Partisan Sentiment and Returns from Online Political Betting Markets in the 2020 U.S. Presidential Election

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Abstract

In this study, we estimate the role of daily partisan sentiment in predicting the returns from political betting markets on the PredictIt platform for ten of the most competitive states in the 2020 US presidential election. We utilize a textual analysis approach (Multinomial Inverse Regression Method) in measuring partisan sentiment for market participants through message board posts contained on each market's web page. Our results suggest that estimated partisan sentiment may play a role in the mispricing of political betting markets. Results are strongest for Republican assets and are robust to different specifications.

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1 Introduction

As partisan beliefs influence how individuals perceive political events, groups of people may hold contrasting views of the same reality (Jerit and Barabas (2012); Pennycook and Rand (2019); Pretus et al. (2023); Bartels (2002)). Because there are limited financial assets directly linked to political outcomes, asset pricing literature thus far has failed to explore whether this type of partisan sentiment influences investor behavior. This study aims to fill this gap, and we believe that the 2020 election, due to its politically charged and contentious

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outcome, creates a valuable opportunity to study the relationship between partisan sentiment and asset mispricing.

Political betting markets offer a singular arena to understand partisan investor sentiment as payouts directly correlate with political outcomes and financial returns, thus revealing how partisan biases may influence investor behavior. Moreover, high-quality "pricing" information, such as state-level polls and election forecasts, is readily available daily. For example, election prediction models from FiveThirtyEight and the Economist, as well as other third-party polls, offer direct information regarding likely market outcomes.

While political betting markets have had less public consciousness compared to sports betting markets, there has long been historical importance of organized political betting markets both domestically and internationally (Rhode and Strumpf (2004, 2013)), with discussions of the extent and eccentricity of political betting going back to the early 20^{th} century (Gilliams (1901)). With the introduction of cryptocurrencies and online off-shore betting, political betting markets have increased in popularity.

We focus our analysis on the political betting website PredictIt.com (PredictIt), a primary and secondary binary options market where participants buy or sell shares of the potential outcomes of elections and other political-related questions. PredictIt has several advantages over other online political betting markets (e.g., Smarkets, Betus, etc.). All market participants on PredictIt must reside in the U.S. and provide proof through a government-issued identification, and all transactions must take place in U.S. dollars. This aspect ensures a higher likelihood of U.S. partisans actively participating, compared to other markets where participants may be outside the U.S.

The PredictIt platform provides an ideal political betting market to study the relationship between sentiment and asset returns because frictions to arbitrage including market betting limits, an inability to short, illiquidity, and high transaction costs, may encourage the persistence of mispricing. Further, unlike financial markets, where relevant sentiment is often vague, scattered, and nonspecific, sentiment for assets traded in the PredictIt markets is abundant and focused. A Disqus.com comment board (Disqus board) is directly connected to each market, and a unique Disqus board is located at the bottom of each market's page. Additionally, a PredictIt account is required to post on the Disqus board. This directly connects the partisan feelings of market participants and the market prices.

Moreover, the 2020 U.S. Presidential election offers a unique ability to measure the relationship between partisan sentiment and asset returns because party sentiment regarding the election results was fervent. For example, belief in the legitimacy of the election lays along party lines, and post-election surveys suggest that most Democrats believe the election results were legitimate, while a majority of Republicans believe that the results are completely illegitimate or likely illegitimate.[1] Further, research has shown conservative partisans are more likely to believe (Pennycook and Rand (2019)) and spread (Pretus et al. (2023)) misinformation. Other research has found that partisans generally are more likely to distrust institutions (Clark et al. (2023)), are more cognitively inflexible (Zmigrod et al. (2020)), exhibit biased information processing about economic performance (Bartels (2002)), and view the world consistent with their partisan lens (Jerit and Barabas (2012)). To this end, recent behavioral finance literature has focused on determining the role partisanship plays in financial markets and asset valuation (Cookson et al. (2020); Dagostino et al. (2023); Kempf et al. (2023)). These studies have found an indirect role of partisanship in impacting financial markets, where partisanship influences sentiment regarding economic conditions, thus leading to differences in pricing.

For this study, we gather daily state level pricing data for the ten most competitive races in the 2020 election by popular vote from September 1, 2020 to November 3, 2020 for Republican and Democratic shares for prediction markets regarding the 2020 U.S. presidential election. We further gather all comments from each corresponding market Disqus Board and utilize the multinomial inverse regression (MNIR) method as developed by Taddy (2013a) to estimate partisan sentiment.

We estimate the relationship between concurrent partisan sentiment and the returns from the shares of each asset in each market. We find partisan sentiment is significantly related to asset price returns for the ten closest states by popular vote. This result is robust after accounting for information available from prediction models. Our finding follows the literature that partisanship can drive asset prices.

This study shows a direct connection between partisan sentiment and asset prices. While the indirect channel of partisan sentiment may still play a role in mispricing, partisan investors differ in optimism, representing how they internally price the probability of one

[1]See: Republicans believe Trump won, January 2022. Further, a May 2023 Monmouth University Poll survey revealed that an estimated 30% of Americans believed the results of the 2020 election were decided by voter fraud, underscoring the depth of the partisan divide and the importance of its potential implications on market dynamics. See Monmouth University Poll, May 2023.

candidate winning vs. another. For example, suppose a Democratic/liberal investor views that the Trump administration has employed unpopular policies leading to worse economic outcomes (economic optimism). In that case, they may overestimate the probability of Joe Biden winning the election. Due to confirmation bias, the direct channel may play a more significant role in this market. Specifically, the partisan investor may filter information through a partisan lens, discounting negative information and accentuating positive information regarding their preferred candidate and party, thus mispricing the asset.

As an extension and a further test of market efficiency, we determine the marginal forecastability of partisan sentiment utilizing out-of-sample forecasting evaluation for the ten closest states by popular vote in the 2020 election. We find evidence that some models containing partisan sentiment increase forecast accuracy compared to a model of the historic average. The gain in forecast accuracy is found to be the largest in the closest states in the 2020 election, suggesting that the effect of sentiment is increasing in asset price uncertainty (Baker and Wurgler (2007)); any information in these markets tend to cause investors to speculate more.

2 Literature Review

Our paper adds to a growing body of literature on determining the role of partisanship and political sentiment in financial decision-making and markets.

As noted by Dagostino et al. (2023), it is difficult to disentangle the impact of partisan investors on actual asset pricing. As such, the focus has been on identifying the effect of the partisanship of individual decision-makers on pricing in financial markets when the current President differs from their party. Studies have found partisanship of decision-makers impacting credit rating downgrades (Kempf and Tsoutsoura (2021)), corporate loan pricing (Dagostino et al. (2023)), fund portfolio allocation (Cassidy and Vorsatz (2021); Khawar (2021); Kempf et al. (2023)), and insider trading decisions of firm management (Rice (2020)). Partisanship has also been shown to impact the investment decisions of wealthy households (Pan et al. (2023) and brokerage investors (Bonaparte et al. (2017)). Guest et al. (2023) show institutional investors have higher holdings of firms headquartered in counties with similar political ideology as their own county. Other studies have found partisanship relating to innovation: patent productivity (Engelberg et al. (2023)) and rates of entrepreneurship (Engelberg et al. (2022)). Further diverse political opinions in a firm may be related to higher abnormal returns. Fos et al. (2022) shows lower abnormal returns relating to the departure of politically misaligned employees.

The literature often relies on the economic expectations channel, where partisans differ in belief about future economic outcomes under different political regimes, to explain the connection between partisan beliefs and financial market outcomes (for example see: Cassidy and Vorsatz (2021); Kempf and Tsoutsoura (2021); Dagostino et al. (2023)). Pricing decisions in this context may be rational and represent maximizing behavior. Meeuwis et al. (2022) notes how partisans live in different regions and are employed in different industries and as such may be affected differently by changes in policy due to changes in regimes; this may explain rational mispricing by investors. Meeuwis et al. (2022) present an alternative behavioral theory, where partisan investors price risk lower (higher) when their preferred candidate is (not) elected conditional on changes in regional and firm risks due to different policies.

In our study, the events themselves are the election. Thus, the economic expectations channel cannot have a direct impact on the pricing of assets on PredictIt. Pricing beyond market information, we argue, is primarily due to partisan leanings (similar to the behavioral theory presented in Meeuwis et al. (2022)). Through the behavioral theory, partisan investors may place a lower (higher) weight on negative (positive) information about their preferred candidate. This effect of this may be magnified if partisans obtain information primarily from partisan/biased media sources. While not directly studying partisanship, Cookson et al. (2023) shows that users on a stock market-focused social media site, StockTwits, are more likely to follow users who share similar views. Evidence shows that investors in these "echo chambers" underperform the market by more than those with more diverse StockTwits feeds. In regards to media bias, Goldman et al. (2021) finds that newspapers are more likely to publish positive news regarding politically aligned firms, with abnormal trading volume higher for firms when newspapers disagree on tone.

Other literature has focused on partisanship in asset pricing during the beginning stages of the COVID-19 pandemic. Cookson et al. (2020) attempts to identify Republican/conservative posters on Stocktwits (a stock market-based social media site) at the start of the COVID-19 pandemic and finds that optimism of Republican/conservative posters explains abnormal turnover. Sheng et al. (2023) finds Republican-associated firms have higher risk-adjusted returns than Democratic-associated stocks during COVID-19-related news days.[2]

[2]Sheng et al. (2023) identifies stocks' partisan lean by election history of corporate headquarters and

While this is the first study of our knowledge that has attempted to study the efficiency of political betting markets, the sports betting market literature is more developed. Like the sports betting market, the political betting market has a clear outcome and defined ending point. For example, Merz et al. (2019) and Feddersen et al. (2020) find that pricing is more inefficient for events more prone to sentiment or casual bettors, respectively. Avery and Chevalier (1999) suggests sources of sentiment bias in asset pricing (specifically for sports betting) could be "so-called" expert opinions, "hot-handed" bias, and a bias toward prestige. This is analogous to political betting markets, where the expert opinions may come from cable news commentators, "hot-handed" bias could be due to incumbency, and a bias towards well-known candidates could represent bias toward prestige. Evidence shows that bettors like to wager on popular teams (bias toward prestige) no matter what price bookmakers set (Avery and Chevalier (1999); Forrest and Simmons (2008)).

3 Data and Empirical Methods

In the following section, we describe the nature of the PredictIt markets and the data utilized in our study.

3.1 PredictIt

We gather data from the political betting marketplace, PredictIt, for the 2020 U.S. Presidential state electoral college election markets. The markets are framed by the question, "Which party will win *the State/Electoral College Vote* in the 2020 presidential election?" Investors purchase a contract for most potential outcomes on a discount, which pays out USD 1 if the selected party wins and USD 0 otherwise.[3]

Figure 1 shows the PredictIt page for the Michigan market. In this case, the prices are USD 0.96 to purchase a Democratic asset and USD 0.05 to purchase a Republican asset. Assets can be traded between market participants, where holders can offer a number of shares at a bid price or purchase shares at an ask price. Coordination between market participants

Facebook connection data.

