

Limits to Arbitrage and Prediction Market Efficiency: the Case of PredictIt

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PRELIMINARY DRAFT, COMMENTS WELCOME

Abstract: PredictIt is a CFTC-regulated US prediction market focused on political outcomes. It was very successful in attracting participants in the 2016-22 period, running liquid markets on topics predecessors had tried unsuccessfully. During this period, investors were limited to \$850 positions in each contract, which limited arbitrage trading. PredictIt exhibited much larger pricing biases than previously studied prediction markets. Bid prices often persistently added to more than 110, implying an immediate arbitrage profit even after fees. Prices exhibited an overpricing of longshots that was larger than in other prediction markets. The experience of PredictIt suggests that limiting stakes may undermine the ability of prediction markets to accurately price event probabilities.

¹ I would like to thank PredictIt for sharing some of the data used in this paper and for making other data available via its API or website, as part of its mission to support academic research. Thanks also to Charles Manski, Lionel Page and Justin Wolfers for helpful comments.

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I. Introduction

Prediction market participants trade securities with payoffs linked to the outcome of events, such as elections. Past research has found that, despite their small scale, these markets are generally quite efficient (Arrow, et. al., 2008). Prediction market prices yield well-calibrated event probabilities, and their prices generally do not allow for predictable returns.

This paper finds that PredictIt, the primary public prediction market available to U.S. participants from 2014-24, is an exception to this statement. During this period, prices on PredictIt diverged significantly from probabilities, allowing predictable trading profits even after fees.

PredictIt prices exhibited two well-known biases -- to a much greater degree than in other prediction markets. PredictIt traders exhibit short aversion, preferring to purchase “Yes” securities (i.e., betting on a specified outcome) even when a better price could be obtained by purchasing “No” securities on other outcomes (i.e., short selling/betting against these outcomes). This led its securities in multi-outcome markets to be generally overpriced. The sum of bid prices on PredictIt’s multi-outcome markets was usually greater than 100, and the most active markets often had bids that sum to between 110 and 125, implying an easy arbitrage opportunity from short selling every outcome, even after fees.

In addition to overpricing, PredictIt prices also exhibited a longshot bias, in which low-probability events are overpriced and high-probability events are underpriced. The longshot bias was more pronounced on topics where one might expect strong partisanship to exist, such as elections or whether a particular politician or aide would be indicted.

The overpricing and longshot biases were likely the result of limits to arbitrage that were imposed by regulation. The most important restriction is that traders on PredictIt were limited to taking \$850 of downside risk on each outcome.² This has two implications. First, it means that a trader who is betting on a low-probability outcome can take a much larger position than one who is

² Contracts were also limited to 5000 participants. This limit bound for the most popular contracts on the 2020 Presidential election (on the winning party and individual), beginning in late October.

betting against the outcome. This can cause the price of a low-probability outcome to be above the mean beliefs, contributing to overpricing longshots.

Second, because the \$850 downside risk limit does not account for any hedging from positions on other outcomes in the same market, traders who profit from overpricing by selling every contract are limited in their ability to do so. They can only sell about 850-900 contracts for each outcome, and once they have done so, they are effectively locked out of trading to profit from other mispricings, except by closing their existing positions.

The most active markets on PredictIt provide the largest opportunities to profit from overpricing, presumably because there are not enough traders following the sell-every-contact strategy to offset it. There is weak evidence that markets with more overpricing have stronger longshot pricing biases, consistent with some informed traders having taken the easy arbitrage of trading against overpricing, leaving them essentially locked out of trading against other pricing biases.

The experience of PredictIt illustrates how a seemingly benign regulation – a limitation on downside risk – can undermine the central goal of a prediction market: aggregating the beliefs of its participants to yield minimally biased predictions. It also illustrates how a constraint on arbitrage can cause inefficiencies to be larger in the most liquid markets, even in markets many orders of magnitude smaller than the financial markets we normally study.

The results in this paper connect to several extant literatures. Shleifer and Vishny (1997) motivated an extensive empirical literature on the impact of limited arbitrage on pricing anomalies. Many of the limits explored in this literature, such as short selling constraints (e.g., Chu, Hirshleifer, and Ma, 2020) or limits to market-wide funding liquidity (e.g., Sadka and Scherbina, 2007) are not an issue on PredictIt, given that short selling is unconstrained and maximum losses are capped well below many traders' presumed access to funds. Unlike other settings, in which arbitrage limits vary across securities and over time, on PredictIt arbitrage limits were constant, and what varied was participation by behaviorally biased traders. This plausibly explains the different relationship between liquidity and efficiency.

As mentioned, PredictIt provides an exception to the literature's general conclusion about the efficiency of even very low-volume prediction markets. The PredictIt results are anticipated by Manski (2006), who applies an insight from Ali (1977) to prediction markets with limited stakes. In

Manski’s model, risk-neutral participants face a limit on the downside risk they can take on any contract. Participants therefore “max out” whenever their belief differs from the equilibrium market price. In this setting, a prediction market security will trade at 10 when the 90th percentile of the belief distribution is $p = 0.1$, since equilibrium will require there be 9 times as many maxed-out sellers as maxed-out buyers. When beliefs vary and the average belief is unbiased, the stake limit can produce a significant longshot bias.

Manski’s assumption was arguably not a close fit for then extant prediction markets, which either imposed no position limit (Betfair, Intrade) or a limit that applied across the entire exchange and that also was likely not binding (the Iowa Electronic Markets). Manski’s stark prediction is weakened when traders have an incentive to invest more when subjective expected returns are higher, e.g. due to risk aversion (Gjerstad, 2005; Wolfers and Zitzewitz, 2006; Ottaviani and Sorensen, 2015) or an exchange-wide risk constraint. That said, his assumption is an excellent fit for PredictIt, where downside risk was limited at the contract level and high volumes created the opportunity for that limit to bind.

The remainder of the paper is organized as follows. The next section provides background on PredictIt in the context of other public prediction markets. Section III discusses the data. Section IV presents the evidence on overpricing, and Section V presents the evidence on the longshot bias. A conclusion follows.

II. Background

Betting on current events, such as elections, has a long history in the United States and elsewhere. Odds from election betting odds outside the New York Stock Exchange were reported in newspapers from the Civil War to 1940 (Rhode and Strumpf, 2004). The modern era of public, online prediction markets began with the Iowa Electronic Markets (IEM), small-scale markets run by academics at the University of Iowa and used in many early empirical prediction market papers.³ The IEM obtained a No-Action Letter from the Commodity Futures and Trade Commission (CFTC), allowing them to operate legally in the United States. The conditions of operation included

³ Forsythe, Nelson, Neumann, and Wright (1992) describe the IEM. Berg, Forsythe, Nelson, and Rietz (2008) and Berg, Nelson, Rietz (2008) report on the predictive performance of its election markets.

limiting participants to a maximum downside exposure of \$500, although given the limited trading volume on the IEM, this constraint likely rarely was binding.⁴

Larger-scale, for-profit prediction markets were launched by Betfair in 2000 and Intrade in 2002. Betfair is an exchange based in the United Kingdom. It focuses on sports, but it also offers contracts on elections and current events. Betfair reportedly refuses business from U.S. customers. It still exists as of mid-2026, but blocks traffic from U.S. IP addresses.

Intrade, which was initially known as Tradesports, was based in Ireland, but it advertised in the U.S., and its mix of sports and politics contracts was consistent with a largely U.S. clientele. Intrade ceased offering sports contracts in 2007, but it continued to offer election and financial contracts.⁵ While the CFTC appeared to be tolerating Intrade for several years, it sued Intrade in 2012, leading to its closure.

In 2014, PredictIt was launched as a collaboration between the Victoria University of Wellington, New Zealand and Aristotle, a U.S.-based political consulting firm. PredictIt obtained a new No-Action Letter from the CFTC, which was based on the original IEM letter, but increased the maximum downside exposure to \$850 and allowed PredictIt to advertise and to charge fees.⁶ The CFTC had declined a 2012 request by the North American Derivatives Exchange (NADEX) to offer election contracts without a position limit, so the position limit was presumably important to PredictIt obtaining approval.

Despite the position limit, PredictIt attracted volumes comparable to those on Intrade, which had not been similarly constrained. Table 1 traces the evolution of political prediction markets by reporting the volume in the most active market on each U.S. Presidential election since 1988 and, when available, the total volume in political prediction markets in that calendar year. PredictIt's volumes in the most heavily traded market (in each case the market tracking the individual elected U.S. President) were lower than on Intrade, presumably due in part to the position limit.⁷ But overall

⁴ A 1993 update to the original No-Action Letter is available at <https://www.cftc.gov/sites/default/files/files/foia/repfoia/foirf0503b004.pdf> (last accessed May 12, 2026).

⁵ Tetlock (2004, 2008), Zitzewitz (2006), and Page and Clemen (2013) analyze the efficiency of Intrade prediction markets.

⁶ See <https://www.cftc.gov/csl/14-130/download> (last accessed May 6, 2025). PredictIt obtained a new No Action letter when it relaunched in 2025, which allowed an increase in this limit to \$3500. See <https://www.cftc.gov/csl/25-20/download> (last accessed July 31, 2025).

⁷ PredictIt was also limited to 5,000 participants in each contract. This limit bound for the most popular contracts on the 2020 general election. This limit was eliminated by the 2025 No Action Letter.

trading in political contracts was higher on PredictIt.⁸ This reflected the fact that PredictIt was successful in attracting liquidity to a broader range of topics than Intrade. As one example, Intrade generally failed to attract liquidity to markets on the overall winner of high-profile U.S. House of Representative races. PredictIt ran liquid markets on the *margin of victory* in high-profile *primaries* in House races.

PredictIt had several differences with Intrade that may have helped offset the impact of the position limit. Transferring money to Intrade was cumbersome for U.S. customers, especially after the Unlawful Internet Gambling Enforcement Act of 2006 prohibited U.S. financial institutions from facilitating these transfers. PredictIt's onshore, regulated status allowed it to accept deposits via electronic funds transfers and credit cards. PredictIt advertised and offered signup and referral bonuses to attract new users. PredictIt's user interface was arguably more accessible for novice traders. Short selling an outcome was framed as "Buying a 'No' contract." In addition, a message board for discussing the market was integrated with the trading page, so users could engage with each other while waiting for their limit orders to fill.

PredictIt also introduced a wider range of contracts than political prediction markets had previously offered. Table 2 provides my categorization of their offerings. Markets on election outcomes accounted for 30 percent of the markets and 58 percent of the trading volume. Other popular categories included markets on polling (e.g., job approval and electoral support), campaign events (e.g., running for office, dropping out, and participating in debates), appointments and departures (e.g., for cabinet officials), and Congressional votes (including confirmation votes). Non-US topics accounted for about 5.8 percent of the markets and 2.0 percent of the volume.

Trading on election outcomes was concentrated around U.S. Presidential primaries, the Presidential general elections, and the midterms (Figure 1). PredictIt offered markets that appear designed to keep users engaged between elections. The most popular of these were on the number of messages President Trump or other politicians would post on Twitter each week; these markets accounted for 50 percent and 33 percent of trading in 2017 and 2018, respectively (Figure 2).

