benchmark opens the possibility to calculate the returns based on the Market Model. When controlling for the market return (polls), the event effect could be measured more accurately.

Polls such as the RCPA, however, are not always right; the RCPA on election day showed a spread of Clinton – Trump by +2.1. In reality, Trump won the election. In 2016, most polls favored Clinton's odds in winning the election, and that is because of three reasons, according to Pew Research Center, a think-tank (Mercer, 2016). First, nonresponsive bias; lots of Trump supporters were demographically hard for pollsters to reach. Second, 'shy Trumpers'; this idea suggests that voting for Trump was socially undesirable and therefore refused to admit their support. Third, pollsters identified likely voters by making the wrong assumptions. Even minor adjustments in assumptions can lead to sizeable differences in the predictions. Thus it is essential to assess the accuracy of polls before using it as a benchmark.

In November 2020, PredictIt provides researchers with data from the markets of the 2020 elections. To run-up to the recent election, there have been surprising news events in September and October 2020, such as Trump mocking fallen soldiers (Goldberg, 2020), its contamination of the coronavirus (Walker, 2020), or the death of Supreme Court Judge Ruth Bader Ginsburg (Asthana, 2020). Therefore, a suggestion is to compare the 2016 election to the 2020 election, whether 2020 bettors are less susceptible to overreaction than in 2016. One could test this hypothesis based on the article of Oliven and Rietz (2004), where well-performing bettors tend to continue to play, whereas bad-performing bettors tend to drop out.

8. Conclusion

This research aimed to find the occurrence of overreaction in prediction markets. Based on qualitative and quantitative analysis of the effectiveness and efficiency of the prediction market, it can be concluded that overreaction does occur in prediction markets and that it causes mispricing of the contracts. The results indicate that surprising news events, both bad and good news, could equally spark overreaction among betters. This paper applied the methodology of the financial market to the prediction market, leading to clear results, but since the application is new, it might be questionable to the methodology's effectiveness. Based on these conclusions, bettors should be aware that overreaction causes mispricing and should incorporate this information into their trading strategy. It is further essential to assess the surprisingness of each event to underlying factors that determine the outcome to overcome overreaction. To better understand the implications of these results, future studies could focus more on the applicability of event studies in the prediction market by experimenting with polls or using more prediction platforms. The main contribution of this paper is that bettors are prone to overreaction, and it has been proven that surprising news events trigger the updating of one's beliefs significantly.