[3]There is no third-party choice contract on PredictIt for individual states for the 2020 Presidential Elections. As such, no contracts for the Libertarian Party, Green Party, or "none of the above" are offered. Since tick sizes are given in USD 0.01 intervals, its inclusion would likely overstate the probability either party would win.

sets the equilibrium price. At the initial offering, prices for both assets are set at USD 0.50, and Republican and Democratic shares are bought and sold between market participants until the event is realized and the market is settled.

Studying the political markets on PredictIt has a number of advantages compared to other political betting sites. First, retail domestic investors dominate PredictIt, and prices are directly set by these market participants. Second, bettors must be at least 18 years old and U.S. permanent residents or citizens. Third, bets can be traded, and transactions are conducted in USD (not cryptocurrency).[4] Finally, a message board through the embedded platform Disqus is available for each market and populated exclusively by PredictIt users. We posit that partisan sentiment, as measured from the Disqus board posts, will have a significant relationship with returns from these markets.

While traditional asset pricing models such as CAPM assume efficient markets with no transaction costs and rational investors acting upon homogeneous knowledge and expectations, the limits outlined in the PredictIt political betting markets deviate from these assumptions to a greater extent than more traditional financial markets.[5] There are limits to the number of investors in a market and how much any individual can invest within a market, thereby limiting liquidity and investor size. The result is that the market is dominated by smaller retail investors, more prone to discard rational decision making when investing towards their preferred *political* result. Shares are traded with a one-cent tick size, which is sizable due to shares being priced no greater than one dollar, further limiting liquidity and increasing transaction costs.[6] Additionally, investors are assessed a fee on profits earned both when market positions are closed and when funds are withdrawn.

The behavioral finance theory, as described in Baker and Wurgler (2007), theorizes that limited information or greater uncertainty leads to speculation. As such, markets where the election outcome was most in doubt are likely to be most impacted by sentiment. Further, markets from Electoral College votes where the outcome is almost certain (e.g., the Democratic candidate will win California) quickly reach a steady state price after the market opens, so there is little information to be learned. For example, Figure 2 shows the daily

[4]The total amount of shares available in the market for purchase for each asset per person is 850.

[5]PredictIt is regulated by the Commodity Futures Trading Commission (CFTC), due to the nature of the securities it administers.

[6]While much of the literature on tick size and liquidity find decreasing liquidity measures with smaller minimum ticks, studies such as Goldstein and Kavajecz (2000) show reduced costs for smaller orders, which PredictIt transactions would be considered.

Republican price for six of the least competitive markets over the period September 2020 to November 2020. As can be seen here, the prices are relatively stable, with one to two cent changes each day. Further, in these non-competitive states, little new election information is released daily (e.g., very little polling). Therefore, we limit our sample to only the ten closest states by popular vote in the 2020 Presidential Election. For the 2020 Presidential Election, this includes the markets for Wisconsin, Florida, Michigan, Nevada, Pennsylvania, Arizona, Georgia, Texas, Minnesota, and North Carolina.[7]

We calculate the holding period return from each Democratic or Republican party asset (i) for each state market (s) for each day (t) by the log difference of the day's closing price.[8]

$$R_{i,s,t} = p_{i,s,t} - p_{i,s,t-1} \tag{1}$$

3.2 Election Outcome Predictions

Even with the hypothesized impact of partisan investors driving asset prices in these markets, rational investors should utilize polls and forecasts to correctly price assets, and anecdotal evidence shows that many market participants discuss election forecasts.[9] For the 2020 Presidential race, high-quality state-level polling and election forecasts from FiveThirtyEight and the Economist were widely available and updated daily.

We focus our analysis on the election probability forecast from FiveThirtyEight (FiveThirtyEight model) as it has several advantages compared to either polling alone or the Economist forecast. The FiveThirtyEight model is free (i.e. no paywall) and available daily. Predictors included in the model include polls and economic conditions, and probability estimates include demographic voting uncertainty. Polls by themselves provide less information as they do not account for the additional impact of these factors and often rely on weighting schemes based on demographics from previous elections. Kennedy et al. (2018) details the possible sources for polling errors in the 2016 Presidential Election. Other evidence has shown that partisans are likely to discount poll results that do not agree with their political leanings (Madson and Hillygus (2020)). Further, the FiveThirtyEight model estimates the probability of winning for each candidate for each electoral college, whereas the Economist Presidential

[7]As an alternative screening method, we limit our sample to electoral college markets where the standard deviation of prices is greater than 3 percent. This results in a sample relatively similar to the one we utilize. All analyses provided in this study were also done on this sample with similar results.

[8]p represents $ln(P)$

[9]Note at least four percent of all posts refer to polling, national polling firms, or FiveThirtyEight.

Election forecasts the race overall. [10]

Evidence from FiveThirtyEight itself shows that its election forecasting model was relatively accurate and outperformed expectations, with only predictions for Florida, North Carolina, and Maine's 2nd District being incorrectly predicted.[11] Evidence from Bullock et al. (2013), detail how rational investors would likely utilize this information in forming expectations. Bullock et al. (2013) found that partisans are more likely to state objective facts when offered financial benefits for being truthful. Like Bullock et al. (2013), participants in political betting markets have financial incentives to price these assets correctly.

As such, we control for the probability of a payout using estimated margins of victory for each party from 538. We calculate the log difference of the 538 probability of victory and use this as an estimate of the daily change in the probability of a win for each asset.

Because the FiveThirtyEight estimate may be the best guess of the election outcome, differences between this estimate and the price of the Republican or Democratic asset offers a measure of "mispricing."[12] Figure 3 shows the difference between the price of the Republican asset and the FiveThirtyEight estimated probability of victory for Trump over the two months preceding the 2020 election for the ten closest states. For most states, "mispricing" is positive, representing a higher probability given by the market for Trump winning compared to FiveThirtyEight. All states see an increase, with some states approaching USD 0.30 per share "mispricing" prior to the election. The graph suggests that "mispricing" is greatest when the races are closest (by popular vote margin) and may be particularly susceptible to speculation as described in Baker and Wurgler (2007). Further, if the "mispricing" is due to discounting (unlikely given the relative size), the difference should decline as the election day approaches. Given this empirical fact, we hypothesize that the partisan sentiment of market participants may help explain this "mispricing."

[10] See "How FiveThirtyEights 2020 Presidential Forecast Works and What's Different Because of COVID-19" for a full description of their prediction.

[11] See "How FiveThirtyEight's 2020 Forecasts Did And What We'll Be Thinking About For 2022", Nate Silver, June 8th 2021

[12] Some differences would be expected due to discounting and transaction costs.

3.3 Sentiment

We obtain all available raw social media posts from the Disqus boards associated with every electoral college market for the entire period the market is open.[13] Disqus is a comment hosting service that externally hosts users' comments for PredictIt and other websites. Users must first login to their PredictIt account, which can be connected to their Disqus account, Facebook, Twitter, or Google to post a message. Users then have the choice to either reply to another post or post on their own. From this, we obtain 338,796 unique messages and replies.[14]

While other broad social media sources can also be used to estimate partisan sentiment (See Taddy (2013b) for Twitter, Cookson et al. (2020, 2023) for StockTwits, and Feddersen et al. (2017) for Facebook), the Disqus comment boards are directly connected to each market, and users must be logged in to their PredictIt account to post. This allows us for a more direct measure of the partisan opinions of the market participants than any other social media site.[15] Figure 1 shows how comments are linked directly to each betting market, in this case, Michigan. There is only one discussion board for each state, and we use all Disqus posts to estimate partisan sentiment for each candidate.

3.3.1 Multinominal Inverse Regression Approach

To identify partisan sentiment in the Disqus posts, we employ the multinomial inverse regression (MNIR) as developed in Taddy (2013b) and follow the same notation. After cleaning the data, we tokenize all posts by separating the text into exchangeable unigram (for one-word phrases) tokens.[16] Each social media post can be thought of as a document, and letting p represent the total number of unique tokens in all social media posts, the counts of all unigrams can be transformed into a sparse vector:

$$x_i = [x_{1i}, ..., x_{pi}]' \tag{2}$$

[13]We gather all available social media posts from all 53 electoral college vote markets and one overall market.

[14]Given Disqus community use guidelines, a number of original posts and replies were removed automatically or by Disqus moderators from the message board for obscene and offensive content prior to scraping. As such, there is a very small percentage of messages which were unable to be obtained.

[15]It cannot be determined due to the masking of market participants' transactions if the users actually participated in any specific market. However, it can be argued that they are at least more likely to be a potential participant than a random user on an alternative social media platform.

[16]This is also done by bigrams, or two-word phrases.

In this study, p is limited to 10,000 of the most frequently used unigrams. All posts are identified as separate documents and include an associated unique user name, date, and state. See Table 1 for an example.

Table 1: Example Disqus Comment

User	Text	Date	Market
AIBets	"you stupid maga chimps can't even get trump to 0.50 wtf"	11/5/2020	Georgia

Note: Table 1 provides an example of a Disqus comment.

The frequency of each token in a given document is defined as:

$$f_i = \frac{x_i}{m_i}; \text{ where } m_i = \sum_{j=1}^{p} x_{ij} \tag{3}$$

Each tokenized document count, x_i, can be thought of as being represented by a sentiment variable y_i, similar to a Bullish-Bearish variable in Stocktwits posts (Renault (2017); Cookson et al. (2023)). In the case of this study, y_i is assigned 1 for one party if the partisan sentiment is positive toward the Democratic Party's candidate (Biden) or negative to the Republican Party's candidate (Trump), -1 for the opposite, or 0 if the comment does not favor either candidate. Note that under the MNIR procedure, ordering the classes is not a requirement.

Given that each x_i can be represented by y_i, documents can be collapsed by each possible discrete y value (where $y \in \mathcal{Y}$).

$$x_y = \sum_{i:y_i=y} x_i \tag{4}$$

x_y represents the sum of token document counts by each y. In this study, x_y is a $10,000 \times 3$ sparse matrix of the sum of document token counts by each y value.

From this, a MNIR model can be constructed as:

$$x_y \sim MN(q_y, m_y); \text{ where } q_{yj} = \frac{exp[\alpha_j + y\varphi]}{\sum_{l=1}^{p} exp[\alpha_l + y\varphi_l]} \\ j = 1, 2, ..., p; \; y_i \in \mathcal{Y} \tag{5}$$

There is a p-dimensional multinomial distribution for each element of y. The size of the total token counts for all documents in each multinomial distribution is m_y where

$m_y = \sum_{i:y_i=y} m_i$. q_{yj} is the probability, conditional on y, of specific token j being in x_y.