⁸ Intrade also ran markets on daily changes in financial variables such as the Dow 30 index. I exclude the volume in these markets from Table 1 since PredictIt did not run comparable markets.

PredictIt ended its Tweet markets in June 2020, plausibly in response to regulatory pressure from the CFTC.⁹ In August 2022, the CFTC announced that it was revoking PredictIt's No-Action letter and gave it six months to cease operations. PredictIt obtained an injunction against the order to close, and it remains open. Its launching of new contracts was very limited between August 2022 and May 2025, however, and trading volumes are lower than prior to that date.¹⁰

The decline in activity on PredictIt in 2023-24 was also related to the emergence of Polymarket and Kalshi as competitors. Polymarket is an offshore, crypto currency-based exchange that offers contracts on politics, sports, and other topics. It originally refused users from the United States, but as of May 2026 offers a US version of its platform that excludes geopolitical contracts that are prohibited by CFTC rules.¹¹ Kalshi has offered non-election-related event contracts (e.g., on weather, economic numbers) since 2021, and it won legal permission to offer election contracts in early October 2024.¹² Volumes on Polymarket were very high compared with Intrade or PredictIt, and the fact that volumes on Kalshi for the 2024 election roughly matched prior highs on Intrade or PredictIt was impressive given that it began only a month before the election (Table 1).

PredictIt relaunched in Spring 2025, and as of August 2026 it was offering more markets than it did in August 2022 (236 vs. 163). Volume is less than one tenth as high though (1.4 million versus 25 million), presumably because of competition from Kalshi and Polymarket. I will focus the analysis in this paper on 2016-22, when PredictIt was the only onshore prediction market available to U.S. traders and when its market offerings were not yet constrained by the CFTC's action.¹³

This narrative highlights several features of PredictIt that are relevant for an analysis of its efficiency. First, PredictIt was, for most U.S. topics, the only real-money prediction market active for

⁹ The ending of these markets might be connected to death threats received by Presidential candidate Andrew Yang in December 2019 instructing him to stop tweeting so that bets made in an online market, presumably PredictIt, would pay off (<https://thehill.com/homenews/campaign/472928-yang-campaign-receives-death-threats-in-new-hampshire/>, last accessed May 12, 2026).

¹⁰ For example, the final 90 days of the 2020 U.S. Presidential winner market had \$26.2 million in volume, compared with \$12 million in 2024. PredictIt offered 214 unique markets on November 1, 2020, compared with 10 on the same date in 2024.

¹¹ See, e.g. <https://tech-insider.org/prediction-markets/is-polymarket-legal-in-the-usa/> (last accessed September 17, 2026).

¹² Buergi, Deng, and Whelan (2025) and Kagan and Baiocchi (2026) analyze the efficiency of Kalshi's prediction markets. Reichenbach and Walther (2025) do the same for Polymarket.

¹³ I extend the sample period to the end of 2022 to capture the end of trading in most of the markets PredictIt had launched by the CFTC's action in August 2022. All markets that existed in 2022 had settled by the end of 2024, and I incorporate the outcome of these markets into the analysis.

close to a decade.¹⁴ Prediction markets offer academics and others an objective means of measuring aggregated beliefs about the probabilities of economically important events, and understanding how well-calibrated these markets are is important to their potential users. Second, PredictIt's success in exceeding volumes on Intrade despite position limits appears due in part to successfully attracting users with signup bonuses, easy financial transactions, a simple interface, and an engaging discussion forum. One might expect pricing biases to emerge from this user base, particularly if arbitrage is constrained.

III. Data

I have two types of pricing data from PredictIt: quote data (bid and ask prices as of a point in time) and trade data (open/high/low/close prices and trading volume during an hour or day). The quote data were collected by me in real time from PredictIt's Application Programmable Interface (API); the trade data were provided to me by PredictIt and supplemented with data collected from the website. I have trade data beginning in late December 2015 and quote data from June 8, 2019 onwards.

PredictIt ran both single-outcome and multi-outcome markets. Single-outcome markets predicted the answer to a yes-or-no question (e.g., "Will Kamala Harris Become the 47th U.S. President?"). Multi-outcome markets predicted the answer to a multiple-choice question (e.g., "Who Will Win the 2020 U.S. Presidential Election?"). Some multi-outcome markets began with a set of possible answers that exhausted all possibilities, such as markets on which bin a variable (e.g., vote margin, number of Tweets) would fall into or which of a defined set of leaders will leave office first. Other multi-outcome markets were necessarily open-ended, such as markets on which individual would win an election or receive an appointment. Additional outcomes were often added to these markets as new candidates emerged (e.g., Michael Bloomberg as a Presidential candidate in 2020).

Several of the multi-outcome markets were or became de facto two-outcome markets. Markets on which party would win an election often had only two plausible answers, but were launched by PredictIt as multiple-outcome markets in case a third-party contender emerged. Other

¹⁴ Betfair and offshore bookmakers offer markets on U.S. politics, but their offerings are typically limited to the highest profile events. Play-money markets, such as Manifold Markets, also operated during this time period. The literature on whether play-money markets are as accurate as real-money markets is mixed (e.g., Servan-Schreiber, et. al. 2004; Rosenbloom and Notz, 2006).

markets became de facto two outcome markets due to events, such as the market on the 2020 Democratic nomination after the field narrowed to Joe Biden and Bernie Sanders. In the analysis, I will distinguish between yes/no, two-outcome, de facto two-outcome, and true multi-outcome markets.

IV. Overpricing

Some prediction market investors find it easier or more appealing to bet on an outcome instead of betting against the other possible outcomes. This can sometimes cause the prices of contracts linked to mutually exclusive contracts to sum to more than one. This creates a potential arbitrage opportunity for traders, but a complication for analysts seeking to infer probabilities from prediction market prices.

Different prediction markets have dealt with this issue in different ways. The IEM allows traders to either purchase securities linked to the outcomes they wished to bet on or to exchange \$1 for a basket of securities linked to all possible outcomes and sell the other securities. A trader could take a position in whichever way was cheaper, e.g. by buying outcome A or exchanging \$1 for A and B and then selling B. If the bid prices on all outcomes added to more than one, a trader could exchange \$1, sell every outcome, and earn the difference as profit. Importantly, doing so would not count against the \$500 investment limit, so even a single arbitrageur could repeatedly sell the complete set of outcomes, keeping the sum of bid prices from exceeding one.

Intrade allowed traders to either buy or sell outcomes short. The margin required against a position in a market was based on a worst-case scenario, so if a trader sold short every outcome but one, it would tie up one minus the sum of the prices received. Intrade did not have position limits, so if prices summed to more than one, an arbitrageur could sell all possible outcomes as often as was profitable.

PredictIt also allows traders to buy or sell short outcomes, but frames it differently. Buying is framed as buying a “Yes” security, selling short as buying a “No.” The bid for the No security is one minus the ask for the Yes, and vice versa. As on Intrade, the margin requirement against a position is based on the worst-case scenario. Unlike with Intrade and the IEM, traders are limited to \$850 of downside risk on any contract, and the hedging effects of positions in other contracts are not taken

into account. So a trader buying Nos on every outcome can buy up to \$850 of each contract, but then can only close their positions by selling the contracts back.

In addition to position limits, arbitrage was also limited by fees. PredictIt charges 10 percent of the profits on winning positions. These fees are assessed at the contract level, which significantly limits arbitrage. Suppose a trader sold the 11 outcomes for a possible market for 10 cents each (which would be framed as buying 11 No securities for 90 cents each). Their profit before fees would be +10 cents each on the 10 winning No securities and -90 cents on the losing one, for a net of +10 cents. After fees though, they would earn only 9 cents on each of the 10 winning Nos, and thus would only break even. So in this example, bid prices that sum to 110 would not allow for profitable arbitrage.

Fees are a greater barrier to arbitrage when there are many low probability outcomes. For example, suppose probability is as fragmented as possible across outcomes. Given PredictIt's minimum tick size of 1 percentage point, this would imply every Yes security being priced at 1 cent. If a trader buys 111 Nos at 99 cents each, they will earn 0.9 cents each after fees on the 110 winning Nos (for a total of +99 cents) but lose 99 cents on the losing No. So they will breakeven after fees, despite bid prices summing to 111.

In contrast, a trader who can purchase two Nos at 47 cents each will earn a net $53 \times 0.9 - 47 = 0.7$, and thus arbitrage involving two equally priced securities will be profitable when the bid prices sum to 106. When the two outcomes have unequal prices, the required bid price sum is lower. For example, if a trader can buy Nos on one outcome for 4 cents and on another for 95 cents, they can earn positive profits for certain by buying 11 of the first No security and 10 of the second. If the first security wins, they earn a net of $11 \times .96 \times .9 - 10 \times .95 = 0.004$; if the second wins, they earn $10 \times .05 \times .9 - 11 \times .04 = .01$. Fees are higher when the lower priced No (i.e., the higher probability outcome) wins, but a trader can hedge this by buying more of that contract. When probability is sufficiently concentrated on one outcome, arbitrage is possible even when bid prices sum only to 101.

As these examples illustrate, the extent to which fees constrain arbitrage depends on the concentration of probability in outcomes. Appendix A derives a formula for arbitrage profits after fees for both buying Nos when bids prices sum to more than 100, or the less commonly possible

arbitrage of buying Yeses when ask prices sum to less than 100. In each case, fees are roughly $(100/9)*(1 - H)$, where H is the Herfindahl index of outcome probability concentration.

Even when fees prevent the simple arbitrage of buying or selling every outcome, bid prices summing to 100 or more, or ask prices to 100 or less, can represent a puzzle. For example, if the bid prices in a two-outcome market sum to 100, a trader placing an order to buy a Yes at the bid could have gotten immediate execution on the same economic terms by purchasing the No on the other outcome. Therefore any limit orders placed which create a situation with two bid prices summing to 100 represents a mistake by the trader placing the limit order.

With more than two outcomes, the arithmetic is more complicated, since fees are paid on the winning Nos even when the overall position loses money. But it is still the case that there will be a range of bid price sums where arbitrage profits from selling every outcome are not available, but individual traders would be better off selling Nos immediately than waiting to buy a Yes at the bid.¹⁵

Table 3 reports the average share of PredictIt's markets experiencing different degrees of over and underpricing by calendar quarter. PredictIt's API refreshes its quotes approximately every 61 seconds. I collected most of these refreshes, but to keep the sample size manageable I include only the first collected refresh for each hour.¹⁶

For overpricing, I report the average share of markets where: 1) potential buyers of at least one contract would have been better off buying Nos on other contracts rather than waiting to buy at the bid, 2) the share of markets where potential buyers of *all* contracts would have been better off buying Nos, 3) the share of markets where arbitrage profits were available from selling every contract, and 4) the share of markets where arbitrage profits were available in every quote refresh that I collected that hour.