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Appendices

Appendix A

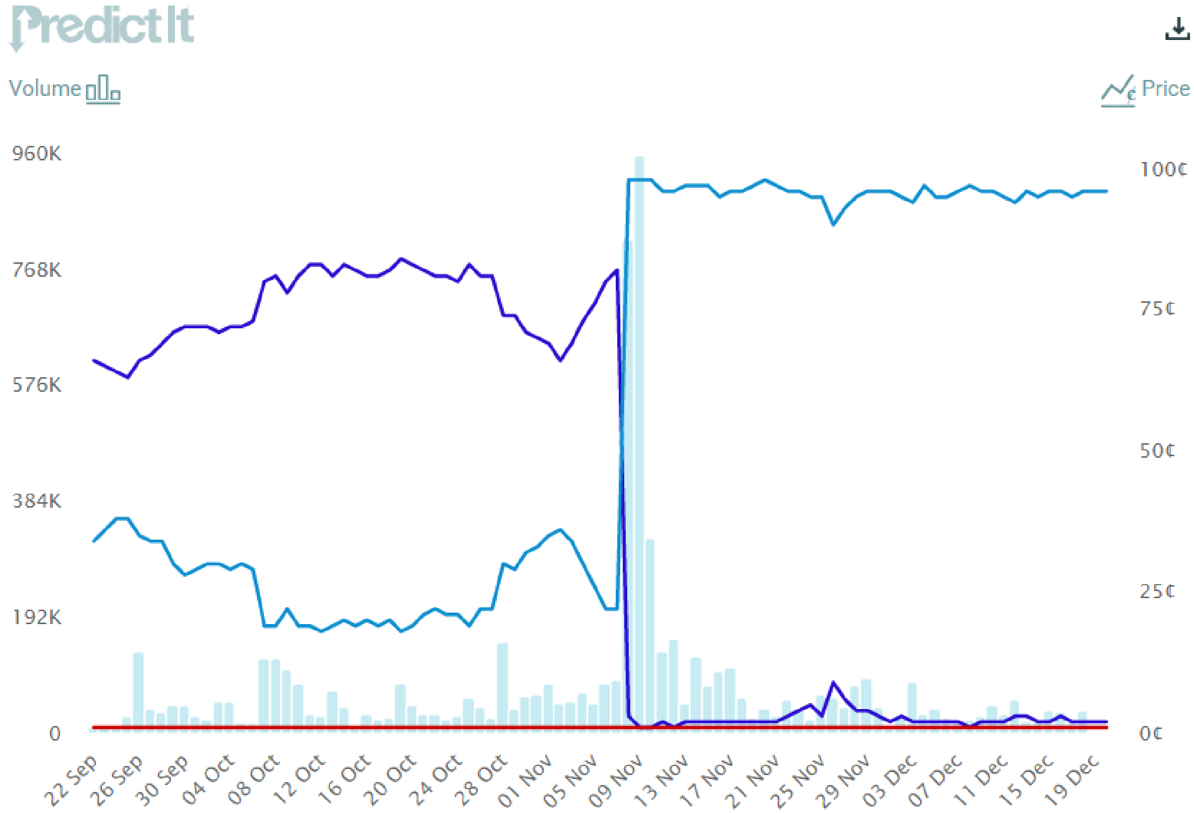

Figure 10 Prediction US Presidential Election. Where the dark blue line represents the probability of Hillary Clinton to win and the light blue line Donald Trump

Appendix B

Table 4 Description of twelve events

	Twelve Events		
Event	**Date**	**Description**	**Market**
1	06-Feb-16	Marco Rubio mocked by Republican Candidate Chris Christie during the GOP debate as being a robot. Leading to a reversal in his momentum	Republican Nominee
2	09-Feb-16	Sanders had a decisive win over Hilary Clinton in New Hampshire, leading to questions whether Hilary Clinton had enough appeal to female and young voters.	Democratic Nominee
3	26-Feb-16	Former Republican and fiercely rival candidate Chris Christie endorsed Donald Trump in his election. Surprisingly, Donald Trump stated earlier that he does not seek endorsements.	Republican Nominee
4	08-Mar-16	Hilary Clinton was expected to win in the rust belt states, but Sanders narrowly defeated Clinton.	Democratic Nominee
5	03-May-16	Ted Cruz dropped out of the race; this leads to an increase in the likelihood that Trump could be the GOP nominee. A day later, John Kasich dropped out as well.	Republican Nominee
6	20-Jul-16	Ted Cruz refused to endorse the Republican nominee, leading to a more significant division within the Republican party.	Election Markets
7	24-Jul-16	Mails were leaked where Wasserman Schultz seemed to help Hillary Clinton to win the Dem election.	Election Markets
8	09-Sep-16	Hillary Clinton described Trump Supporters as deplorables, generalizing all his supporters.	Election Markets
9	11-Sep-16	Hillary Clinton almost collapsed during the 9/11 ceremony due to overheating. This event led to the question of whether she was fit for the role of a president.	Election Markets
10	07-Oct-16	A private tape where Donald Trump bragged about being able to have sex with married women since he is a "star." Including his phrase: "Grab them by the pussy".	Election Markets
11	07-Oct-16	WikiLeaks leaked speeches and emails, including confidential information about Clinton's campaign	Election Markets
12	28-Oct-16		Election Markets

	James Comey announced new information about the FBI's investigation of Hillary Clinton's emails, eleven days before the election.	