α_j and φ_j are $y \times 1$ vectors of parameters for each class specific to each token j. Intuitively, α_j can be thought of as a frequency parameter for token j. The more frequently that token j occurs, across all elements in y, the larger the estimate of α_j. Where φ_j is a parameter relating to relative frequency for each value in y.

Taddy (2013b) shows that using a Laplace prior for each φ_j and maximizing the posterior likelihood given the priors leads to sufficient dimension reduction where many elements in φ' equal zero. Since only tokens relevant to predicting each element in y are used in sentiment estimation, the matrix φ is sparse.

By fitting on frequencies, this allows for the MNIR to account for differences in document length. As noted by Loughran and McDonald (2016), textual analysis methods that do not account for document length can lead to incorrect sentiment estimation.

Taddy (2013b) shows that through the MNIR procedure, sentiment information for each document is described as a linear combination of $\varphi' f_i$ equal to z_i, a vector of sentiment score for each element of y. In our study, z represents the *Democratic*, *Republican*, and *neutral* sentiment scores for each Disqus post.

3.3.2 Supervised Learning

Because the document set includes the text of social media posts, we have a large number of documents with no direct measure of y_i. To estimate Equation 5, we follow the literature by creating a training set of manually labeled values for y_i to predict sentiment for the entire corpus. In a similar study, Taddy (2013a) uses emoticons as an identifier for y_i and employs a third party, Amazon Mechanical Turk service employees, to manually label a training set.[17]

We take a random sample of approximately 1.5 percent of the total documents, 5218 posts, and use it as our training set. This sample is split into seven sub-samples which are manually labeled by researchers and a research assistant.

[17] There would be several challenges to using emoticons or emojis to label our data set. These are not as common in our data set as compared to Twitter, and identifying which posts are referring to which candidate is harder than on Twitter, as hashtags are not widely used.

Each of the social media posts in the training set is reviewed and put into one of three categories to obtain partisan sentiment, either *Democratic*, *Republican*, or neutral. Posts are generally considered *Democratic* if they contain positive views about Joe Biden/Democrats/liberals or negative views about Donald Trump/Republicans/conservatives. For *Republican*, the opposite is true. The result is that each non-neutral post explicitly represents one party or the other. The neutral category was assigned when the post contained neutral sentiment for either candidate, contained no partisan sentiment or was completely irrelevant.

Since perceived sentiment is subjective and labeling by one person might lead to bias, each sub-sample overlaps by between 250-500 social media posts. Therefore 1,253 posts in the training set are reviewed more than once. Approximately 80.4% of the categorizations match completely, and only 65 social media posts were labeled contrarily for an error rate of 5.2%.[18]. The error rate can be explained primarily by reviewer error. All mismatched labeled social media posts social media posts were reviewed again to make sure of labeling accuracy. We use this training set to estimate Equation 5.

Table 2 shows all significant unigrams and their estimated coefficients from the MNIR procedure. The first two columns show the unigrams associated with being labeled *Democratic*, while the remaining three columns show the results for *Republican*. The table offers evidence that the MNIR procedure assigns larger coefficients to the common words/phrases that are most partisan and relevant to the 2020 Presidential election.

For example, the unigram "q" that references a conspiracy theory followed by some Trump supporters, is identified as being highly related to Democratic sentiment. For Republican sentiment, the procedure identified the unigram "tony." This is related to critiques that some Republicans placed on Anthony Fauci, the Director of the National Institute of Allergy and Infectious Diseases, for COVID-19 policies/recommendations.

While there is no direct way to determine if the training set accurately identifies the true sentiment of the social media post, we would generally expect that many of these n-grams would be important determinants for partisan sentiment in the 2020 Presidential Election. Further, when estimating partisan sentiment, $z_i = \varphi' f_i$, we find the estimated sentiment score anecdotally matches our perceived sentiment. For example, one of the posts with the strongest *Republican* estimated sentiment is:

[18]A majority of the mismatched labeled posts, around 148, differed in that one reviewer viewed it as irrelevant while the other viewed it as another category

> "**Libtards**, Keep your Marxism out of our schools, your socialism out of our economy, your **identity** politics out of our **law enforcement**, your environmentalism out of our **oil** industry, your censorship out of our social **media** platforms, your illegal aliens out of our country, and your confused men out of our women's sports & bathrooms. We just want to be **left** alone. Sincerely,The Deplorables"

This post details many policy positions/issues of concern about liberal policies for Republican voters in the 2020 Election and touches on many issues where U.S. partisans disagree.[19] Other examples of these are provided for *Democratic* in Table **??** and for *Republican* in Table **??**, respectively. These tables show examples of some of the strongest social media posts based on the estimate of z_i for each category. Similar to the previous example, estimates seem to be accurate.

As our goal is to obtain partisan sentiment, we first remove all posts that provide no partisan sentiment information (i.e., estimates of z_i are equal to the estimated constant) in either class. We then take the mean value of sentiment estimated in all markets for each day. We label sentiment, S_c. Where S denotes sentiment and c denotes the class, either *Democratic* (D) or *Republican* (R). We also estimate the daily change in sentiment, ΔS_c, as:

$$\Delta S_c = S_{c,t} - S_{c,t-1} \tag{6}$$

Figure 4 shows the change in overall *Republican* sentiment measured weekly for the ten closest states by popular vote from September 1, 2020 to November 3, 2020 (dashed line) along with the weekly return on the Republican asset by each state (solid lines in colors). Figure 4 is divided into two panels where the top panel represents the states with the highest return (Nevada, North Carolina, Pennsylvania, Arizona, Pennsylvania and Flordia) and the bottom panel the next five in terms of mean returns (Georgia, Wisconsin, Texas, Michigan, and Minnesota). Visual inspection reveals that the weekly sentiment measure and the weekly return on the Republican asset move in the same direction, with the only deviation happening during the time between the individual Biden and Trump town halls and the second presidential debate. We suspect this fall in sentiment is likely due to the aftermath of Trump's COVID-19 diagnosis. There seems to be some empirical relationship present here.

[19]See `https://news.gallup.com/poll/276932/several-issues-tie-important-2020-election.aspx`

3.4 Descriptive Statistics

Table A2 shows descriptive statistics for the daily values of all variables used in this study. S_R is the daily measure of *Republican* sentiment from all Disqus message board posts. Daily messages are scored using the MNIR process described in section 3.3.1, and all posts for the day are averaged. The same process is applied to all daily posts to generate a *Democratic* sentiment measure, S_D. ΔS_D and ΔS_R are the changes in the daily sentiment measures described above and defined in equation 6.

While the levels of sentiment cannot be interpreted, the changes in daily sentiment can be and have a negative mean near zero. This indicates an overall reduction in partisan sentiment over the entire sample.

The daily percent change in probability of victory for each party, $\%\Delta Pr(538)_D$ and $\%\Delta Pr(538)_R$, is the percent change in the probability estimates from the FiveThirtyEight model. For example, the positive value for $\%\Delta Pr(538)_D$ indicates an increase in the likelihood of the Democratic candidate winning over the sample period.

Returns for the *Republican* assets are lower than the *Democratic* assets while also having a higher standard deviation, indicating that the *Republican* assets are relatively riskier.

3.5 Empirical Methods

To determine the relationship between partisan sentiment and political betting market returns, we estimate the following reduced-form model utilizing ordinary least squares.

$$R_{ist} = \beta_0 + \beta_1 S_{it} + \beta_2 \Delta Pr(538)_{ist} + \beta_3 R_{D/R,st} + \theta_s + \epsilon_{ist} \tag{7}$$

In the model, i refers to the political party of the asset, either Democratic or Republican, s refers to the state, and t refers to time. The dependent variable is the holding period return from each Democratic or Republican party asset and is given by equation 1. S_{it} represents the positive market sentiment for each party i at time t, and is measured as either the level of sentiment (S_{it}) or in alternative specifications as the change in sentiment (ΔS_{it}). $\Delta Pr(538)_{ist}$ is the percentage change in probability of a win for party i in state s estimated by the 538 model. $R_{D/R,t}$ is the return on the other party asset, Republican when i is Democrat and vice versa, at time t. θ_s is state fixed effects, and ϵ_{ist} represents an error term. In alternative specifications, we assume either $\beta_2 = 0$, $\beta_3 = 0$, or both.

The political betting markets are unique as the two assets available for each market are based on the same outcome but payout in opposite outcomes. For example, with the Democratic win becoming more likely, the Republican win is less likely, and vice versa. The model given in equation 7 includes the opposite party's contemporaneous returns, and as returns from each asset would likely be determined simultaneously, we estimate a two-stage least squares model as a robustness test. The first stage equation models the return on each asset, Democratic and Republican, and is given in equation 8.

$$R_{ist} = \alpha_0 + \alpha_1 \Delta Pr(538)_{is,t-1} + \alpha_2 \Delta Pr(538)_{is,t} + \alpha_3 S_{D/R,t-1} + \alpha_4 S_{D/R,t} + \Phi_s + u_{ist} \quad (8)$$

The dependent variable is the holding period return on the Democratic or Republican asset and is given by equation 1. Independent variables are the percentage change in the probability of a win estimated by the FiveThirtyEight model for the same party ($\Delta Pr(538)_{is,t}$) and its lag ($\Delta Pr(538)_{is,t-1}$); the sentiment variable for the *other* party ($S_{D/R,t}$) and its lag ($S_{D/R,t-1}$). Φ_s is state fixed effects, and u_{ist} represents an error term.

We argue that both $\Delta Pr(538)$ and $S_{D/R}$ are likely to be exogenous. The PredictIt market is small compared to the general electorate, and the returns from these markets are not utilized in the FiveThirtyEight model, thus $\Delta Pr(538)$ is unlikely being driven by returns. For $S_{D/R}$, political views, and thus sentiment, is determined outside of the prediction markets. While estimating sentiment in the manual labeling process, we remove all numbers to limit the likelihood of posts referring to actual market conditions and label posts mentioning market conditions generally as irrelevant.

$$R_{ist} = \beta_0 + \beta_1 S_{it} + \beta_2 \Delta Pr(538)_{ist} + \beta_3 R_{D/R,st} * + \theta_s + \epsilon_{ist} \quad (9)$$

In the second stage (given by equation 9), the holding period return from each Democratic or Republican asset is estimated similarly as it is in equation 7, except that the other party return, $Return_{D/R}*$ is the estimated value using the alphas calculated from equation 8.