¹⁵ For example, if five outcomes are each bid 21, a trader buying one of them at the bid price will earn $79*0.9 = 71.1$ if they win and -21 if they lose. A trader buying Nos on the other four outcomes (for 79 each) will earn $21*4*0.9 = 75.6$ if they win and $26*2*0.9 - 74 = -22.3$ if they lose. The former implies a breakeven probability of $21/(21+71.1) = 22.80$ percent and the latter $22.3/(22.3+75.6) = 22.78$ percent. So with five equally priced outcomes, when bid prices sum to 105 waiting to buy a Yes at the bid is less attractive than immediately buying the other four Nos. In contrast, bid prices would need to sum to 109 to allow arbitrage profits from buying every No.

¹⁶ On average I successfully collected 56.7 quote refreshes in each hour in the sample, out of the 59 that PredictIt published in a typical hour. During the main sample period (June 8, 2019 to December 31, 2022), 99.75 percent of possible hours are represented in the sample. Almost all of those missing are due to technology issues at my end presumably exogenous to PredictIt (Windows updates, Internet or power outages). The 9-10 PM period on Election night 2020 (11/3/2020) is omitted due to PredictIt being overwhelmed with traffic that evening.

Three distinct eras can be observed. During the main sample period for which quotes are available, June 2019 to December 2022, markets frequently offered better pricing to No buyers, implying that traders who placed bid orders to buy Yeses were making mistakes. Arbitrage opportunities were available in 1.9 percent of markets at any one time, and most of these opportunities were persistent. In 2023-24, after the CFTC revoked PredictIt's No Action letter and its markets on the 2022 midterms closed, PredictIt was running only 10 markets on average, and these markets were long-lived and high-volume. Overpricing was extremely common during this period. Conversely, in 2025-6, when PredictIt has launched many new markets but is struggling to attract volume, the overpricing issue has largely disappeared.

Underpricing is much less common. Underpricing is only relevant for markets where the contracts exhaust the possible outcomes, i.e. where one contract is guaranteed to win. These include markets that predict the value of a variable (e.g., number of tweets, a polling outcome) and those that predict which of a listed set of leaders will leave office first. This group excludes markets on the election- winning party or individual, since these typically provide for additional parties or candidates to be added, and therefore ask prices on current outcomes summing to less than 100 need not imply an arbitrage.

For the subset of markets with exclusive outcomes, underpricing large enough to imply an arbitrage opportunity occurred less than 0.1 percent of the time during the main sample period (Table A1). This was less than one-twentieth as frequent as overpricing.

Table 4 lists the markets that exhibited overpricing most frequently. Many are long-lived, high-volume markets on important events, but a few are shorter-term markets on tweets, debate speaking time, or when the Georgia Senators newly elected in 2020 would take their seats. With the exception of the market on the Congressional balance of power after the 2022 midterms, all of the markets that exhibit the most frequent overpricing have seven or more possible outcomes. Six of the 19 markets PredictIt ran in the first 11 months of 2024 are listed in the table.

Figures 3 and 4 plot the history of two of the most frequently overpriced markets, on the 2020 Democratic nomination and the 2020 Presidential election winner. Each market exhibited long time periods in which bid prices summed to 115-120, allowing traders to sell every contract at the bid and earn certain profits of 5-10 cents per contract, or \$45-90 in each market, assuming

traders sold the maximum number of contracts on each candidate.¹⁷ In both markets, overpricing was reduced when the Democratic field narrowed to Joe Biden and Bernie Sanders in late February 2020.

To have such large overpricings be so persistent in what were arguably the most salient markets seems impossible in the absence of stake limitations. The list of most frequently overpriced markets suggests it is more common in high-volume, long-lived markets with a large number of possible outcomes.

Table 5A examines the frequency of bids summing to greater than 100, asks summing to less than 100, and of overpricing and underpricing-related arbitrage opportunities by number of outcomes with a positive bid price.¹⁸ Overpricing is more common in markets with 4 or more outcomes and is especially common in the few markets with 11 or more outcomes. Identifying overpricing is relatively simple in markets with two outcomes, since one can simply compare the cost of buying a Yes with buying a No on the other outcome. In markets with three or more outcomes, it involves comparing the cost of a Yes with the sum of the costs of the other Nos less 100 multiplied by the number of Nos minus one and then making an adjustment for the difference in expected fees. This becomes cognitively more taxing as the number of outcomes rises. Underpricing, which is cognitively simpler to identify since it involves adding the ask prices of Yes securities and comparing the sum to 100, does not appear related to the number of outcomes.

Table 5B presents regressions predicting overpricing using volume, cumulative volume, and the number of outcomes. Controlling for the number of outcomes, overpricing is more common following high volume days and when a market's cumulative volume is higher. Interestingly, the relationship between overpricing and both the number of outcomes and volume persists when controlling for market fixed effects, consistent with overpricing becoming more likely over time in popular markets, but less likely when the field of plausible outcomes narrows (as observed in Figures 1 and 2).¹⁹

¹⁷ The \$850 limit implies that a trader could purchase a maximum of 858 Nos at 99 cents. PredictIt does not publish depth in its quote data, but I recall that bid sizes were typically greater than 850 contracts on all outcomes in these markets during this time period, implying that a trader could immediately take a maximum-size arbitrage position.

¹⁸ PredictIt does not eliminate outcomes from a market when they become unlikely (e.g., due to a candidate dropping out of a race). To identify the number of relevant outcomes at a given point in time, I count the number of outcomes with a bid price of at least 1.

¹⁹ Underpricing does not appear related to either the number of outcomes or volume, as analogous unreported regressions predicting underpricing all have F-test p-values greater than 0.1.

Taken together the evidence is consistent with overpricing arising from many investors preferring to buy rather than sell outcomes, from the opportunity to obtain better pricing being less obvious in multi-outcome markets, and from stake limits preventing arbitrage from eliminating the overpricing, especially in high-volume markets.

V. Longshot Bias

I now turn to the question of whether PredictIt's prices, once adjusted for over or underpricing, yield well-calibrated market probabilities. This requires a method for adjusting for over/underpricing, and a method for measuring longshot bias.

V.A. Methods

V.A.1. Adjusting for over/underpricing

I have quote data for approximately half of my main 2016-2022 sample (from June 8, 2019 onwards). Quote data has the advantage of providing pricing information that is synchronized across all contracts in a given market. Data on the price of the most recent trade, in contrast, can reflect trades from different times. I will prioritize quote data for the period in which it is available, but will also use trade data when I have at least one trade for each contract in a market from the prior hour. In practice, conclusions about longshot bias from quote and trade data are very similar.²⁰

For both types of data, I adjust for under/overpricing using a simple approach that I think would have been reasonable for consumers of PredictIt's prices to adopt in real time. In single-contract markets (i.e., markets in which there is one contract that pays \$1 if the answer to a Yes/No question is Yes), there cannot be overpricing, so I simply use the bid-ask midpoint or most recent trade as an indication of price.

For multi-outcome markets where I have a fresh trade for each outcome in the most recent hour, I divide each trade price by the sum of the prices on all the outcomes. When this sum is outside the range 90-110, I discard the observation.

²⁰ For the sample in which both quote and trade data are available, estimates of the longshot bias are quite similar regardless of which is used (Table A2). My measures of overpricing-adjusted prices from the two sources are highly correlated ($r = 0.9985$).

For multi-outcome quote data, I add the bid and ask prices and distinguish between three cases: bid prices summing to 100 or more, ask prices summing to 100 or less, or bids summing to less than 100 and asks summing to more than 100.²¹ If bids sum to 100 or more, I use bid prices divided by the sum of bids as my market probability. If asks sum to 100 or less, I use ask prices divided by the sum of asks. The general idea is to use pricing from the side of the market that is getting the better deal (contract sellers when there is overpricing and buyers when there is underpricing). For intermediate cases, I use a midpoint that weights bids and asks identically across markets to obtain market probabilities that sum to one.²²

For multi-outcome quote data, this approach assigns a zero probability to contracts with a bid price of 0 when a market's bid prices sum to 100 or more. When bid prices sum to less than 100, it will assign a probability that is very close to zero. Empirically, this is close to justified by outcomes. In the main sample, ending in 2022, contracts with a bid price of zero paid off about 0.049 percent of the time when bid prices summed to 100 or more and about 0.146 percent of the time when bid prices summed to less than 100.

The minimum tick size on PredictIt is one percentage point, and about half of price quotes with positive bids had bid-ask spreads of a single percentage points. I condition the quote sample on each outcome in a market trading at a single-point bid-ask spread. Almost all markets had pricing observations with tight spreads at some point in their history; so imposing this condition excludes very few markets from the sample.²³

I also exclude from the sample trading on elections markets that occurs after election day. I do this mainly because my sample includes the 2020 U.S. Presidential election, and PredictIt's markets on the overall outcome and on several swing states remained open until December 18, 2020, during the period in which President Trump was contesting the election result. During most of this time period, securities that would have paid \$1 if Trump was reelected traded at prices between 9 and 16 cents (see Appendix B for details). Arguably this reflected an overpricing of a longshot which was sustainable due to the arbitrage limits that are the subject of this paper.

²¹ Note that since ask prices are always one percentage point or more higher than bid prices, exactly one of these situations will apply.

²² Specifically, $p_i = b_i + (a_i - b_i) \cdot (1 - \sum b_j) \div (\sum a_j - \sum b_j)$.

²³ Specifically while only 32 percent of pricing observations from the quotes sample had single-point bid-ask spreads on all contracts, 90 percent of markets satisfied this criteria at some point in their (pre-event) history. Imposing this condition does not meaningfully affect conclusions about the longshot bias (Table A3).

Including this period would have strengthened the conclusions about the longshot bias in this paper, but particularly given it was a unique period in history, I decided to err on the conservative side and exclude it.

V.A.2. Measuring longshot bias

In order to compare the magnitude of any longshot bias across groups of markets, it will be helpful to estimate a parametric function that maps prices and probabilities. One popular functional form is linear-in-log-odds, in which the price is the probability perceived by the marginal investor:

$$p(\pi) = \frac{\alpha \cdot \pi^\beta}{\alpha \cdot \pi^\beta + (1 - \pi)^\beta} \leftrightarrow \ln \left[\frac{p(\pi)}{1 - p(\pi)} \right] = \ln(\alpha) + \beta \cdot \ln\left(\frac{\pi}{1 - \pi}\right)$$

where π is the true probability (Lattimore, Baker, and Witte, 1992). This implies a linear relationship between $\ln[p/(1-p)]$ and $\ln[\pi/(1 - \pi)]$, i.e. between the log odds ratio for outcome probabilities and prices. The parameter $\alpha > 1$ captures any tendency to overestimate 50-50 probabilities; the parameter $\beta < 1$ captures a tendency to underprice favorites and overprice longshots. Efficient pricing implies $\alpha = \beta = 1$.