1. (Goldmacher, 2016a)
2. (Gass, 2016)
3. (O'Donnell, 2016)
4. (Mccaskill, 2016)
5. (Goldmacher, 2016b)
6. (Goldmacher, 2016c)
7. (Caputo, 2016)
8. (Lima, 2016)
9. (Karni, 2016)
10. (Goldmacher, 2016d)
11. (Cheney, 2016)
12. (Gerstein, 2016)

Table 5 Assessment of surprisingness events

	Google Search on surpising news events	
Event	**Keywords**	**Result**
1	Marco Rubio debate before:2016-02-05	-
2	Bernie Sanders New Hampshire win before:2016-02-08	CNN stated Bernie's lead over Clinton 4 days before the event.
3	Chris Christie before:2016-02-25	-
4	Bernie Sanders Michigan win before:2016-03-07	-
5	Ted Cruz drops out before:2016-05-02	-
6	Ted Cruz endorses Trump before:2016-07-19	-
7	Wasserman Schultz before:2016-07-24	The Observer announced this event earlier
8	Hillary Clinton fundraising speech before:2016-09-08	-
9	Hillary Clinton health before:2016-09-10	-
10	Donald Trump woman before:2016-10-06	-
11	Hillary Clinton Wikileaks Wall Street before:2016-10-06	-
12	FBI Hillary Clinton before:2016-10-27	-

2. (Agiesta, 2016)

7. (Sainato, 2016)

Table 6 Market Descriptions

Market Description		
Market	**Binary market**	**Shares traded (Sum Volume)**
Nomination		
Democrat Nominees	No	11.714.736
Republican Nominees	No	26.397.730
Election		
Which party	No	13.529.639
Woman	Yes	6.207.145
Who will win?	No	42.290.123
Swing		
Colorado	Yes	1.472.431
Florida	Yes	4.468.159
Iowa	Yes	1.137.114
Michigan	Yes	2.583.269
Minnesota	Yes	865.586
North Carolina	Yes	2.414.063
New Hampshire	Yes	2.222.644
Nevada	Yes	2.053.302
Ohio	Yes	2.215.988
Pennsylvania	Yes	2.584.139
Virginia	Yes	1.329.598
370		
Landslide Democrats	No	1.029.403
Landslide Republicans	No	2.232.084

Appendix C

Table 7 Robustness of Nomination Markets. Event window [-2,2], Estimation window 100 days

	Nomination Markets CAR [-2,2]			
	Events			
Contracts	**Event 1**	**Event 3**	**Event 4**	**Event 5**
Clinton	-	-	-4.79%	-
			(0.474)	
Kasich	118.21%	-16.75%	-	-63.69%
	(0.207)	(0.877)		(0.317)
Rubio	-82.29%***	-45.05%**	-	-
	0.000	(0.037)		
Sanders	-	-	32.72%	-
			(0.175)	
Trump	32.01%**	5.56%	-	6.61%
	(0.049)	(0.777)		(0.720)

Table 8 Robustness of Election Markets. Event window [-2,2], Estimation window 100 days