4 Results

4.1 Cross Sectional Results

This section presents our main results. We estimate regressions from Equation 7 and report results in Table 3. Panel A details the results for the level of sentiment for party i at time t (S_{it}), and Panel B shows the results for the percentage change in sentiment for party i at time t (ΔS_{it}). The sample is the ten closest state markets by popular vote margin, and the dependent variables are the returns on the Democrat asset for the first three columns and the returns on the Republican asset for the last three columns. Note that the independent variables $S_{D(/R)}$ and $\Delta S_{D(/R)}$ in Table 3, are the pro-Democratic sentiment measure for the regressions where the dependent variable is the return on the Democratic (Republican) asset, thereby matching the independent sentiment variable with the dependent return variable by party.

The first three columns of Panel A provide evidence that the level of sentiment is not a significant positive factor in the contemporaneous return on the Democratic asset. The coefficient on the sentiment variable, S_{it}, is not significant for any of the three Democrat specifications. The positive prediction model coefficient $\Delta PR(538)_{D/R}$, for the Democrat asset suggests that returns on the Democrat asset are related to the expectations offered by prediction experts. As expected, a positive return on the Republican asset is associated with a negative contemporaneous return on the Democratic asset.

Alternatively, the sentiment variable is positive and significant for all three specifications where the dependent variable is the return on the Republican asset. The prediction model coefficient, $\Delta PR(538)_{D/R}$, is not significant, suggesting that returns on the Republican asset are not related to third party information on election outcomes. The negative coefficient on the Democratic asset return implies that positive returns on the Democrat asset are associated with negative Republican asset returns.

Panel B presents results for estimations including the change in sentiment, ΔS_{it}. For the models where the dependent variable is the return on the Democratic asset, the coefficient on the change in sentiment is positive and significant for the first two specifications but not for the specification that includes all three independent variables. The results for returns on the Republican asset are similar to those given in Table Panel A as the coefficient on the change in sentiment variable is significant in all three specifications. The second specification, however, indicates that election outcome probabilities from FiveThirtyEight are negatively related to changes in the value of the Republican asset.

Results support the hypothesis that the pro-Trump sentiment expressed by bettors in the Republican asset market has a significant effect on Republican asset returns. This sentiment is even more important than the news from experts regarding the election outcome. These results support the idea that bettors may be engaged in “wishful thinking” and that bettors are, in effect, voting with their dollars and betting with their feelings. This result is consistent with the results found in Cookson et al. (2020, 2023). Particularly, investors internalizing information in their own echo chamber. Evidence from a 2020 Pew Research Center poll found self identified Republican/Conservatives are less likely to trust traditional media sources compared to self-identified Democrats/Liberal.[20] This follows with evidence found in Jerit and Barabas (2012), which find partisans internalize information differently and perceive the world consistently with their partisan views.

Returns on the Democratic asset seem to have a limited to no relationship with market participants’ sentiment towards Biden. These results support the idea that sentiment influences asset prices and possibly leads to price inefficiencies (Merz et al. (2019)). This result make be indicative of the result in Jerit and Barabas (2012) and explained in the 2020 Pew Research Poll on media trust. Democratic asset holders may be more willing to trust media predictions about the outcome of the election, or more willing to believe media due to reporting fitting into their ex-ante beliefs. This then leads to no role for sentiment in explaining asset returns.

4.2 Two Stage Least Squares Results

Because the two assets complete the set of outcomes from the event, we recognize that returns from each asset are being determined simultaneously. We therefore utilize two stage least squares and estimate the other party return, $R_{D/R}$, as the estimated value using the alpha coefficients from equation 8. This estimated coefficient is used as the other party return variable in the equation 7. Results for the ten closest state markets by popular vote margin are found in Table 4.

Those columns with headings of ’First’ indicate results from the first stage. The columns with the headings of ’Second’ contain results from the second stage and suggest that sentiment has a significant relationship with concurrent asset returns for the Republican asset,

[20]See the Pew Research report, ”Democrats report much higher levels of trust.”

although in these specifications the sign on the coefficient has changed to negative. Similar to the results found in Table 3, in both of the Second Republican columns in Table 4 the return on the Republican asset is not related to prediction information from FiveThirtyEight; while evidence from returns in the Democratic market suggest that participants here include FiveThirtyEight prediction data in their decision making. Opposite party return continues to have a negative and significant relationship with asset returns, as expected.

5 Out-of-Sample Forecasting

To further understand the relationship between partisan sentiment and asset returns, we forecast future returns in individual state markets for both Democratic and Republican assets. We hypothesize that due to the market's illiquidity, high transaction costs, and retail investor base, partisan sentiment will be a useful predictor of future asset returns. Specifically, we utilize out-of-sample forecasting evaluation to determine the marginal forecasting accuracy gains from partisan sentiment over baseline models. We choose out-of-sample forecasting to limit the potential of over-fitting with in-sample analysis (as described in Clark (2004)).

5.1 Forecasting Methods

Our goal in this forecasting exercise is to determine the marginal gain in forecast accuracy from models containing partisan sentiment. We utilize an out-of-sample rolling/recursive algorithm starting with 32 observations used to initially estimate the parameters (P) and 32 forecasted observation (R). Resulting in P/R ratio of 0.5.

As we are limited by the number of time observations in our data set, we only estimate a one-step-ahead forecast. We estimate a number of baseline models that are all nested in the following model.

$$R_{i,s,t+1} = \mu + X_t\beta + \epsilon_{i,s,t+1} \tag{10}$$

In equation 10, i refers to the political party of the asset, either Democratic or Republican, and s refers to the state. X_t is a vector of predictors other than partisan sentiment, which is either return from the asset at time t ($R_{i,s,t}$), return from the other asset at time t (Democratic for the Republican asset and vice versa), and $\%\Delta Pr(538)$. β is a vector of coefficient estimates for all elements in X at time t utilizing the rolling estimation method.

Our baseline models include the Mean model, an ARDL containing returns from the other asset ($ARDL1$), and an ARDL model containing all predictors other than sentiment ($ARDL2$). These models place certain restrictions on the values of the coefficients in β in equation 10. For example, in the Mean model, it is assumed that elements in *beta* are equal to zero.

To determine the marginal forecasting ability of partisan sentiment, we estimate the following model, which nests equation 10

$$R_{i,s,t+1} = \mu + \gamma S_t + X_t \beta + \epsilon_{i,s,t+1} \tag{11}$$

As equation 10 is nested in equation 11, all variable definitions are the same except for the inclusion of either the level of partisan sentiment (S_t) or the change in partisan sentiment (ΔS_{it}) at time t.

To estimate the added predictability of partisan sentiment, we estimate the out-of-sample R-squared statistic (R^2_{OOS}) as discussed in Campbell and Thompson (2008). Further, we use the Clark-West Adjusted MSFE test (CW test) to determine forecast accuracy as developed in Clark and West (2007). [21]

5.2 Forecasting Results

Tables 5 and **??** show the out-sample forecasting comparison results for the five closest states and the next five closest by popular vote, respectively. Results presented are estimated for one-day ahead of out-of-sample forecasts utilizing a rolling and recursive algorithm.[22] Both results from the R^2_{OOS} and CW test (in comparison to the Mean model) are shown for each model. Panel A and B show the results for the Republican assets for the rolling and recursive algorithms, respectively. While Panels C and D show the results for the Democratic assets in each state. Columns separate the results by each state.

The results overall provide evidence that partisan sentiment is a valid predictor of returns from PredictIt markets. Interestingly, results are strongest for the Democratic assets particularly the markets for Georgia, Arizona, Wisconsin, and North Carolina. Partisan sentiment produces the largest gain in accuracy for the Democratic Asset in Arizona, around 14 percent, and significant at the 5 percent level based on the CW test, using the recursive

[21] Further discsussion on Forecasting techniques are found in the Appendix. Other baseline models were utilized for the CW test, and results are as expected and can be provided upon request.

[22] Note as described in Clark and West (2007) the rolling algorithm is more reliable compared to the recursive algorithm in the application of the CW test.

method for the $ARDL2 + \Delta S$ model.

The overall strongest results for both assets are found in Georgia where most estimated models perform better than the mean model. For the Democratic asset, the largest gain is found from the $ARDL2 + S$ model for the rolling algorithm, which is also significant at 5 percent for the CW test. For the recursive, the $ARDL2+\Delta S$ and $ARDL2$ perform similarly.

For the Republican asset, models including the level of sentiment and non-sentiment predictors offer better predictive power than the Mean model for the Georgia and Arizona races. For the Georgia, Arizona, and Wisconsin Republican assets, significant models including the level/change in sentiment along with at least one other non-sentiment predictor outperform the Mean model with gains in accuracy ranging from -8-12 percent for the recursive algorithm and -1.5 - 12 percent for the rolling algorithm. Generally, although most significant models here produce positive R^2_{OOS} values.

Figure 5 and 6 shows the squared forecasting errors over the out-of-sample period utilizing the recursive algorithm for the mean model, $ARDL2 + S$, and $ARDL2 + \Delta S$ for Arizona and Georgia (Figure 5 and North Carolina and Wisconsin (Figure 6). Democratic Assets are shown in the top panel and Republican Assets are shown in the bottom panel. Generally, the models containing partisan sentiment do a marginally better/similar job at forecasting on days with small errors, with Arizona Democratic asset being the exception. The real gain in forecasting accuracy is found in days with large forecasting errors. Particularly, there seems to be a large forecasting error days around October 26th. This large error might be related to the US Senate confirmation of Amy Coney Barrett to the Supreme Court. Partisan Sentiment here seems to have forecasted better the next day's return.

It is important to note that while sentiment did produce an increase in forecast accuracy for some states, it largely produced insignificant results compared to the mean model utilizing the CW test. These include Pennsylvania, Nevada, Texas, and Minnesota. Further, no significant result was found for the CW test for the Republican Asset for Michigan and North Carolina.

Our results suggest that partisan sentiment is more often a valid predictor when the race is close. For example, outside of the top three closest races, the forecasting models fail to outperform the Mean model for the Republican asset. This supports the idea that limited information can lead to speculation, thereby impacting asset returns (Baker and Wurgler

(2007)).

With the 2024 election looming, it is possible to utilize these methods to produce higher returns from holding Presidential market assets from PredictIt.

6 Conclusion

The relation between information and asset prices is a fundamental question in finance, and past research has investigated the role investor sentiment plays in determining asset prices. Challenges to performing research in this area include isolating and measuring investor sentiment and directly linking what may be general market sentiment to specific assets. Recent literature has focused on determining the role partisan sentiment has in determining pricing in financial markets generally. This study adds to this literature by identifying the impact of partisan sentiment in explaining returns from market directly linked to political outcomes.

By using the PredictIt political betting markets and the posts contained within the provided message boards, we can observe and quantify investor sentiment. PredictIt is an online betting marketplace which allows users to purchase assets reflecting the outcome of events, especially elections. Therefore, we can match asset returns with partisan sentiment specific to the election outcome. Investors or bettors will lose money if purchased assets underperform, and the asset value goes to zero for incorrect bets when the outcome is realized. In other words, investors have a real economic incentive to bet rationally.