For binary markets (i.e., Yes/No and two-outcome markets), this function can be estimated empirically with a logit regression of the market outcome on the log price ratio; with the slope yielding an estimate of β^{-1} and the constant an estimate of $\frac{-\ln(\alpha)}{\beta}$. Page and Clemen (2013) use this functional form to parameterize the favorite-longshot bias in Intrade's prediction markets, so using this approach will allow for a direct comparison with their results.

This model has a latent variable interpretation that fits well with an election setting. Suppose two candidates have current electoral strengths a and b , each will have their strength increase by a random variable drawn independently from a Gumbel(0,1) distribution, and then the strongest candidate will win.²⁴ Given that the difference of any two independent Gumbel(0,1) random variables is distributed Logistic(0,1), candidate A will win with probability

²⁴ The Gumbel distribution is also known as type-one extreme value.

$$\pi = \frac{e^{a-b}}{1 + e^{a-b}} \leftrightarrow \ln\left(\frac{\pi}{1-\pi}\right) = a - b$$

Suppose the marginal investor in a prediction market misperceives the difference in strength of the candidates as $a - b + \ln(\alpha)$ and spread of the future changes in strength as β^{-1} . In this case, the prediction market price p will satisfy

$$p = \frac{\alpha e^{\beta(a-b)}}{1 + \alpha e^{\beta(a-b)}} \leftrightarrow \ln\left(\frac{p}{1-p}\right) = \ln(\alpha) + \beta \cdot (a - b) = \ln(\alpha) + \beta \cdot \ln\left(\frac{\pi}{1-\pi}\right)$$

So this setting yields the linear-in-log-odds misperceptions of Lattimore, Baker, and Witte (1992). $\alpha > 1$ implies that the market is overestimating the strength of the candidate in question, and $\beta < 1$ implies that the market is overestimating the spread of future changes, which would lead to an overpricing of longshots.

This approach can be extended to markets with more than two outcomes using a multinomial logit model (see, e.g., Berg and Rietz, 2019). In this model, each candidate i has a current strength x_i , to which is added an independent Gumbel(0,1) random variable, and then the strongest candidate wins. Candidate i will win with probability:

$$\pi_i = \frac{e^{x_i}}{\sum e^{x_j}}$$

The log of candidate i 's victory probability and that of the leading candidate 0 is given by:

$$\ln(\pi_i) = x_i - \ln\left(\sum e^{x_j}\right)$$

where the second term is identical for all candidates in a given market at a given time period. The ratio of candidate i 's probability and that of the leading candidate 0 would be given by:

$$\ln\left(\frac{\pi_i}{\pi_0}\right) = x_i - x_0$$

If the marginal investor misperceives candidate i 's relative strength by $\ln(\alpha_i)$ and the spread of future changes in strength by β^{-1} , the market will produce log price ratios of:

$$\ln \left[\frac{p_i}{p_0} \right] = \ln(\alpha_i) + \beta \cdot (x_i - x_0) = \ln(\alpha_i) + \beta \cdot \ln \left[\frac{\pi_i}{\pi_0} \right]$$

This model can be estimated with a multinomial logit regression.

The assumption that the shocks affecting each candidate are i.i.d. yields the well-known independence of irrelevant alternatives (IIA) feature of the multinomial logit model. This IIA assumption is unrealistic in some settings. For example, the early stages of the 2020 Democratic primary were characterized as a competition to become the leading candidate of the “left lane” (Bernie Sanders, Elizabeth Warren) and the “center lane” (Joe Biden, Pete Buttigieg).²⁵ In such a setting, one might expect a negative shock to help other candidates in the same lane more than those in other lanes, such as when Elizabeth Warren’s odds increased after Bernie Sanders’ October 2019 heart attack. IIA rules this out.²⁶ Furthermore, one should be able to improve on the multinomial logit model for prediction markets on which bin an underlying variable (polling strength, Tweets) will fall into by directly modeling innovations in the underlying variable.

The advantage of the multinomial logit approach is that it yields estimates that are directly comparable to those from binary markets. Given that most of my multi-outcome sample comes from election markets, I will use the multinomial logit approach in this analysis, and save refinements that better match specific non-election settings for future work.

Finally, given that I will be using the log of overpricing corrected prices in my estimation, one might be concerned that prices close to zero (and therefore log prices or odds ratios that are very negative) might excessively influence the results. Prices close to one create an analogous problem in binary markets, since $\ln[p/(1-p)]$ will be very large. In my central results, I include only prices between 1.5 and 98.5 percentage points in the sample. Expanding the sample to include all prices between 0 and 1 does not meaningfully affect the results (Table A3).

²⁵ See, e.g., <https://centerforpolitics.org/crystalball/democrats-dilemma-ideology-electability-and-the-2020-presidential-nomination-in-iowa-and-the-nation/> (last accessed, June 27, 2026).

²⁶ There is an extensive literature in industrial organization about an analogous problem, when products fall into categories, such as domestic and foreign cars. See, e.g., Hess and Daly (2024).

V.B. Results

Table 6 presents estimates of the logit model for single outcome (yes/no) markets, two outcome markets, and markets with more than two outcomes. The estimates for the one and two-outcome imply a marginal investor that overestimates the variance of future changes in strength by a factor of 1.38 and 1.51, respectively.

Figures 5A and 6A plot the win probability-price relationship for one and two-outcome markets. To make differences with the 45-degree line easier to see, Figures 5B and 6B plot return-to-expiry (i.e., win probability minus price) on the y-axis but are otherwise identical.

Both the parametric estimates and the bin scatter plots imply a substantial overpricing of longshots. The parametric estimates imply that one and two-outcome longshots priced at 0.2 pay off with probability 0.13 and 0.11, respectively. The scatter plots suggest larger mispricings than implied by the parametric estimates for contracts priced below 0.2 and above 0.8.

This is a much larger bias than has been found in prior work. In an analogous analysis of the Kalshi prediction market, Buergi, Deng, and Whelan (2025, Figure 3) find payoff probabilities of about 0.18 for outcomes priced at 0.2.²⁷ Tetlock (2004 and 2008) finds a roughly similarly sized longshot bias on Tradesports/Intrade, but only in the most liquid sports prediction markets. Studies of the Iowa Electronic Markets have found essentially no evidence of one (e.g., Berg and Reitz, 2019). Deleep, et. al. (2026) finds no evidence of a longshot bias in either Polymarket or Kalshi data.

The strongest prior evidence of a longshot bias comes from Page and Clemen (2013), which estimates the same parametric model as I do on Intrade data, finding a slope coefficient of 1.25 (Table 2, column 1).²⁸ They find a large longshot bias in election markets with more than 100 days to expiry, a more modest bias in close-to-expiry election markets, and close to efficient pricing in sports and other non-political markets (their Figure 7).

Table 6 also reports estimates of a longshot bias for markets with three or more outcomes. Here, the longshot bias is more modest, consistent with an overestimation of future strength changes by a factor of 1.14. The slope coefficient is roughly equal in markets with and without a strong favorite (defined as a probability greater than 0.5). The slope coefficient is slightly higher in markets that are

²⁷ Kagan and Baiocchi (2026) reach similar conclusions in a more recent sample.

²⁸ The gamma reported in Page and Clemen (2013) is the reciprocal of the slope coefficient I report, but it is estimated via maximum likelihood in the same way.

defacto binary markets (markets where only two outcomes have positive bid prices). But this difference is not statistically significant, and the markets with higher number of positive-bid outcomes have a slope coefficient of 1.13, hardly different from that of the full sample.

Table 7 examines how the degree of the longshot bias varies with the topic of the market. For simplicity, and since essentially all of the two-outcome and most of the three-or-more-outcome markets deal with elections, I focus this analysis on single-outcome (yes/no) markets. Longshot biases differ by category ($p=0.02$) and are largest in markets on elections and investigation-related topics (e.g., will Huma Abedin or Paul Manafort be indicted?). These categories are arguably those most likely to inspire partisan feelings. Formal tests find that election markets exhibit more longshot bias than non-election markets (1.84 vs. 1.31; $p = 0.05$); and election and investigation-related, taken together, also exhibit more longshot bias (1.76 vs. 1.24; $p = 0.01$).

Table 8 examines how longshot bias in election markets varies with the time remaining before the election. Each regression only includes the most recent pricing observations for each market as of 1 day, 1 week, 4 weeks, 8 weeks, and 16 weeks prior to the election.

The results suggest that the longshot bias does not decline significantly as the election approaches.²⁹ This differs from the results for Intrade in Page and Clemen (2013), where the longshot bias in election markets declines as the election approaches. This difference is consistent with differences in the limits to arbitrage on the two exchanges. Intrade did not impose position limits; the main costs of arbitrage were transaction costs and the cost of funding positions, given that Intrade did not pay interest. Both of these costs should have declined as the election approached. In contrast, arbitrageurs on Predictit face limits on downside risk that might become more binding over time, as arbitrageurs accumulate positions, including by trading against overpricing.

The results in Table 8 include each market only once; they therefore equal-weight markets. Table 6 weights markets by the number of pricing observations that qualify for the sample, and so weights longer-lived, liquid markets more heavily. The fact that the estimates of the longshot bias are similar in Tables 6 and 8 suggests that the Table 6 results are not driven by weighting.

I also conducted tests for whether overpricing and longshot bias were connected. I tested whether prices from overpriced markets exhibited more longshot bias. I found a meaningful difference in the

²⁹ Regressions that include interactions of the price variable and days to expiry find an interaction coefficient that is very close to zero.

bias (1.31 vs. 1.54) that was not statistically significant ($p = 0.23$). I also tested whether markets that had been more overpriced in the past had prices that exhibited more longshot bias. Specifically, at the beginning of each calendar day (US Eastern time), I calculated the share of prior price observations that exhibited overpricing large enough to allow for arbitrage (i.e., positive profits from selling all outcomes). I found that pricing on markets with a history of overpricing exhibited more longshot bias, but not to a statistically significant degree ($p = 0.22$).

V.C. Comparison with Betfair

Assessing pricing efficiency by comparing prices with outcomes requires large sample sizes. The standard deviation of a binary variable is $\sqrt{p(1-p)}$, which peaks at 0.5 and is above 0.3 when $0.1 < p < 0.9$. The standard error of an average of N independent outcomes will be roughly $0.4 \cdot \sqrt{N}$. Getting estimates that are precise enough to detect mispricing of 2 percentage points requires a standard error of one percentage point, which requires a sample size of roughly 1600 *independent* outcomes, and political prediction markets often have correlated outcomes.

The 2016-2022 sample in this paper includes just over 5,000 markets. While these markets do cover correlated outcomes, I adjust standard errors for clustering about markets that cover events/elections on the same day.³⁰ Given the size of the longshot bias in PredictIt's markets, the null hypothesis is generally rejected.

In such settings, more precise estimates of pricing biases can be obtained when one compares one market with another. The UK-based Betfair was the main alternative to PredictIt during the 2016-22 sample period. PredictIt only allowed participation by U.S.-based clients, while Betfair has been very aggressive about refusing business from the U.S. Its markets focus largely on sports, and its politics markets focus on the UK. Nevertheless, some topics overlap with PredictIt.