	Election Markets CAR [-2,2]				
	Events				
Contracts	**Event 6**	**Event 8**	**Event 9**	**Event 10/11**	**Event 12**
Woman	2.58%	-3.82%	-9.55%**	10.89%**	-18.40%***
	(0.760)	(0.433)	(0.035)	(0.048)	(0.001)
Clinton	2.68%	-6.56%	-13.56%***	8.02%	-16.29%***
	(0.573)	(0.164)	(0.002)	(0.137)	(0.005)
Democratic	3.16%	-3.58%	-7.78%**	9.68%**	-17.49%***
	(0.477)	(0.345)	(0.027)	(0.034)	(0.001)
CAAR Patell	2.92%	-5.07%*	-10.67%***	8.85%***	-16.89%***
	(0.361)	(0.094)	(0.000)	(0.010)	(0.000)
Republican	-3.94%	1.80%	16.49%*	-18.53%*	58.37%***
	(0.640)	(0.851)	(0.058)	(0.074)	(0.000)
Trump	-6.09%	7.95%	17.23%*	-18.68%*	60.55%***
	(0.620)	(0.430)	(0.058)	(0.087)	(0.000)
CAAR Patell	-5.02%	4.88%	16.86%***	-18.60%**	59.46%***
	(0.490)	(0.484)	(0.007)	(0.012)	(0.000)
370 Democrat	-2.06%	-2.60%	-2.36%	45.12%**	-47.29%*
	(0.899)	(0.882)	(0.880)	(0.035)	(0.076)
370 Republican	-0.75%	23.66%	33.41%	-10.06%	41.62%
	(0.970)	(0.328)	(0.125)	(0.697)	(0.163)
CAAR Patell	-1.41%	10.53%	15.53%	17.53%	-2.84%
	(0.906)	(0.552)	(0.323)	(0.217)	(0.787)
Colorado	-2.21%	-3.59%	-3.44%	3.70%	-15.25%**
	(0.780)	(0.574)	(0.543)	(0.566)	(0.015)
Florida	-5.45%	-4.03%	-3.85%	12.01%	-29.99%***
	(0.481)	(0.605)	(0.564)	(0.164)	(0.001)
Iowa	-1.46%	0.39%	4.25%	30.09%**	-25.65%
	(0.841)	(0.957)	(0.510)	(0.019)	(0.174)
Michigan	1.87%	1.89%	-1.84%	4.37%	-11.17%*
	(0.763)	(0.705)	(0.701)	(0.443)	(0.055)
Minnesota	2.88%	0.11%	-2.22%	4.48%	-4.81%
	(0.285)	(0.974)	(0.467)	(0.188)	(0.253)
Nevada	-2.01%	-6.49%	-3.01%	7.75%	-21.21%**
	(0.749)	(0.350)	(0.632)	(0.388)	(0.030)
New Hampshire	-4.12%	1.59%	-9.13%	-0.92%	-14.86%*
	(0.562)	(0.818)	(0.144)	(0.903)	(0.055)
North Carolina	1.43%	-7.02%	-8.37%	15.56%	-17.58%
	(0.894)	(0.465)	(0.336)	(0.151)	(0.121)
Ohio	5.86%	-0.82%	-1.97%	40.12%***	-26.43%**
	(0.449)	(0.908)	(0.760)	(0.000)	(0.047)
Pennsylvania	6.23%	-5.32%	-2.21%	4.19%	-10.68%*
	(0.244)	(0.319)	(0.648)	(0.495)	(0.095)
Virginia	4.85%	-2.30%	-2.11%	1.51%	-6.75%
	(0.542)	(0.607)	(0.590)	(0.753)	(0.175)
CAAR Patell	0.71%	-2.33%	-3.08%*	11.17%***	-16.76%***
	(0.540)	(0.261)	(0.075)	(0.000)	(0.000)

Table 9 Robustness of Nomination Markets. Event window [-1,1], Estimation window 100 days

Nomination Markets CAR [-1,1]				
	Events			
Contracts	**Event 1**	**Event 3**	**Event 4**	**Event 5**
Clinton	-	-	-4.60%	-
			-36.92%	
Kasich	73.27%	-3.39%	-	-24.88%
	-0.2637	-96.74%		-61.01%
Rubio	-19.96%*	-12.51%	-	-
	-0.0506	-45.06%		
Sanders	-	-	40.68%**	-
			-2.81%	
Trump	12.48%	-1.63%	-	4.73%
	-0.2737	-91.36%		-73.80%

Table 10 Robustness of Election Markets. Event window [-1,1], Estimation window 100 days