We scrape message board posts and utilize the MNIR method developed in Taddy (2013b) to generate a measure of partisan sentiment. We then use this measure to study the relationship between sentiment and asset prices. We find evidence of a relationship between sentiment expressed for a particular party and the asset returns reflecting that party's win. These results are strongest for the asset reflecting the Republican win and when the election races are closest. These results hold after controlling for outside information that may inform investors about expected election outcomes. Models accounting for simultaneity in asset returns suggest a relationship between sentiment and returns.

To further test the implications of the efficient market hypothesis in these markets, we determine the marginal forecastability of partisan sentiment utilizing out-of-sample forecasting evaluation methods. We find evidence that partisan sentiment is a valid predictor, especially for the Democratic assets and for the closest state races in the 2020 Presidential elections.

This is the first study to directly link returns from political betting markets to partisan sentiment. On a general basis, these results offer evidence that there is a relationship between asset mispricing and investor sentiment. Further, our results suggest that asset mispricing is most pronounced when elections are closest, supporting the idea that the effect of sentiment is increasing in asset uncertainty (Baker and Wurgler (2007)). We show that sentiment intensity has a direct relationship with asset returns, and that the economic motive cannot sway investors to rational thinking and overcome pricing discrepancies.

With the 2024 election cycle still underway, future studies may be able to use information to further determine the reliability of political betting markets in forecasting election outcomes as compared to polls. Evidence has shown that these political markets offer precision in prediction (Reade and Williams (2019)).

References

Avery, C. and Chevalier, J. (1999). Identifying investor sentiment from price paths: The case of football betting. *The Journal of Business*, 72(4):493–521.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2):129–152.

Bartels, L. M. (2002). Beyond the running tally: Partisan bias in political perceptions. *Political behavior*, 24:117–150.

Bonaparte, Y., Kumar, A., and Page, J. K. (2017). Political climate, optimism, and investment decisions. *Journal of Financial Markets*, 34:69–94.

Bullock, J. G., Gerber, A. S., Hill, S. J., and Huber, G. A. (2013). Partisan bias in factual beliefs about politics. Technical report, National Bureau of Economic Research.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, 21(4):1509–1531.

Cassidy, W. and Vorsatz, B. (2021). Partisanship and portfolio choice: Evidence from mutual funds. *Available at SSRN 3977887*.

Clark, C. J., Isch, C., Everett, J. A., and Shariff, A. (2023). Even when ideologies align, people distrust politicized institutions. *PsyArXiv*.

Clark, T. E. (2004). Can out-of-sample forecast comparisons help prevent overfitting? *Journal of forecasting*, 23(2):115–139.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, 138(1):291—-311.

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2020). Does partisanship shape investor beliefs? evidence from the covid-19 pandemic. *The Review of Asset Pricing Studies*, 10(4):863–893.

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2023). Echo chambers. *The Review of Financial Studies*, 36(2):450–500.

Dagostino, R., Gao, J., and Ma, P. (2023). Partisanship in loan pricing. *Journal of Financial Economics*, 150(3):103717.

Engelberg, J., Guzman, J., Lu, R., and Mullins, W. (2022). Partisan entrepreneurship. Technical report, National Bureau of Economic Research.

Engelberg, J., Lu, R., Mullins, W., and Townsend, R. R. (2023). Political sentiment and innovation: Evidence from patenters. Technical report, National Bureau of Economic Research.

Feddersen, A., Humphreys, B. R., and Soebbing, B. P. (2017). Sentiment bias and asset prices: Evidence from sports betting markets and social media. *Economic Inquiry*, 55(2):1119–1129.

Feddersen, A., Humphreys, B. R., and Soebbing, B. P. (2020). Casual bettors and sentiment bias in nba and nfl betting. *Applied Economics*, 52(53):5797–5806.

Forrest, D. and Simmons, R. (2008). Sentiment in the betting market on spanish football. *Applied Economics*, 40(1):119–126.

Fos, V., Kempf, E., and Tsoutsoura, M. (2022). The political polarization of corporate america. Technical report, National Bureau of Economic Research.

Gilliams, E. L. (1901). Election bets in america. *Strand Magazine: An Illustrated Monthly*, 21(122):185–191.

Goldman, E., Gupta, N., and Israelsen, R. D. (2021). Political polarization in financial news. *Available at SSRN 3537841*.

Goldstein, M. A. and Kavajecz, K. A. (2000). Eighths, sixteenths, and market depth: changes in tick size and liquidity provision on the nyse. *Journal of Financial Economics*, 56(1):125–149.

Guest, N. M., Twedt, B. J., and Murren Vosse, M. (2023). Institutional investors and echo chambers: Evidence from social media connections and political ideologies. *Available at SSRN*.

Jerit, J. and Barabas, J. (2012). Partisan perceptual bias and the information environment. *The Journal of Politics*, 74(3):672–684.

Kempf, E., Luo, M., Schäfer, L., and Tsoutsoura, M. (2023). Political ideology and international capital allocation. *Journal of Financial Economics*, 148(2):150–173.

Kempf, E. and Tsoutsoura, M. (2021). Partisan professionals: Evidence from credit rating analysts. *The journal of finance*, 76(6):2805–2856.

Kennedy, C., Blumenthal, M., Clement, S., Clinton, J. D., Durand, C., Franklin, C., McGeeney, K., Miringoff, L., Olson, K., Rivers, D., et al. (2018). An evaluation of the 2016 election polls in the united states. *Public Opinion Quarterly*, 82(1):1–33.

Khawar, O. M. (2021). Partisanship in mutual fund portfolios. *Available at SSRN 3896677*.

Loughran, T. and McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4):1187–1230.

Madson, G. J. and Hillygus, D. S. (2020). All the best polls agree with me: Bias in evaluations of political polling. *Political Behavior*, 42(4):1055–1072.

Meeuwis, M., Parker, J. A., Schoar, A., and Simester, D. (2022). Belief disagreement and portfolio choice. *The Journal of Finance*, 77(6):3191–3247.

Merz, O., Flepp, R., and Franck, E. P. (2019). Does sentiment harm market efficiency? an empirical analysis using a betting exchange setting. *University of Zurich, Institute of Business Administration, UZH Business Working Paper*, (381).

Pan, Y., Pikulina, E., Siegel, S., and Wang, T. Y. (2023). Political divide and the composition of households' equity portfolios. *Available at SSRN 4381330*.

Pennycook, G. and Rand, D. G. (2019). Lazy, not biased: Susceptibility to partisan fake news is better explained by lack of reasoning than by motivated reasoning. *Cognition*, 188:39–50.

Pretus, C., Servin-Barthet, C., Harris, E. A., Brady, W. J., Vilarroya, O., and Van Bavel, J. J. (2023). The role of political devotion in sharing partisan misinformation and resistance to fact-checking. *Journal of Experimental Psychology: General*.

Reade, J. J. and Williams, L. V. (2019). Polls to probabilities: Comparing prediction markets and opinion polls. *International Journal of Forecasting*, 35(1):336–350.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the us stock market. *Journal of Banking & Finance*, 84:25–40.

Rhode, P. W. and Strumpf, K. (2013). The long history of political betting markets: An international perspective. *The Oxford handbook of the economics of gambling*.

Rhode, P. W. and Strumpf, K. S. (2004). Historical presidential betting markets. *Journal of Economic Perspectives*, 18(2):127–142.

Rice, A. B. (2020). Executive partisanship and corporate investment. *Journal of Financial and Quantitative Analysis*, pages 1–48.

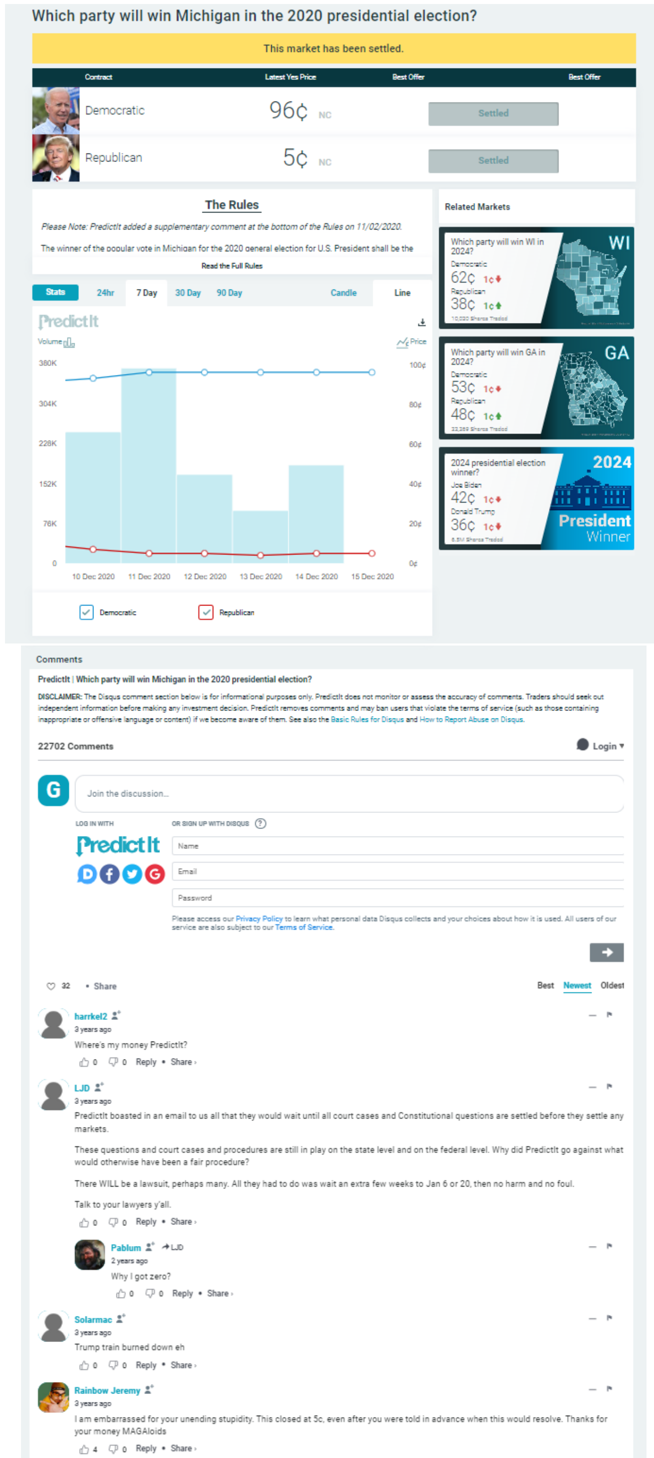
Sheng, J., Sun, Z., and Wang, W. (2023). Partisan return gap: The polarized stock market in the time of a pandemic. *Available at SSRN 3809575*.