In particular, I am able to match 191 markets from the August 2019 to December 2022 time period. Most of these markets are on state-level outcomes in the 2020 U.S. Presidential election, individual

³⁰ For non-election events, I use the last day of trading for that market. For most non-election markets, this is the end of a prescheduled window (e.g., what will the Congressional Generic Ballot polling margin be on date X). For elections, I use the scheduled election date as the event date. This causes the standard errors to treat all U.S. general elections, and all primary elections occurring on the same day, as potentially correlated. The resulting standard errors are within 10-20% of standard errors that cluster on market, suggesting that correlations between markets expiring on the same day are minor.

U.S. Senate and gubernatorial races in 2020, 2021, and 2022, and 2020 Democratic Presidential primaries and caucuses. In addition, there are markets on national elections in several countries (Brazil, France, Germany, Israel, Poland, and Spain), on UK parliamentary by-elections, on local elections in Boston and New York, on Brexit, and on the potential early departure of U.S. and UK leaders.

For the overlapping topics, this creates the opportunity to compare PredictIt's pricing with pricing on another prediction market tracking the same events. While the sample size of overlapping markets is smaller than the overall sample, if we treat Betfair pricing as efficient, we can obtain an estimate of any additional longshot bias in PredictIt's prices that is reasonably precise. Specifically, for binary markets we can estimate the model

$$\ln\left(\frac{p_{BF}}{1 - p_{BF}}\right) = \alpha + \beta \cdot \ln\left(\frac{p_{PI}}{1 - p_{PI}}\right)$$

A $\beta > 1$ would imply a larger longshot bias in PredictIt prices than in Betfair. Likewise, for multiple-outcome markets, we can estimate the within-market relationship between log prices, in manner analogous to the multinomial logit approach discussed above. Again a $\beta > 1$ would imply a larger longshot bias in PredictIt prices than in Betfair:

$$\ln\left(\frac{p_{BF}^i}{p_{BF}^0}\right) = \alpha + \beta \cdot \ln\left(\frac{p_{PI}^i}{p_{PI}^0}\right)$$

I match each collection of Betfair prices with PredictIt prices closest in time; given that PredictIt updated its prices every 61 seconds, I can typically make a very close match. I construct adjusted-prices for Betfair using the same method as for PredictIt. There is essentially no overpricing in Betfair's markets; only 0.0005% of multi-outcome pricing observations have bid prices that sum to more than one, and 90% of those sum to less than 1.01. This is unsurprising given the lack of position limits on Betfair, along with the fact that fees are applied on profits calculated at the market level, and therefore selling all outcomes is profitable after fees any time bid prices sum to more than one. Therefore for most observations my adjusted prices are weighted bid-ask midpoints, using the weights that yield adjusted prices that sum to one (see footnote 22).

Table 9 reports the results from these regressions on binary markets and markets with 3 or more outcomes.³¹ The results imply that the longshot bias in PredictIt's prices is larger than in Betfair's prices by a factor of roughly 1.15. Figure 7 plots differences in Betfair and PredictIt prices as a function of PredictIt prices. Betfair prices are below PredictIt on average for low-priced outcomes and are higher for high-priced outcomes, consistent with a larger longshot bias in PredictIt prices.

A comparison of Betfair and PredictIt prices also reveals that arbitrage opportunities between the two exchanges were reasonably common, even after bid-ask spreads and fees. Table 10 reports average bid and ask prices for the two exchanges for all observations, for observations that allowed for arbitrage without regard for fees, and for observations that allow for arbitrage even after conservatively allowing for fees.³² About 15 percent of pricing observations allowed for arbitrage after fees. On average, arbitrage involves selling low-probability and buying high-probability outcomes on PredictIt, consistent with a larger longshot bias on Predictit.

V.D. Comparison with PredictIt in 2025-26

As mentioned, PredictIt ran very few markets in 2023-24. With such a limited number of markets, it is impossible to assess longshot bias in this period, particularly given how many of the markets were linked to the 2024 general election.

PredictIt relaunched their market in 2025 and by spring 2026 were running slightly more markets than they were in spring 2022. Volumes were nevertheless lower by a factor of roughly 10 in 2025-26 than 2021-22, despite PredictIt having quadrupled the downside risk limit to \$3,400. The downside risk limit to arbitrage was therefore much less binding in 2025-26 than it had been in 2016-22. A comparison of longshot bias in 2021-22 and 2025-26 might therefore speak to the role of downside risk limits in producing a longshot bias.

Table 11 reports a regression that estimates the longshot bias for the combined sample of two-outcome and multiple outcome markets. Estimates are reported for both the quotes sample from

³¹ There are very few single-outcome (Yes/No) markets in the sample that overlaps with Betfair, so I aggregated them with the two-outcome markets.

³² As discussed, Predictit charged 10 percent of $\max(0, \text{profits})$; Betfair had multiple fee options, but they offered a simple fee option of 2 percent of $\max(0, \text{profits})$. If pricing is efficient, the expected value of $\max(0, \text{profits})$ is maximized at 0.25 at a price of 0.5. A price difference of 3 percentage points (0.12×0.25) is therefore sufficient to cover expected fees.

2019-22 and a second quotes sample from 2025-26. There is no evidence of a longshot bias in 2025-26, and we can reject the level of longshot bias that existed in 2019-22.³³

VI. Conclusions

During most of its history, PredictIt exhibited overpricing and a longshot bias that were much larger than have been observed at other prediction markets. Both pricing biases are likely sustainable only due to limits to arbitrage, particularly position limits and fees. Absent position limits, a single trader could have reduced overpricing by selling every outcome, at least to the point where it was no longer profitable due to fees. PredictIt's position limits were on downside risk, and therefore were more limiting when purchasing favorites than purchasing longshots, likely contributing to the longshot bias.

These conclusions are reinforced by comparisons across exchanges, time periods, and markets. Betfair had no position limits and lower fees, and its prices exhibited essentially no overpricing and significantly less longshot bias. Other prediction markets either did not have position limits (Tradesports/Intrade, Kalshi, Polymarket) or position limits that likely did not bind (IEM). Other work has found much more limited overpricing and longshot biases on these markets.

PredictIt's position limit became much less binding after its relaunch in 2025, given the four-fold increase in the limit combined with a decline in volume by a factor of 10-15. Overpricing is now much rarer than in the main 2016-22 sample, and the longshot bias has disappeared. This suggests that the higher volumes of 2016-22 were overwhelming arbitrageurs' capacity. Within the 2016-22 sample, overpricing was more common for markets with high current and cumulative volume, which is also consistent with the mechanism.

These results have implications for regulation, prediction market operators, and researchers. The position limits on PredictIt were imposed by the CFTC as a condition for its operation. Limits may prove attractive to regulators in the future, either motivated by consumer protection or a desire to allow academic-scale but not commercial-scale prediction markets.

³³ The settlement of markets linked to the 2026 general election will allow me to expand the sample size of this analysis in a later draft.

The experience of PredictIt reveals the importance of how these limits are implemented and how they interact with fees. PredictIt limited positions at the contract level and did not adjust for offsetting positions in other contracts. This limited traders who were trading against overpricing to selling about 850 contracts of each outcome. During the long period of time in which the highest-profile markets (2020 Democratic nominee and Presidential election winner) were constantly overpriced by significantly more than could be explained by fees, there clearly were not enough arbitrageurs to eliminate the overpricing. PredictIt (or the CFTC) could have instead limited the worst-case-scenario loss from a market, taking offsetting positions into account, and had a Betfair-like fee structure that taxed profits at the market level rather than the contract level. Had it done so, one arbitrageur would have been sufficient to eliminate the overpricing.

Moreover, had position limits limited total exposure, rather than downside risk, they would not have had the asymmetric effect on the pricing of longshots anticipated by Ali (1977) and Manski (2006).

Would this have been in PredictIt's interest? On the one hand, the fact that prices added to 1.2 in its highest profile markets may have created a barrier to use of prediction market prices in journalism and academic work. High pricing of longshots such as Andrew Yang (whose bid price to win the Presidency averaged 7.1 in the second half of 2019) might have likewise undermined credibility. Against this, overpricing essentially provided a signup bonus for new users, funded by price-insensitive, long-only clients. Overpriced longshots might have likewise attracted new users. PredictIt was so successful in attracting liquidity, including to markets on topics that Intrade had tried unsuccessfully, that one is reluctant to criticize.

PredictIt was the only U.S.-based, real-money political prediction market for almost a decade.. PredictIt's success in attracting liquidity makes it a potentially valuable archive of real-time probabilistic beliefs, a crucial input to some forms of research (e.g., Snowberg, Wolfers, and Zitzewitz, 2007 and 2011). The results about overpricing and longshot bias are sobering for potential consumers of these data. This paper outlines a procedure for adjusting for overpricing and a parameterization of the longshot bias that may be useful for converting prices into probabilities.

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Appendix A – Arbitrage Profits after Fees

In this appendix, I derive the conditions for arbitrage profits to be available after fees from buying or selling every outcome in a market. In these derivations, I will assume for simplicity that a trader can purchase non-integer quantities of contracts; in practice a trader will only be able to approximate this and thus will need slightly more attractive prices to earn certain profits.

A. Arbitrage involving buying every contract

I will begin with the rarer situation, when arbitrage profits are available from buying every outcome and holding to expiry, since the algebra is simpler.

Suppose a market has N possible outcomes, the outcomes are defined so as to be exhaustive, and the ask prices of the contracts are given by $a_1, a_2, \dots, a_n$. The trader will purchase quantities $q_1, q_2, \dots, q_n$ to earn equal profits, regardless of the winning outcome. PredictitIt charges a 10 percent fee on profits at the contract level, so the profit after fees if outcome i wins is:

$$Y_i = .9q_i(1 - a_i) - \sum_{j \neq i} q_j a_j$$

In words, 90 percent of the profit earned on contract i , less the cost of the other contracts. This can be rewritten:

$$Y_i = .9q_i + .1q_i a_i - \sum_{j \neq i} q_j a_j$$

Since the final term is constant across outcomes, equalizing profits across outcomes will require that the quantities purchased are given by:

$$q_i = \frac{C}{.9 + .1a_i}$$

where C is a constant. In words, the trader will buy slightly more of the lower-priced outcomes, to hedge against the fact that fees will be higher if a low-priced contract wins.

Substituting this expression into the profit expression yields the following condition for positive profits:

$$\begin{aligned}
Y_i &= C - C \sum \frac{a_j}{.9 + .1a_j} > 0 \Leftrightarrow \\
&\sum \frac{a_j}{.9 + .1a_j} < 1 \Leftrightarrow \\
.1 \sum a_j \frac{1 - a_j}{.9 + .1a_j} &< 1 - \sum a_j
\end{aligned}$$

The right-hand side of the final inequality is the profit from buying every contract before fees and the left-hand side is the (certain) cost of fully hedging the fees. The left-hand side is approximately equal to

$$\frac{1 - H}{9}$$

where H is the Herfindahl index of the contract prices. Fully-hedged fees are lower when there are fewer outcomes, and when the outcome probabilities are more concentrated.