Election Markets CAR [-1,1]					
	Events				
Contracts	**Event 6**	**Event 8**	**Event 9**	**Event 10/11**	**Event 12**
Woman	2.80%	-0.67%	-10.77%***	10.66%**	-8.51%**
	(0.666)	(0.858)	(0.001)	(0.012)	(0.048)
Clinton	-0.23%	3.77%	-10.34%***	11.93%***	-9.35%**
	(0.950)	(0.297)	(0.001)	(0.004)	(0.034)
Democratic	3.13%	2.42%	-3.07%	12.02%***	-8.08%*
	(0.358)	(0.406)	(0.211)	(0.001)	(0.053)
CAAR Patell	1.45%	3.10%	-6.71%***	11.97%***	-8.71%***
	(0.543)	(0.183)	(0.001)	(0.000)	(0.004)
Republican	-6.22%	-2.44%	10.14%*	-10.83%	30.41%***
	(0.336)	(0.740)	(0.096)	(0.173)	(0.004)
Trump	0.85%	-2.24%	18.90%***	-37.88%***	33.86%***
	(0.928)	(0.772)	(0.003)	(0.000)	(0.003)
CAAR Patell	-2.69%	-2.34%	14.52%***	-24.36%***	32.14%***
	(0.536)	(0.659)	(0.001)	(0.000)	0.000
370 Democrat	5.03%	9.73%	-8.00%	90.06%***	-39.60%*
	(0.685)	(0.471)	(0.464)	(0.000)	(0.053)
370 Republican	-7.58%	-16.47%	33.13%**	-11.98%	22.41%
	(0.621)	(0.375)	(0.030)	(0.546)	(0.327)
CAAR Patell	-1.27%	-3.37%	12.57%	39.04%***	-8.59%
	(0.950)	(0.907)	(0.308)	(0.001)	(0.498)
Colorado	4.65%	-4.27%	-1.73%	6.21%	-8.60%*
	(0.441)	(0.383)	(0.663)	(0.209)	(0.073)
Florida	-5.02%	-0.51%	-3.51%	17.36%***	-13.57%*
	(0.395)	(0.932)	(0.453)	(0.009)	(0.056)
Iowa	-6.07%	0.11%	3.92%	53.26%***	-3.09%
	(0.276)	(0.984)	(0.385)	(0.000)	(0.831)
Michigan	5.90%	-4.05%	-2.87%	7.94%*	-8.64%*
	(0.211)	(0.291)	(0.392)	(0.069)	(0.053)
Minnesota	5.17%**	-2.21%	1.21%	2.28%	-2.42%
	(0.011)	(0.391)	(0.570)	(0.383)	(0.453)
Nevada	5.24%	-0.22%	-7.69%*	16.08%**	-8.54%
	(0.276)	(0.967)	(0.080)	(0.020)	(0.254)
New Hampshire	0.07%	1.85%	-8.49%*	7.91%	-12.94%**
	(0.989)	(0.728)	(0.052)	(0.175)	(0.029)
North Carolina	1.63%	-0.71%	-4.25%	30.68%***	-9.43%
	(0.842)	(0.924)	(0.486)	(0.000)	(0.279)
Ohio	2.83%	1.24%	-3.56%	38.32%***	-19.15%*
	(0.632)	(0.820)	(0.431)	(0.000)	(0.061)
Pennsylvania	-1.43%	-3.43%	-4.41%	7.87%*	-6.37%
	(0.727)	(0.402)	(0.195)	(0.095)	(0.194)
Virginia	3.78%	1.72%	-2.80%	2.99%	-8.57%**
	(0.534)	(0.617)	(0.308)	(0.415)	(0.025)
CAAR Patell	1.52%	-0.95%	-3.11%**	17.36%***	-9.21%***
	(0.149)	(0.404)	(0.015)	(0.000)	(0.000)

Table 11 Robustness of Nomination Markets. Event window [0,1], Estimation window 100 days

Nomination Markets CAR [0,1]				
	Events			
Contracts	**Event 1**	**Event 3**	**Event 4**	**Event 5**
Clinton	-	-	-7.99%*	-
			-5.51%	
Kasich	19.14%	36.63%	-	2.35%
	-0.6783	-0.5867		-83.82%
Rubio	-8.14%	-20.63%	-	-
	-0.2571	-0.1258		
Sanders	-	-	62.62%***	-
			0.00%	
Trump	-9.84%	2.55%	-	2.35%
	-0.2202	-0.8347		-83.82%

Table 12 Robustness of Election Markets. Event window [0,1], Estimation window 100 days