Taddy, M. (2013a). Measuring political sentiment on twitter: Factor optimal design for multinomial inverse regression. *Technometrics*, 55(4):415–425.

Taddy, M. (2013b). Multinomial inverse regression for text analysis. *Journal of the American Statistical Association*, 108(503):755–770.

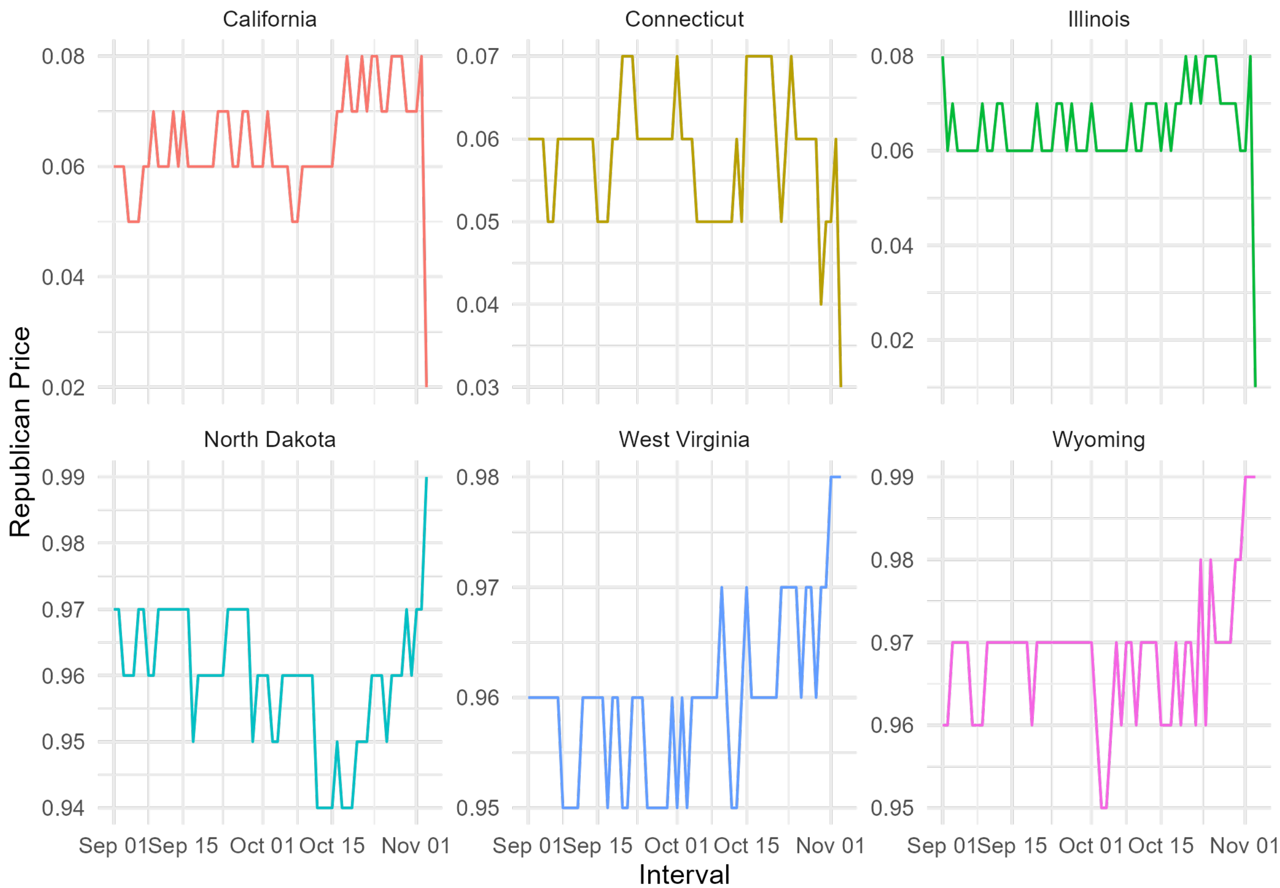
Zmigrod, L., Rentfrow, P. J., and Robbins, T. W. (2020). The partisan mind: Is extreme political partisanship related to cognitive inflexibility? *Journal of Experimental Psychology: General*, 149(3):407.

Figure 1: Predictit Michigan Market 2020



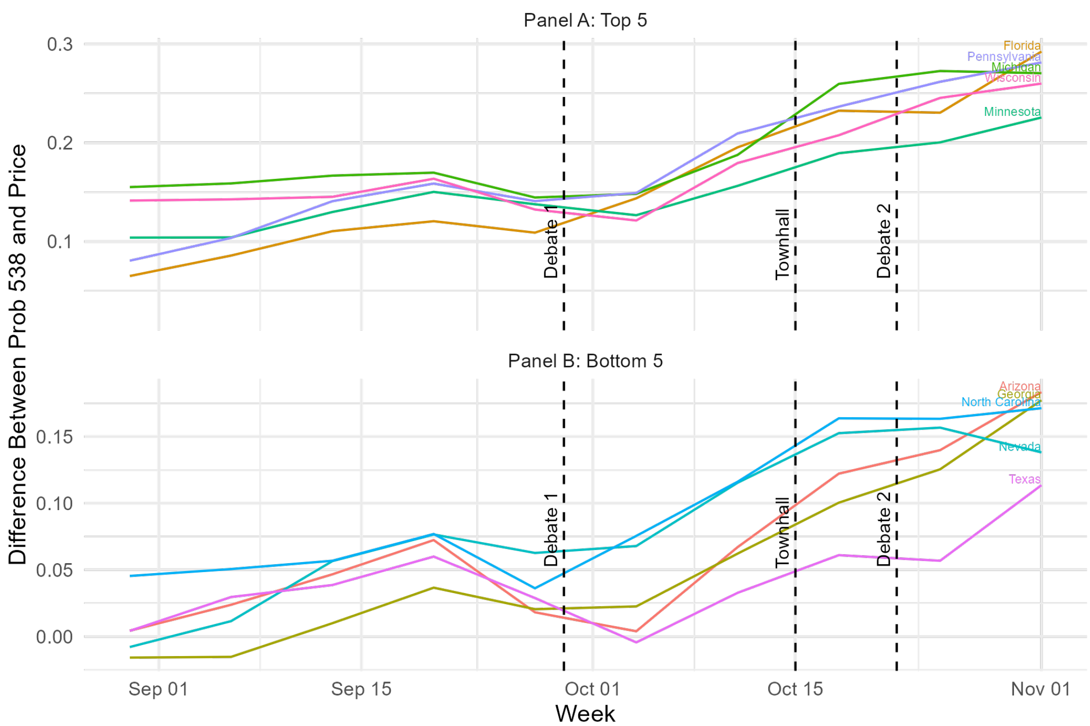
Note: Figure 1 shows an example of the presidential election market for Michigan in 2020. Note both pricing and message board are shown on the same page.

Figure 2: Republican Prices in Non-competitive State Markets (September 2020-November 2020)



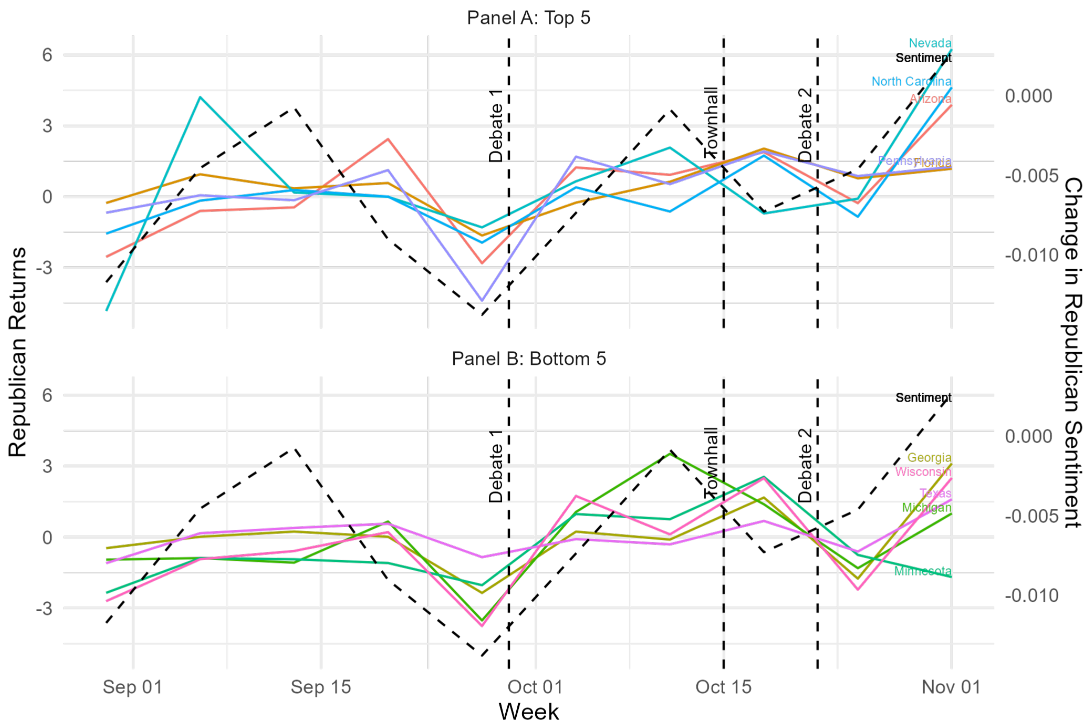
Note: Figure 2 shows the Republican price for some of the least "competitive" state prediction markets in the 2020 Presidential Elections from September 2020 to November 2020. These include California, Connecticut, Illinois, North Dakota, West Virginia, and Wyoming. As it is shown and expected, the asset prices are relatively stable. The Democratic candidate won the states of California, Connecticut, and Illinois by an average margin of around 22 percent. While the Republican candidate won the states of North Dakota, West Virginia and Wyoming by an average margin of around 39 percent.