B. Arbitrage involving selling every contract

If instead a trader is selling quantities $q_1, q_2, \dots, q_n$ of contracts at bid prices $b_1, b_2, \dots, b_n$, the profit if outcome I wins will be:

$$Y_i = .9 \sum_{-i} q_j b_j - q_i (1 - b_i)$$

In words, 90 percent of the profit earned from selling the losing outcomes, less the loss from being short the winning outcome. This can again be rewritten:

$$Y_i = .9 \sum q_j b_j - q_i + .1 q_i b_i$$

Since the first term is constant across outcomes, equalizing profits across outcomes will require that the quantities purchased are given by:

$$q_i = \frac{C}{1 - .1b_i}$$

where C is a constant. When selling outcomes, the trader will sell slightly more of the higher-priced outcomes, since fees will be lower if the high-priced outcome wins, so the trader can afford a larger short position against that outcome.

Substituting this expression into the profit expression yields the following condition for positive profits:

$$\begin{aligned}
Y_i &= .9C \sum \frac{b_j}{1 - .1b_j} - C > 0 \Leftrightarrow \\
&\sum \frac{b_j}{1 - .1b_j} > \frac{1}{.9} \Leftrightarrow \\
.1 \sum b_j \frac{b_j}{1 - .1b_j} &> \frac{1}{.9} - \sum b_j \\
\frac{1}{9} (1 - \sum b_j \frac{b_j}{1 - .1b_j}) &< \sum b_j - 1
\end{aligned}$$

The right-hand side of the final inequality is the profit from selling every contract before fees and the left-hand side is the cost of fully hedging the fees. The left-hand side is again approximately equal to

$$\frac{1 - H}{9}$$

As when purchasing all outcomes, fully-hedged fees are lower when there are fewer outcomes and when the outcome probabilities are more concentrated.

C. Betting on an outcome by selling the other outcomes

A final situation to consider is when bid prices in a multi-outcome market are not high enough to allow immediate arbitrage profits from selling every outcome, but are high enough to make betting on an outcome less attractive than betting against all other outcomes. For example, in a two-outcome market, if both outcomes have bid prices of 50, betting immediately against (i.e., selling) outcome B is better than either waiting to purchase outcome A at the bid or purchasing it immediately at a higher price.

Suppose a trader purchases q_i of outcome I at bid price b_i . If outcome i wins her payoff will be

$$Y_i = .9q_i(1 - b_i)$$

if a different outcome j wins, her payoff will be

$$Y_j = -q_i b_i$$

Suppose instead that the trader instead sells every outcome but I, choosing contract quantities to equalize profits across the other outcomes. The profits if i pays off will be

$$Z_i = .9 \sum_{-i} q_k b_k$$

And if a different outcome j pays off, the payoff will be

$$Z_j = .9 \sum_{-i,j} q_k b_k - q_j(1 - b_j)$$

Which can be rewritten as

$$Z_j = .9 \sum_{-i} q_k b_k - q_j + .1q_j b_j$$

equalizing payoffs across the outcomes again involves setting positions equal to

$$q_j = \frac{C}{1 - .1b_j}$$

This will yield payoffs of

$$Z_i = .9C \sum_{-i} \frac{b_k}{1 - .1b_k}$$

$$Z_j = .9C \sum_{-i} \frac{b_k}{1 - .1b_k} - C$$

In other words, the trader will receive C more if outcome i wins than if another outcome wins.

In order to achieve the same difference in profits by betting directly on outcome i , q_i would need to satisfy

$$Y_i - Y_j = .9q_i(1 - b_i) + q_i b_i = .9q_i + .1q_i b_i = C$$

Given this position size, outcome i will yield a payoff of

$$Y_i = \frac{.9C(1 - b_i)}{.9 + .1b_i}$$

If this payoff is lower than the payoff from betting against the outcomes, then betting against the other outcomes will be optimal. This will be the case when

$$Y_i - Z_i = .9C \left[\sum_{-i} \frac{b_k}{1 - .1b_k} - \frac{(1 - b_i)}{.9 + .1b_i} \right] > 0$$

This can be rewritten as

$$\sum \frac{b_j}{1 - .1b_j} + .19 \frac{b_i(1 - b_i)}{.9(1 + .1b_i)(1 - .1b_i)} > \frac{1}{.9}$$

This expression is the same as the condition above for selling every contract to be profitable, except for the introduction of the second term. This term will always be positive, so there can be markets where selling every outcome does not produce an arbitrage, but it is still optimal to take positions via selling rather than buying, even when one desires a long position in a single outcome.

In the special case when there are two outcomes and their bid prices add to 1, simplifying the expression above reveals that it holds with equality. This makes sense, as with two outcomes, purchasing outcome A at a price of p and selling outcome B at a price of $1-p$ should yield equivalent payoffs.

Appendix B – The post-2020 election period

In the six weeks after the 2020 Presidential election, PredictIt's prediction market prices implied a 10-15 percent chance that President Trump would be successful in his effort to overturn the apparent result of the 2020 election (Figure A1). Betfair's prediction markets prices implied a significantly lower probability of about 5 percent.

On PredictIt, there were at least eight securities that could be used to bet on a Trump win, either by purchasing a Yes (Trump to win the Presidency, the Republican candidate to win) or a No (Biden to win, the Democratic candidate to win, the winner of the MA, SC, and TX Democratic primaries to also win the Presidency, and the popular vote winner to win).³⁴ The prices exhibited substantial dispersion; from November 9 to December 10, 2020, the difference between the securities with the highest and lowest average price averaged 5.6 percentage points.³⁵ Betfair also had multiple contracts linked to a Trump win, but they exhibited lower prices and much less price dispersion (Figure A2).³⁶

The gap between the PredictIt contracts, and between PredictIt and Betfair's contracts, was large enough to imply an arbitrage opportunity after fees.³⁷ In practice, this arbitrage was prevented to most potential traders in four of the contracts by the 5,000 trader limit, which the "party to win" and "person to win" contracts reached in late October.³⁸

As discussed in Section V, a trader betting against Trump would be able to acquire fewer contracts than a trader betting on Trump, due to the \$850 position limit. The higher pricing of the longshot outcome (i.e., Trump to win) on PredictIt than on Betfair, where traders are not similarly constrained, does suggest that this episode provides an example of limits to arbitrage contributing to

³⁴ A trader could also have bought securities in the Electoral Vote margin market for all bins that implied a Trump win.

³⁵ These contracts were on the Republican nominee (i.e., Trump) to win and the popular vote winner (presumptively Biden) to lose. The contract on the popular vote winner losing the election might have had a slightly lower true probability that the other contracts, assuming there was some probability that Trump's legal challenges would alter the election results to the point where he also won the popular vote. That said, the gap between "Republican to win" and "Biden to lose" averaged 3.6 percentage points, and there was presumably a zero probability that the first contract would win while the second did not.

³⁶ Probabilities increased and decreased in ways that appear consistent with the events during that period (see [https://en.wikipedia.org/wiki/Timeline_of_the_2020_United_States_presidential_election_\(November_2020%E2%80%93January_2021\)#November_2020](https://en.wikipedia.org/wiki/Timeline_of_the_2020_United_States_presidential_election_(November_2020%E2%80%93January_2021)#November_2020) for a timeline). For example, the Trump win probability increased when his campaign began its legal challenges and the PA Supreme Court agreed to hear an appeal (November 7-10). It declined when MI, MN, NV, and PA certified their election results (November 23-24), but then increased when Trump expressed reluctance to concede in a press conference (November 26). The odds declined sharply when the Supreme Court declined to hear *Texas v. Pennsylvania* (December 11). Betfair closed its markets on the day that Joe Biden officially received 306 electoral votes (December 14); PredictIt did so four days later (December 18).

³⁷ Given PredictIt's fee of 10 percent of profits, a trader buying at 10 would need an event probability of $.1/(.1 + .9*.9) = .1/.91 = 10.99$ percent. A trader selling at 15 (or buying a No at 85) would need an event probability of $(.15 * .9)/(.85 + .15*.9) = 13.71$ percent. So a gap of 3 points between the ask price of the lower-priced security and the bid price of the higher-priced security is sufficient to imply arbitrage profits after fees. Given that the bid-ask spread on these contracts was a single point 88 percent of the time during this period, this would typically require a difference between midpoints of 4 points.

Betfair's commission structure was complicated, but included an option for fees that were 2 percent of profits. The price difference with Betfair clearly implied arbitrage profits, so long as one assumed no difference in the exchanges' adjudication of the contracts.

³⁸ See the notes added to <https://www.predictit.org/markets/detail/2721?tab=rules> and <https://www.predictit.org/markets/detail/3698?tab=rules> (last accessed May 27, 2026).

pricing biases through the same mechanism as in Section V. Nevertheless, because this period was after the election date in question, it is left out of the sample analyzed in that section.

Table 1. Political prediction market volume by U.S. Presidential election year

Year	Exchange	Volume (2024\$ millions)	
		Presidential election winner	All politics markets
1884	NYSE Curb	23.9	
1916	NYSE Curb	288	
1928	NYSE Curb	18.3	
1988	Iowa electronic market (IEM)	0.11	0.11
1992	IEM	0.52	0.93
1996	IEM	1.23	4.03
2000	IEM	0.76	2.22
2004	Tradesports/Intrade	23.9	45.3
2008	Intrade	227	636
2012	Intrade	423	962
2016	PredictIt	51.6	648
2020	PredictIt	96.8	1,767
2024 (Q4 only)	Kalshi	259.3	1,506
2024	Polymarket	3,686	

Volumes are reported for the sum of trading volume during the calendar year of the election in all contracts on the winner of the U.S. Presidential election and the sum of trading volume in all politics contracts. When there are multiple markets linked to the winner of the Presidential election, the highest volume market is used. Politics contracts include all contracts for the IEM and PredictIt, contracts categorized as such by Intrade, and contracts linked to election outcomes or political appointments for Kalshi. Trading volume is expressed in contracts, multiplied by the maximum payoff of that contract (USD 10 for Tradesports/Intrade; USD 1 for other prediction markets). 1884-1928 are from Rhode and Strumpf (2004, Table 1). Other data were collected by the author from the exchange in question.