	Election Markets CAR [0,1]				
	Events				
Contracts	**Event 6**	**Event 8**	**Event 9**	**Event 10/11**	**Event 12**
Woman	1.34%	-3.28%	-3.35%	9.34%***	-8.28%**
	(0.800)	(0.280)	(0.133)	(0.007)	(0.018)
Clinton	-0.14%	-0.40%	-0.24%	10.64%***	-9.12%**
	(0.961)	(0.892)	(0.911)	(0.002)	(0.011)
Democratic	1.57%	-1.75%	2.77%	12.07%***	-6.63%*
	(0.572)	(0.459)	(0.109)	(0.000)	(0.050)
CAAR Patell	0.71%	-1.07%	1.27%	11.35%***	-7.87%***
	(0.715)	(0.536)	(0.294)	(0.000)	(0.001)
Republican	-5.98%	0.45%	0.23%	-10.79%*	25.51%***
	(0.256)	(0.940)	(0.957)	(0.095)	(0.003)
Trump	-1.31%	0.62%	9.02%**	-34.52%***	33.58%***
	(0.864)	(0.921)	(0.044)	(0.000)	(0.000)
CAAR Patell	-3.64%	0.54%	4.63%	-22.66%***	29.55%***
	(0.356)	(0.901)	(0.146)	(0.000)	(0.000)
370 Democrat	1.16%	9.82%	0.00%	60.10%***	-22.21%
	(0.908)	(0.370)	(1.000)	(0.000)	(0.182)
370 Republican	0.87%	0.13%	-7.00%	-11.69%	10.31%
	(0.944)	(0.993)	(0.514)	(0.468)	(0.579)
CAAR Patell	1.02%	4.97%	-3.50%	24.21%***	-5.95%
	(0.896)	(0.523)	(0.646)	(0.007)	(0.581)
Colorado	2.17%	-1.69%	-0.26%	6.26%	-9.65%**
	(0.658)	(0.671)	(0.925)	(0.119)	(0.013)
Florida	-1.73%	-0.34%	-0.17%	15.91%***	-10.24%*
	(0.718)	(0.944)	(0.959)	(0.003)	(0.076)
Iowa	-3.06%	0.12%	-1.76%	52.89%***	-9.74%
	(0.498)	(0.978)	(0.579)	(0.000)	(0.407)
Michigan	7.39%*	2.27%	-3.95%*	5.65%	-12.16%***
	(0.053)	(0.466)	(0.095)	(0.112)	(0.001)
Minnesota	1.35%	1.25%	0.02%	2.29%	-0.11%
	(0.407)	(0.549)	(0.991)	(0.281)	(0.966)
Nevada	3.96%	-0.12%	1.62%	16.13%***	-8.36%
	(0.310)	(0.979)	(0.601)	(0.004)	(0.169)
New Hampshire	-1.41%	-0.52%	-4.32%	8.18%*	-10.31%**
	(0.748)	(0.903)	(0.160)	(0.085)	(0.033)
North Carolina	3.72%	6.85%	-0.37%	24.40%***	-16.27%**
	(0.572)	(0.253)	(0.932)	(0.000)	(0.022)
Ohio	3.03%	3.15%	-3.47%	34.39%***	-21.05%**
	(0.528)	(0.477)	(0.275)	(0.000)	(0.011)
Pennsylvania	0.05%	-1.87%	-0.26%	6.81%*	-9.78%**
	(0.987)	(0.574)	(0.915)	(0.075)	(0.014)
Virginia	2.51%	3.18%	2.23%	3.18%	-8.33%***
	(0.611)	(0.254)	(0.247)	(0.288)	(0.007)
CAAR Patell	1.63%	1.12%	-0.97%	16.01%***	-10.54%***
	(0.167)	(0.343)	(0.312)	(0.000)	(0.000)

Table 13 Robustness of Nomination Markets. Event window [-1,0], Estimation window 10 days

Nomination Markets CAR [-1,0] 10 day Estimation				
	Events			
Contracts	**Event 1**	**Event 3**	**Event 4**	**Event 5**
Clinton	-	-	-3.48%	-
			(0.346)	
Kasich	46.36%	-23.05%	-	65.95***
	(0.395)	(0.487)		(0.010)
Rubio	-20.21%*	-6.03%	-	-
	(0.084)	(0.689)		
Sanders	-	-	41.75%***	-
			(0.032)	
Trump	26.43%*	-5.01%	-	0.91%
	(0.084)	(0.700)		(0.926)