Figure 3: Difference between Predictit Prices (Republican Asset) and 538 Level Probability of Victory, by State



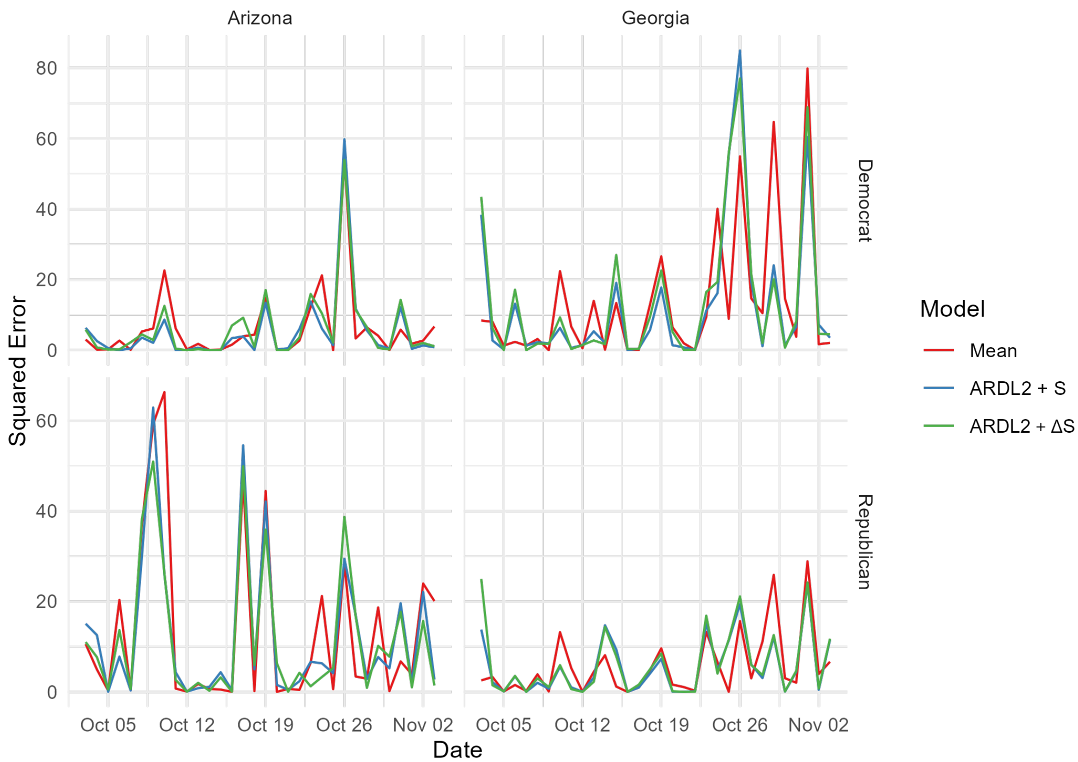
Note: Figure 3 shows the weekly difference between the price of the Republican assets and the predicted probability of victory from the FiveThirtyEight model for the ten closest states by popular vote. A positive value represents possible mispricing in favor of Donald Trump. Vertical dashed lines indicate important events in the election cycle. These include the first presidential debate (Debate 1), individual town halls (Townhall), and the second debate (Debate 2). Panel A contains data for the states with the largest potential mispricing. Panel B contains data for the next five.

Figure 4: Republican Asset Return and Republican Sentiment, by State (September 2020-November 2020)



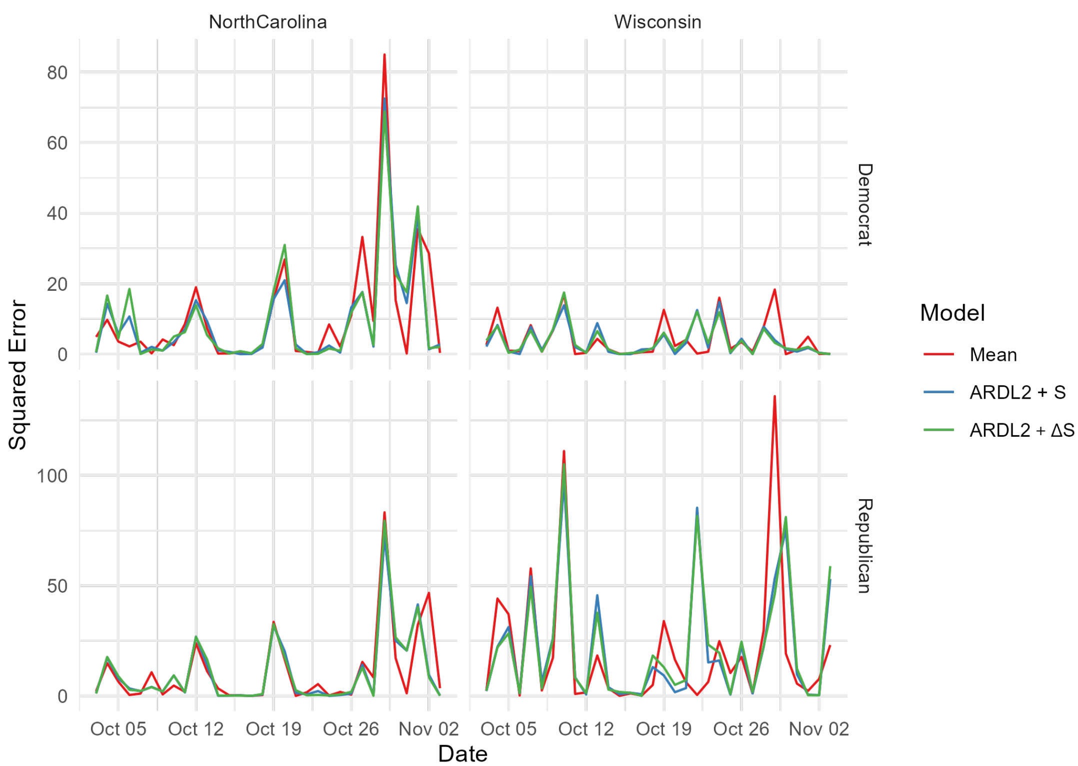
Note: Figure 4 shows a graph of estimated weekly Republican sentiment and returns from the Republican asset for the ten closest states from August 31, 2020 to November 3, 2020, in solid colored lines and the Change in Republican Sentiment (ΔS_R), the dashed line. The left axis shows Republican Returns, while the right axis shows the change in sentiment. Vertical dashed lines indicate important events in the election cycle. These include the first presidential debate (Debate 1), individual town halls (Townhall), and the second debate (Debate 2). Panel A contains data for the five states with the mean highest returns. Panel B contains data for the states with the next five largest returns.

Figure 5: Squared Forecasting Errors for Arizona and Georgia (October - November 2020)



Note: Figure 5 shows out-of-sample squared forecasting errors for Arizona and Georgia utilizing the recursive algorithm. The figure depicts the results for mean model (baseline), $ARDL + S$, and $ARDL + \Delta S$ over the period October 3, 2020 to November 3, 2020. The top panel shows the results for the Democratic Asset, while the bottom panel shows the results for the Republican Asset.

Figure 6: Squared Forecasting Errors for North Carolina and Wisconsin (October - November 2020)



Note: Figure 6 shows out-of-sample squared forecasting errors for North Carolina and Georgia utilizing the recursive algorithm. The figure depicts the results for mean model (baseline), $ARDL+S$, and $ARDL+\Delta S$ over the period October 3, 2020 to November 3, 2020. The top panel shows the results for the Democratic Asset, while the bottom panel shows the results for the Republican Asset.

Table 2: Top 25 Estimated Coefficients Supervised Method

Democratic		*Republican*	
magat	1.15	sjw	1.52
magatard	1.01	il	1.21
q	0.94	pedo	1.18
maga	0.89	kavanaugh	1.15
trumpkin	0.88	educate	1.13
breitbart	0.88	campaigning	1.11
objective	0.88	aa	1.01
trumpers	0.81	owners	1.01
jail	0.77	oil	0.98
trumpkins	0.68	enforcement	0.97
eligible	0.68	libs	0.97
cult	0.63	chinese	0.95
trump	0.61	tony	0.92
magas	0.61	funded	0.88
fail	0.55	identity	0.88
oann	0.55	rn	0.88
biden	0.54	imagining	0.82
ted	0.5	vocal	0.82
blue	0.42	outperformed	0.79
repubs	0.4	cos	0.70
garbage	0.38	belt	0.69
trumptard	0.37	pres	0.68
delusional	0.36	libtards	0.67
jenna	0.34	quid	0.65
battleground	0.34	blah	0.65

Note: Table 2 shows estimated top 25 non-zero estimated coefficients unigrams. The first column details the "dictionary" for the Democratic sentiment, and the second column is the estimated coefficient. The third column details the "dictionary" for the Republican sentiment following the same convention. It is important to note that some of the unigrams in the Republican "dictionary" are semantically related to the Republican identifiers found in Cookson et al. (2020).

Table 3: Cross Section of Returns from State Races and Sentiment

Panel A: Partisan Sentiment Levels						
	Democratic			Republican		
Variables						
$S_{D/R}$	-1.290	-1.628	-2.869	11.377**	10.979**	6.596**
	(2.379)	(2.328)	(1.730)	(4.333)	(4.277)	(2.982)
$\%\Delta Pr(538)_{D/R}$		0.245***	0.159***		0.047	-0.016
		(0.058)	(0.046)		(0.038)	(0.025)
$Return_{D/R}$			-0.480***			-0.947***
			(0.031)			(0.071)
Fixed-effects						
Market	Yes	Yes	Yes	Yes	Yes	Yes
Observations	640	640	640	640	640	640
R^2	0.007	0.057	0.492	0.016	0.021	0.473
Panel B: Partisan Sentiment Change						
	Democratic			Republican		
Variables						
$\Delta S_{D/R}$	5.025***	4.754***	1.478	9.185**	9.616**	6.220*
	(1.774)	(1.782)	(1.398)	(4.214)	(4.184)	(3.201)
$\%\Delta Pr(538)_{D/R}$		0.243***	0.157***		-0.185***	0.050
		(0.058)	(0.046)		(0.043)	(0.042)
$Return_{D/R}$			-0.478***			-0.955***
			(0.031)			(0.072)
Fixed-effects						
Market	Yes	Yes	Yes	Yes	Yes	Yes
Observations	640	640	640	640	640	640
R^2	0.014	0.064	0.491	0.013	0.028	0.473

Note: Table 3 shows the OLS estimated results from Equation 7 and alternative specification for daily PredictIt share returns in the ten most competitive state races. Results for models estimated for the Democratic asset are given in Columns 1-3 and results for the Republican asset are given in Columns 4-6. Panel A contain results where the independent variable of interest is the level of sentiment ($S_{D/R}$). Panel B shows results for the change in the level of sentiment ($\Delta S_{D/R}$), for the party of the respective asset. For example, S_D is utilized for the Democratic Assets while S_R is utilized for the Republican Asset. Newey-West (L=2) standard-errors in parentheses. Levels of significance are indicated by *** at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level.