Table 2. Types of contracts offered by Predictit, 2016-2022

	Markets	Volume	Share of markets		Highest volume market
			Yes/No	Non-US	
Elections	1,790	2,119,352,194	0.18	0.10	
Winning individual	827	807,431,480	0.17	0.09	Who will win the 2020 Democratic presidential nomination?
Winning party	375	382,593,228	0.00	0.02	Which party will win the 2020 U.S. presidential election?
Margin	233	485,526,253	0.14	0.09	What will be the Electoral College margin in the 2020 presidential election?
Props bets	109	146,234,952	0.66	0.06	When will the 2020 presidential election outcome be called?
Turnout	63	51,491,557	0.13	0.05	How many votes in the 2020 Georgia special Senate runoff election?
Seats won	61	135,103,960	0.13	0.64	How many GOP Senate seats after the 2022 midterms?
Non-winners (2nd, 3rd)	39	23,646,914	0.16	0.11	Who will come in second place in the 2021 NYC Democratic mayoral primary?
Referenda	35	3,620,949	0.97	0.11	Will the UK vote to leave the EU by year-end 2016?
First-round results	31	2,318,193	0.74	0.26	Who will lead after the first round of the 2021 NYC Democratic mayoral primary?
Partisan control (e.g., of Congress)	17	81,384,708	0.47	0.06	What will be the balance of power in Congress after the 2020 election?
Polling	1,283	171,257,777	0.30	0.00	
Job approval	809	119,520,741	0.31	0.00	What will Joe Biden's 538 job approval rating be for 8/31/2021?
Electoral support	211	33,725,372	0.23	0.00	Who will lead in Trump vs. Clinton polling on 6/29/2016?
Congressional generic ballot	99	5,164,576	0.03	0.00	Which party will lead in 538 Congressional generic ballot polling for 4/27/2022?
Direction of country	76	6,388,697	0.32	0.00	What will "Right Direction" poll at on 8/1/2016?
Debate outcomes	50	3,307,907	0.54	0.00	Who will see the biggest polling bump from the 2nd Democratic debate in 2019?
Favorability	38	3,150,484	0.79	0.00	Will Trump's favorable rate be at least 45.0% on 12/15/2016?
Tweets and mentions	1,083	369,181,719	0.20	0.00	
Tweet counts	749	351,594,642	0.00	0.00	How many @realDonaldTrump tweets 5/13 - 5/20/2020?
Mentions of specific words	334	17,587,077	0.66	0.00	How many times will Biden say "Russia" or "Putin" in the 2022 State of the Union?
Legislative votes	524	247,981,278	0.56	0.01	
confirmations	237	142,584,173	0.34	0.00	Who will be the next Senate-confirmed OMB Director by Dec. 31?
other votes	287	105,397,105	0.75	0.02	How many Senators will vote to convict Donald Trump on incitement by 4/29/2021?
Campaign events	366	77,350,128	0.67	0.00	
Debate participation	103	12,302,890	0.64	0.00	Who will speak the most at the 2/25/2020 Democratic debate?
Running for office	100	29,768,709	0.99	0.00	Will Hillary Clinton run for president in 2020?
Dropping out	69	24,171,211	0.72	0.00	Will Joe Biden drop out before 11/1/2020?
Campaign finance	52	3,426,296	0.13	0.00	What will Trump's fundraising be for June 2016?
Endorsements	34	4,770,520	0.53	0.00	Will Sanders endorse Clinton before the 2016 Convention?
Ballot qualification	8	2,910,502	1.00	0.00	Will there be enough signatures by Mar. 17 for a vote on recall of Gov. Newsom?
Hiring and firing	351	445,151,237	0.68	0.23	
Departures	245	83,295,112	0.87	0.32	Will Donald Trump complete his first term?
Appointments	106	361,856,125	0.23	0.04	Who will win the 2020 Democratic VP nomination?
Scandals	241	77,147,993	0.95	0.03	
Investigations	129	59,093,244	0.97	0.06	When will the Senate vote on whether to convict Donald Trump?
Testimony	82	5,331,129	0.95	0.00	Will Trump testify to special counsel in 2018?
Pardons	30	12,723,620	0.90	0.00	Will Trump pardon himself in his first term?
Political decisions	209	83,127,069	0.74	0.30	
Executive decisions	93	8,850,279	0.88	0.03	Where will Trump and Kim hold their 2018 meeting?
Party leadership	41	17,098,210	0.40	0.40	Who will be Speaker of the House in 2023?
Other group decisions	75	57,178,580	0.76	0.57	How many electoral certificates of vote will be formally challenged in Congress?
Other news	220	43,327,574	0.69	0.09	
Policy news	90	22,297,035	0.89	0.02	Will the federal government be shut down on 1/22/2018?
Economic news	26	3,253,822	0.52	0.04	Will there be a recession in Trump's 1st term?
Legal news	22	990,152	1.00	0.05	Will SCOTUS strike down Mississippi ban on pre-viability abortions in Dobbs?
Interest (e.g., TV ratings for debates)	20	5,557,898	0.10	0.00	Will the first 2016 presidential debate be the most watched debate ever?
Geopolitical news	11	1,065,333	0.90	0.70	Will NATO invite Sweden or Finland to begin the accession process in 2022?
Other news	51	10,163,334	0.49	0.16	How many totally false statements will Trump make in August 2016?
Total	6,067	3,633,876,969			

Note: Some market names are edited for clarity and brevity.

Table 3. Share of markets exhibiting overpricing by time period

Quarter	Average number of markets	Markets with securities cheaper to buy via Nos		Markets with No-buying arbitrage opportunity	
		Any security	All securities	At start of hour	For entire hour
2019Q2 & Q3	72	0.27	0.15	0.037	0.034
2019Q4	107	0.32	0.13	0.036	0.030
2020Q1	110	0.37	0.15	0.042	0.026
2020Q2	134	0.26	0.15	0.012	0.009
2020Q3	146	0.38	0.26	0.020	0.017
2020Q4	128	0.36	0.25	0.029	0.017
2021Q1	64	0.20	0.09	0.008	0.003
2021Q2	93	0.21	0.08	0.009	0.006
2021Q3	113	0.24	0.11	0.006	0.003
2021Q4	129	0.24	0.11	0.008	0.005
2022Q1	145	0.24	0.11	0.010	0.008
2022Q2	158	0.24	0.13	0.009	0.007
2022Q3	94	0.38	0.24	0.022	0.019
2022Q4	50	0.45	0.30	0.038	0.029
2023Q1	8	0.46	0.06	0.047	0.043
2023Q2	5	0.84	0.28	0.208	0.190
2023Q3	11	0.75	0.30	0.183	0.171
2023Q4	14	0.73	0.40	0.111	0.102
2024Q1	12	0.66	0.41	0.125	0.118
2024Q2	11	0.65	0.52	0.201	0.192
2024Q3	8	0.91	0.81	0.196	0.185
2024Q4	7	0.67	0.65	0.105	0.097
2025Q1	12	0.19	0.08	0.004	0.001
2025Q2	11	0.25	0.06	0.010	0.005
2025Q3	77	0.17	0.11	0.001	0.000
2025Q4	114	0.15	0.11	0.001	0.001
2026Q1	177	0.10	0.07	0.001	0.000
2026Q2	201	0.11	0.08	0.000	0.000
2019Q3-2022	119	0.29	0.16	0.019	0.014
2023-2024	10	0.70	0.42	0.144	0.135
2025-2026Q2	137	0.13	0.09	0.001	0.001

The quote data begin on June 8, 2019. Given the small portion of 2019Q2 for which quote data are available, I aggregate results for 2019Q2 and Q3.

Table 4. Markets exhibit overpricing-related arbitrage opportunities in more than 20 percent of hourly observations

Market name	Last day	Contracts	Percent of hours with overpricing arbitrage	Average sum of bid prices (all observations)	Arbitrage profit per contract net of fees (condition on positive profit)	Hourly observations with positive profit
Who will win the 2020 U.S. presidential election?	12/18/2020	26	70.6	110.9	3.5	9542 *
Who will win the 2024 Democratic vice presidential nomination?	8/7/2024	17	67.5	110.2	2.7	192
Who will win the 2020 Democratic presidential nomination?	7/31/2020	33	57.9	114.3	5.1	5881 *
What will be the Electoral College margin in the 2020 presidential election?	12/21/2020	16	55.8	112.7	4.3	2928
What will be the Electoral College margin in the 2024 presidential election?	11/25/2024	16	55.0	118.1	7.3	3952
Who will win the 2024 Iowa Republican caucuses?	1/16/2024	8	42.8	103.6	0.8	809
Who will win the 2020 Democratic vice presidential nomination?	8/20/2020	34	38.7	110.7	2.0	2089
Who will speak the most at the Feb. 25, 2020 Democratic debate?	2/26/2020	7	37.0	108.7	1.0	17
Who will be the next Supreme Court nominee?	2/25/2022	17	27.4	107.2	1.0	201
How many tweets will @realDonaldTrump post from noon Dec. 18 to Dec. 31, 2019?	12/31/2019	9	27.0	106.2	1.5	84
What will be the balance of power in Congress after the 2022 election?	11/28/2022	4	26.4	107.0	1.0	3931
Who will win the 2024 Republican presidential nomination?	7/16/2024	21	25.7	109.5	1.9	6789
When will Jon Ossoff be sworn in as a U.S. Senator?	1/20/2021	8	25.3	106.7	1.2	56
How many electoral college votes will be cast for Donald Trump?	12/21/2020	8	24.8	107.4	1.0	117
Who will speak the most at the Feb. 19 Democratic debate?	2/20/2020	6	24.5	109.3	1.6	12
How many tweets will @realDonaldTrump post from noon Nov. 27 to Dec. 4, 2019?	12/4/2019	9	24.0	107.5	1.4	40
Who will win the 2024 US presidential election?	12/11/2024	10	23.8	110.1	2.9	4354
When will Raphael Warnock be sworn in as a U.S. Senator?	1/20/2021	8	23.1	106.4	1.4	51
Who will get the most speaking time at the Houston debate (Sept 12, 2019)?	9/12/2019	10	22.2	108.4	1.1	8
Who will win the 2024 Republican presidential nomination?	12/11/2024	17	23.8	110.1	2.9	4354
Who will speak the least at the Feb. 25, 2020 Democratic debate?	2/26/2020	7	21.7	107.6	1.4	10
What will be the popular vote margin in the 2020 presidential election?	2/1/2021	16	21.1	110.8	0.9	1294
How many Senators will vote to convict Donald Trump on incitement by Apr. 29, 2021?	2/13/2021	10	20.8	109.5	0.8	151

* The markets on the 2020 Presidential election winner and Democratic nominee already existed at the beginning of the quote data, so data for these markets only reflects data from June 8, 2019 onwards.