Table 14 Robustness of Election Markets. Event window [-1,0], Estimation window 10 days

	Election Markets CAR [-1,0] 10 day Estimation				
	Events				
Contracts	**Event 6**	**Event 8**	**Event 9**	**Event 10/11**	**Event 12**
Woman	2.58%	2.22%	-6.38%***	9.96%***	-4.48%
	(0.520)	(0.112)	0.000	(0.010)	(0.129)
Clinton	-0.76%	7.48%***	-9.22%***	9.60%***	-8.44%***
	(0.814)	0.000	0.000	(0.004)	(0.000)
Democratic	3.58%*	5.32%**	-4.89%***	11.05%***	-7.41%***
	(0.068)	(0.034)	(0.008)	(0.004)	(0.000)
CAAR Patel	1.41%	6.40%***	-7.06%***	10.33%***	-7.92%***
	(0.281)	0.000	0.000	(0.000)	0.000
Republican	-3.88%	-5.64%	7.85%**	-22.56%***	19.80%*
	(0.510)	(0.194)	(0.017)	(0.006)	(0.053)
Trump	-1.10%	-7.00%**	8.75%***	-35.87%***	34.17%***
	(0.838)	(0.016)	(0.002)	(0.000)	(0.001)
CAAR Patel	-2.49%	-6.32%**	8.30%***	-29.21%***	26.98%***
	(0.558)	(0.012)	(0.000)	0.000	(0.000)
70 Democr	16.68%***	24.98%**	-6.05%	58.25%**	-31.06%*
	(0.003)	(0.016)	(0.501)	(0.026)	(0.073)
70 Republic	8.62%	-20.51%*	37.17%***	-9.57%	22.20%
	(0.366)	(0.072)	0.000	(0.607)	(0.469)
CAAR Patel	12.65%***	2.24%	15.56%***	24.34%	-4.43%
	(0.008)	(0.683)	(0.001)	(0.244)	(0.469)
Colorado	2.73%	-1.29%	-0.90%	7.27%	-6.36%**
	(0.574)	(0.617)	(0.620)	(0.254)	(0.025)
Florida	2.36%	1.80%	-2.12%	13.46%	-5.61%
	(0.710)	(0.612)	(0.398)	(0.153)	(0.197)
Iowa	-0.76%	-0.34%	7.35%**	43.05%**	-3.89%
	(0.891)	(0.951)	(0.049)	(0.024)	(0.728)
Michigan	1.07%	-0.28%	1.81%	6.60%	-2.15%
	(0.705)	(0.929)	(0.449)	(0.152)	(0.369)
Minnesota	3.73%*	0.73%	1.48%	2.74%*	-3.06%
	(0.061)	(0.708)	(0.263)	(0.100)	(0.496)
Nevada	2.17%	-1.59%	-8.58%***	9.74%	-8.26%***
	(0.344)	(0.743)	(0.006)	(0.283)	(0.003)
ew Hampsh	-0.33%	3.47%	-3.07%	3.84%	-9.11%**
	(0.942)	(0.485)	(0.386)	(0.534)	(0.022)
orth Caroli	-0.85%	4.52%	-3.25%	20.34%*	1.90%
	(0.925)	(0.334)	(0.327)	(0.099)	(0.637)
Ohio	2.50%	3.88%	1.50%	37.18%***	-10.96%
	(0.611)	(0.354)	(0.650)	(0.001)	(0.106)
Pennsylvani	-2.51%	-2.36%	-3.58%	4.53%	-5.92%
	(0.481)	(0.475)	(0.154)	(0.282)	(0.149)
Virginia	0.63%	0.84%	-4.03%**	2.53%	-3.12%
	(0.646)	(0.757)	(0.030)	(0.660)	(0.207)
CAAR Patel	0.98%	0.85%	-1.22%	13.75%***	-5.14%***
	(0.237)	(0.546)	(0.148)	0.000	0.000