Table 4: Cross Section of Returns from State Races and Sentiment (2SLS)

IV stages	First Republican	Second Democratic	First Democratic	Second Republican	First Republican	Second Democratic	First Democratic	Second Republican
Variables								
$S_{D/R,t-1}$	8.647**		-11.745***					
	(3.314)		(2.202)					
$S_{D/R}$	-3.771	-3.713*	9.013***	-6.417**				
	(3.563)	(2.108)	(3.104)	(3.039)				
$\Delta S_{D/R,t-1}$					-2.256		-4.721**	
					(2.736)		(1.790)	
$\Delta S_{D/R}$					-7.189**	0.089	2.033	-6.498**
					(3.121)	(1.880)	(2.850)	(3.231)
$\%\Delta Pr(538)_{D/R,t-1}$	0.111***		0.270***		0.109***		0.270***	
	(0.037)		(0.063)		(0.036)		(0.064)	
$\Delta Pr(538)_{D/R}$	-0.194***	0.102**	-0.071***	-0.019	-0.193***	0.123**	-0.072***	-0.012
	(0.044)	(0.049)	(0.020)	(0.025)	(0.044)	(0.050)	(0.020)	(0.026)
$Return_{D/R*}$		-0.804***		-0.994***		-0.677***		-0.909***
		(0.144)		(0.151)		(0.137)		(0.147)
Fixed-effects								
MarketName	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	630	630	630	630	630	630	630	630
R^2	0.053	0.291	0.112	0.470	0.052	0.413	0.092	0.470

Note: Table 4 shows the two-stage least squares results for daily PredictIt share returns in the ten most competitive state races by levels of sentiment or daily changes in levels of sentiment. Equation 8 is estimated in the first stage, while Equation 9 for the second stage. Variables include raw total Democratic/Republican Sentiment ($S_{D/R}$), daily change in total Democratic/Republican Sentiment ($\Delta S_{D/R}$), daily percent change in probability of victory for the Democrat/Republican candidate as per FiveThirtyEight ($\%\Delta Pr(538)_{D/R}$), and the first stage estimate of the daily return on a PredictIt share for the opposing party candidate based on closing prices ($Return_{R/D*}$). The first lags of $S_{D/R}$ and $Pr(538)_{D/R}$ are also utilized as instruments in the first stage. Data ranges from August 31, 2020, and November 4, 2020. Newey-West (L=2) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table 5: Out-of-Sample Forecasting Evaluation: Five Closest States

	Georgia		Arizona		Wisconsin		Pennsylvania		Nevada	
	$R^2_{OOS}\%$	CW	$R^2_{OOS}\%$	CW	$R^2_{OOS}\%$	CW	$R^2_{OOS}\%$	CW	$R^2_{OOS}\%$	CW
Panel A: Republican - Rolling										
$ARDL1$	-4.728	1.211	8.831	1.077	0.074	3.445	11.679	0.25	13.833	-3.164
$ARDL2$	-5.325	2.111***	9.903	2.855	11.109	2.849	11.815	1.382	11.188	1.051
$ARDL1 + S$	6.452	1.208*	11.372	1.549	3.111	3.074	14.656	0.864	17.531	-2.552
$ARDL2 + S$	3.986	1.908**	12.376	3.247*	15.17	2.078	15.587	1.405	16.281	0.477
$ARDL1 + \Delta S$	0.686	1.004*	13.073	0.514	-0.711	3.565*	12.552	0.351	16.184	-3.876
$ARDL2 + \Delta S$	-1.527	1.925**	15.763	2.223	10.686	2.879	13.156	1.688	12.44	0.832
Panel B: Republican - Recursive										
$ARDL1$	4.732	0.907*	1.596	2.046	5.162	4.057*	-8.263	0.84	-14.972	-3.886
$ARDL2$	3.808	2.022**	11.479	3.659**	-7.148	4.593	-7.509	1.655	-14.014	1.049
$ARDL1 + S$	-11.011	0.502	1.469	2.502*	2.144	3.542*	-11.745	0.323	-21.532	-1.828
$ARDL2 + S$	-8.414	1.58**	12.094	4.388**	-9.918	3.982	-11.211	0.942	-19.14	1.151
$ARDL1 + \Delta S$	0.473	0.798	-1.538	1.816	5.557	4.187*	-9.082	0.59	-15.83	-3.98
$ARDL2 + \Delta S$	0.77	1.89**	7.987	3.36**	-6.548	4.592	-8.459	1.471	-13.93	1.129
Panel C: Democratic - Rolling										
$ARDL1$	-3.654	4.57*	5.875	0.693	1.832	0.605*	14.236	0.775	8.834	-0.099
$ARDL2$	-3.173	6.69**	3.979	1.023	-1.983	1.284**	14.382	0.927	-1.077	0.412
$ARDL1 + S$	4.401	4.068	8.323	0.587	6.341	0.415	18.13	0.363	4.352	0.075
$ARDL2 + S$	4.624	6.456**	6.582	0.894	5.519	1.106	17.708	0.747	-7.841	0.608
$ARDL1 + \Delta S$	1.423	4.177*	4.481	0.924	3.837	0.536	14.935	0.72	13.218	-0.186
$ARDL2 + \Delta S$	-1.293	7.084	2.971	1.202*	2.28	1.228*	15.044	0.958	6.503	0.358
Panel D: Democratic - Recursive										
$ARDL1$	4.968	3.642*	3.255	1.314*	3.35	0.76**	-12.303	0.902	-9.669	-0.096
$ARDL2$	5.543	6.214**	11.797	1.746**	14.733	1.492**	-11.608	0.967	1.072	0.425
$ARDL1 + S$	-4.628	3.195	-4.279	0.832	-1.56	0.57	-16.874	0.495	-6.749	0.047
$ARDL2 + S$	-3.543	6.034**	3.999	1.281*	11.147	1.301**	-14.885	0.586	5.436	0.52
$ARDL1 + \Delta S$	2.836	3.955*	6.352	1.74**	2.24	0.707*	-12.178	0.863	-13.606	-0.157
$ARDL2 + \Delta S$	5.168	6.807**	14.025	2.08**	13.301	1.425**	-11.037	0.941	-7.234	0.359

Note: Table 5 shows forecasting results for the five closest states by popular vote. Rows indicate the prediction model compared to the Mean model; AR(1) represents a one-period auto-regressive model, ARDL1 and ARDL2 represent auto-regressive distributed lag models containing other party returns and all non-sentiment predictors, and S and ΔS represent the levels and changes in levels of sentiment. Column headings indicate the state of the estimated model. $R^2_{OOS}\%$ indicates the improvement/decline in out-of-sample forecast accuracy relative to the mean model, and CW is the value of the Clark-West Adjusted MSFE test statistic with levels of significance indicated by *** at the 0.01 level, ** at the 0.05 level, and * at the 0.1 level.

Appendix

Table A1: Examples of Partisan Identified Comments

Username	Date	Post
		Example Democratic Comments
predictit	9/6/2020	No one thinks they can read minds. It's that Trumpkins parrot whatever comes from the mouths of the Party Leaders (far more than Democrats I'd argue), and he can generally do no wrong in their eyes. If Trump says or does it, it must be good. I'd argue they are more like a personality cult than a political party at this point. No one can seriously argue Biden has a cult of uncritical followers. Trump's supporters all sound like they drank Kool-Aid and started shouting MAGA FAKE NEWS
GuyConcordia	10/24/2020	Incredible value right now. Trump down by 9 or so in the national vote. District polls show him doing even worse. No more debates. Coronavirus cases on the rise. Millions more Democratic votes banked than Republican votes. Youth and Democratic turnout up. Democrats have way more money to spend. On the other side, Trump's supporters are deluding themselves more than ever before. They wanted Trump to win in 2016, were told that was not going to happen, but he won anyway. Now they are convinced that all of the warning signs are fake or irrelevant because ignoring polling averages was the right thing to do last time. They follow Fox, Breitbart, OAN and the President himself so they cannot believe anyone could possibly support the demented communist Sleepy Joe. They think everyone else sees what they see and the liberal media is just lying. Plus if you're a loud, white guy you can get your way with bravado. They actually believe Biden is corrupt because Rudy Giuliani found proof on Hunter Biden's laptop that he left at a blind QAnon computer repairman's shop and forgot about, and it showed emails implying that people were trying to use Hunter to get to Joe even though there's no proof that they did and Joe didn't give them what they wanted anyhow so they're pissed.I guess we'll find out for sure in 10 days.
		Example Republican Comments
predictit	9/10/2020	It is a catchall I use for all libs these days. There may be a few exceptions to it but the tough blue collar Dem party of Kennedy is long dead. Even Bill Clinton was a worthy adversary and a true democrat. The lib party has turned into a party of coastal elite c ucks that get triggered over everything from syrup to saying china virus. Wahhh!!! Trump says mean things. Wahhh!! Everything is racist. Wahhh!!! Lets have biological men steal scholarships from women. Wahhh!! Lib colleges shutting down free speech because they have a different opinion. Wahhhh! Don't dare say radical Islamic terrorism. Wahhh!!! Don't call illegal immigrants illegal. Wahhhh! I could go on and on.SJW coastal elites hijacked the Dem party after beta Obummer trained all of you in the art of being a beta with his actions. Anyone that supports this S show of a lib party is most likely a beta. Liberal men are the most embarrassing. Just look at them. They scream low T. I can at least excuse the women.Libs need a tea party movement. The triggered over everything lib party is messed up. Unfortunately you are training a new set of betas with diaperface wearing fear mongering. Start em young!
predictit	10/31/2020	Libtards,Keep your Marxism out of our schools, your socialism out of our economy, your identity politics out of our law enforcement, your environmentalism out of our oil industry, your censorship out of our social media platforms, your illegal aliens out of our country, and your confused men out of our women's sports & bathrooms.We just want to be left alone. Sincerely,The Deplorables

Note: Table A1 shows examples of the Disqus comments which are estimated to be some of the most partisan. The first column detail the Username of the poster, the second column the Date of posting, and finally the third column the actual post. Please note these are only examples, others were omitted for brevity. All posts can be provided upon request. These posts seem to express either a extremely partisan views - thus providing anecdotal evidence of accuracy of the MNIR procedure in correctly identifying partisan sentiment.

Table A2: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
S_D	640	0.522	0.040	0.431	0.663
S_R	640	0.523	0.033	0.441	0.609
ΔS_D	640	-0.001	0.046	-0.140	0.090
ΔS_R	640	-0.001	0.033	-0.083	0.084
$\%\Delta Pr(538)_D$	640	0.531	2.463	-12.665	14.159
$\%\Delta Pr(538)_R$	640	-1.149	5.432	-32.953	37.911
$Return_D$	640	0.122	2.664	-9.355	12.503
$Return_R$	640	0.026	3.697	-13.017	13.630

Note: Table A2 shows the descriptive statistics for daily observations of the main variables for the ten markets with the smallest final popular vote margins. Summary statistics include the number of observations, mean, standard deviation, minimum, and maximum. Variables include raw total sentiment for party X (S_X), daily change in total partisan sentiment for party X (ΔS_X), daily percent change in probability of victory for party X as per the FiveThirtyEight model ($\%\Delta Pr(538)_X$), and the daily return on a PredictIt share for party X based on closing prices ($Return_X$). Data ranges from August 31, 2020 and November 3, 2020.