Table 5. Frequency of overpricing by market duration, volume, and number of outcomes

Panel A. Number of outcomes (with positive bid prices)

Outcomes	Share of market* days with				Observations
	Sum(Bid)>100	Overpricing arbitrage	Sum(Ask)<100	Underpricing arbitrage	
2	0.197	0.001	0.026	0.00062	61,915
3	0.220	0.010	0.059	0.00068	11,555
4	0.422	0.040	0.056	0.00010	10,588
5	0.253	0.026	0.129	0.00361	7,825
6	0.295	0.027	0.075	0.00212	6,921
7	0.346	0.027	0.056	0.00025	6,653
8	0.413	0.038	0.057	0.00012	5,066
9	0.371	0.031	0.045	0.00011	4,169
10	0.294	0.033	0.041	0.00046	4,330
11 or more	0.645	0.166	0.042	0.00004	3,995

Panel B. Regressions predicting overpricing

Dependent variable	Sum(Bid)>100			Overpricing arbitrage		
ln(Volume (t-1))	0.0160*** (0.0024)	0.0170*** (0.0023)	0.0140*** (0.0014)	0.0032*** (0.0005)	0.0028*** (0.0005)	0.0026*** (0.0006)
ln(Cumulative Volume)	0.0304*** (0.0047)	0.0378*** (0.0055)	0.006 (0.005)	0.0091*** (0.0030)	0.0117*** (0.0039)	0.0080*** (0.0025)
3 outcomes (w positive bid)	0.037 (0.030)	0.048 (0.031)	0.184*** (0.021)	0.0080*** (0.0023)	0.0086** (0.0033)	0.0180*** (0.0046)
4-10 outcomes	0.149*** (0.026)	0.150*** (0.027)	0.297*** (0.021)	0.0285*** (0.0056)	0.0251*** (0.0067)	0.0340*** (0.0077)
11+ outcomes	0.384*** (0.058)	0.337*** (0.059)	0.508*** (0.055)	0.146*** (0.055)	0.136*** (0.050)	0.110** (0.052)
Day fixed effects		X	X		X	X
Market fixed effects			X			X
Observations	107,621	107,621	107,582	107,621	107,621	107,582
Unique markets	1737	1737	1698	1737	1737	1698

Notes: The sample is June 8, 2019 to December 31, 2022; the unit of observation is a market day combination; cumulative volume is from the beginning of the market through day t-1, even if this precedes June 8, 2019. Two outcomes with a positive bid is the omitted category. Standard errors (in parentheses) are adjusted for clustering at the market level.

Table 6. Longshot bias estimates

Subsample	Observations	Unique markets	Unique event dates	Election share	Coefficient	SE
Yes/no markets	1,566,205	3,065	1,009	0.20	1.501***	(0.138)
2-outcome	1,026,530	601	122	0.9993	1.536	(0.362)
3 or more outcomes	4,032,407	1,236	582	0.79	1.423***	(0.110)
Strong favorite ($p > 0.5$)	2,789,111	1,181	558	0.75	1.406***	(0.117)
Strong favorite ($p < 0.5$)	1,231,386	486	325	0.90	1.455*	(0.236)
Two positive-bid outcomes	713,095	751	363	0.79	1.398**	(0.176)
3-6 positive-bid outcomes	899,163	656	398	0.86	1.378**	(0.163)
7+ positive-bid outcomes	1,319,884	469	327	0.83	1.454**	(0.194)

Each row reports the results of a logit regression predicting whether the contract will pay \$1. For the single-outcome (yes-no) markets, the independent variable is $\ln(p/(1-p))$, where p is the market price. For other markets, the right-hand side variable is $\ln(p)$, and the regression includes fixed effects for market*time period. Standard errors adjust for the clustering on event date, which is the date of the event that is the subject of the market (e.g., the election date), or the final trading date for markets that close early. Asterisks indicate coefficients that are statistically significantly different from one at the 10, 5, and 1 percent level.

Table 7. Longshot bias by topic (yes/no markets)

Topic	Observations	Unique markets	Unique event dates	Slope coef.	SE	Constant	SE
All	1,566,205	3,065	1,009	1.501***	(0.138)	0.095	(0.183)
Elections	317,438	704	247	1.946***	(0.261)	0.054	(0.388)
Campaign events (running, dropping out)	307,669	268	144	1.353	(0.398)	0.294	(0.569)
Appointments/departures	270,594	262	96	1.591*	(0.273)	0.642**	(0.305)
Investigations (indictments, testimony)	249,764	230	85	1.912***	(0.174)	0.622	(0.771)
Legislative votes	136,801	317	119	1.338**	(0.153)	-0.687*	(0.372)
Other politics (e.g., party leadership)	89,130	171	110	1.391	(0.212)	-0.264	(0.349)
Polling (approval, electoral)	56,052	642	459	1.332**	(0.149)	-0.185	(0.131)
Mentions and tweets	15,947	309	176	1.739**	(0.304)	-0.397	(0.324)
Other	122,810	162	121	1.029	(0.274)	0.206	(0.522)

Each row reports the results of a logit regression predicting whether the contract will pay \$1. The independent variable is $\ln(p/(1-p))$, where p is the market price. Standard errors adjust for the clustering on event date, which is the date of the event that is the subject of the market (e.g., the election date), or the final trading date for markets that close early. Asterisks indicate coefficients that are statistically significantly different from one (for the slope) and zero (for the constant) at the 10, 5, and 1 percent level.

Table 8. Longshot bias estimates by time to election

Outcomes	Time prior	Observations	Unique markets	Unique event dates	Coefficient	SE
1 or 2	1 day	1,415	892	232	1.474***	(0.151)
1 or 2	1 week	1,210	749	184	1.369**	(0.145)
1 or 2	4 weeks	989	609	135	1.294	(0.199)
1 or 2	8 weeks	854	525	101	1.611**	(0.268)
1 or 2	16 weeks	634	395	71	1.585**	(0.297)
3+	1 day	2,585	996	284	1.250***	(0.081)
3+	1 week	1,986	775	219	1.148	(0.107)
3+	4 weeks	1,877	657	181	1.148	(0.111)
3+	8 weeks	1,618	552	134	1.364**	(0.142)
3+	16 weeks	1,263	394	94	1.311**	(0.137)

Each row reports the results of a logit regression predicting whether the contract will pay \$1, using the same estimation method as in Table 6. Each regression includes the most recent pricing observations for each market as of the indicated time prior to the election. The sample is limited to election markets, and standard errors adjust for the clustering on election date. Asterisks indicate coefficients that are statistically significantly different from one at the 10, 5, and 1 percent level.

Table 9. Regressions comparing longshot biases in Betfair and PredictIt prices

Subsample	Observations	Unique markets	Unique event dates	Coefficient	SE
Binary (1-2 outcome)	278,713	94	17	1.158***	(0.012)
Multi-outcome (3 or more)	336,007	37	28	1.137***	(0.037)

The table reports regressions of Betfair prices on PredictIt prices. As in Table 6, for binary markets, the price variables are $\ln(p)/\ln(1-p)$; for the multi-outcome markets, the price variables are $\ln(p)$ and regressions include a fixed effect for market*time combinations. Standard errors are the higher of those that allow for clustering at the market or event date level. Asterisks indicate coefficients that are statistically significantly different from one at the 10, 5, and 1 percent level

Table 10. Differences between Betfair and PredictIt prices

Sample	Count	PredictIt		Betfair	
		Bid	Ask	Bid	Ask
All observations	279,694	49.5	50.6	48.0	50.3
Betfair Bid > PredictIt Ask	100,771	34.1	35.2	29.1	31.1
Betfair Bid > PredictIt Ask + 3	30,835	40.3	41.4	31.8	33.5
PredictIt Bid > Betfair Ask	78,126	75.6	76.7	78.4	80.0
PredictIt Bid > Betfair Ask + 3	13,984	65.3	66.4	70.9	72.5

This table reports summary statistics for the matched PredictIt-Betfair sample. Statistics are reported for all observations, for observations where the Betfair Bid exceeds the PredictIt Ask or vice versa, and for observations where the difference exceeds 3 percentage points (which, as discussed in the text, would allow for profits after fees).

Table 11. PredictIt longshot bias -- 2019-22 vs. 2025-26

Subsample	Observations	Unique markets	Unique event dates	Coefficient	SE
2019-22	5,162,063	1478	593	1.487***	(0.164)
2025-26	211,224	155	92	0.794	(0.230)

The table reports regressions of Betfair prices on PredictIt prices. As in Table 6, for binary markets, the price variables are $\ln(p)/\ln(1-p)$; for the multi-outcome markets, the price variables are $\ln(p)$ and regressions include a fixed effect for market*time combinations. Standard errors are the higher of those that allow for clustering at the market or event date level. Asterisks indicate coefficients that are statistically significantly different from one at the 10, 5, and 1 percent level

Table A1. Share of markets exhibiting underpricing by time period

Period	Average number of exhaustive- outcome markets	Markets with securities cheaper to short sell via buying Yeses		Markets with Yes-buying arbitrage opportunity	
		Any security	All securities	At start of hour	For entire hour
June 2019-2022	23.4	0.0049	0.0008	0.0008	0.0006
2023-2024	1.6	0.0000	0.0000	0.0000	0.0000
2025-26	10.6	0.0065	0.0007	0.0007	0.0003

Table A2. Robustness of longshot estimates to trade vs. quote data

Number of outcomes	Sample	Data used	Observations	Unique markets	Unique event dates	Coefficient	SE
One (yes/no)	Full	Quotes if available, otherwise trades	1,566,205	3,065	1,009	1.501***	(0.138)
	Trades and quotes both available	Trades	270,142	672	259	1.512***	(0.132)
		Quotes	270,142	672	259	1.527***	(0.134)
Two	Full	Quotes if available, otherwise trades	1,026,530	601	122	1.536	(0.362)
	Trades and quotes both available	Trades	46,822	232	40	1.817*	(0.496)
		Quotes	46,822	232	40	1.803*	(0.490)
Three or more	Full	Quotes if available, otherwise trades	4,032,407	1,236	582	1.423***	(0.110)
	Trades and quotes both available	Trades	35,955	470	304	1.413**	(0.185)
		Quotes	35,955	470	304	1.380*	(0.196)

This table repeats the regressions in the first three lines of Table 6 for the subsample for which trade and quote data are both available.

Table A3. Robustness of estimates to sample inclusion criteria

Subsample	Price data used	Observations included	Observations	Unique markets	Unique event dates	Coefficient	SE
One (yes/no)	Trades & quotes	Price between 1.5 and 98.5 (baseline)	1,566,205	3,065	1,009	1.501***	(0.138)
		All prices	1,890,145	3,089	1,016	1.489***	(0.136)
	Quotes only	All bid-ask spreads equal one (baseline)	1,308,293	663	256	1.565***	(0.199)
		Average spread <= 2	1,678,081	666	257	1.527***	(0.180)
2-outcome	Trades & quotes	Price between 1.5 and 98.5 (baseline)	1,026,530	601	122	1.536	(0.362)
		All prices	1,037,478	616	127	1.534	(0.361)
	Quotes only	All bid-ask spreads equal one (baseline)	928,064	243	42	1.614	(0.409)
		Average spread <= 2	2,165,732	250	42	1.544*	(0.318)
3 or more outcomes	Trades & quotes	Price between 1.5 and 98.5 (baseline)	1,916,815	2,352	1,270	1.364***	(0.120)
		All prices	4,223,954	2,650	1,337	1.388***	(0.101)
	Quotes only	All bid-ask spreads equal one (baseline)	4,032,407	1,236	582	1.423***	(0.110)
		Average spread <= 2	15,623,037	1,557	636	1.143***	(0.041)

This table examines the robustness of the results in the first three lines of Table 6 to variations in the sample. The baseline results in Table 6 include both pricing observations from trades and quotes. For quotes, they require the bid-ask spread to be a single point for all contracts listed in a market.

Figure 1. Volume by category and calendar quarter (\$ millions)

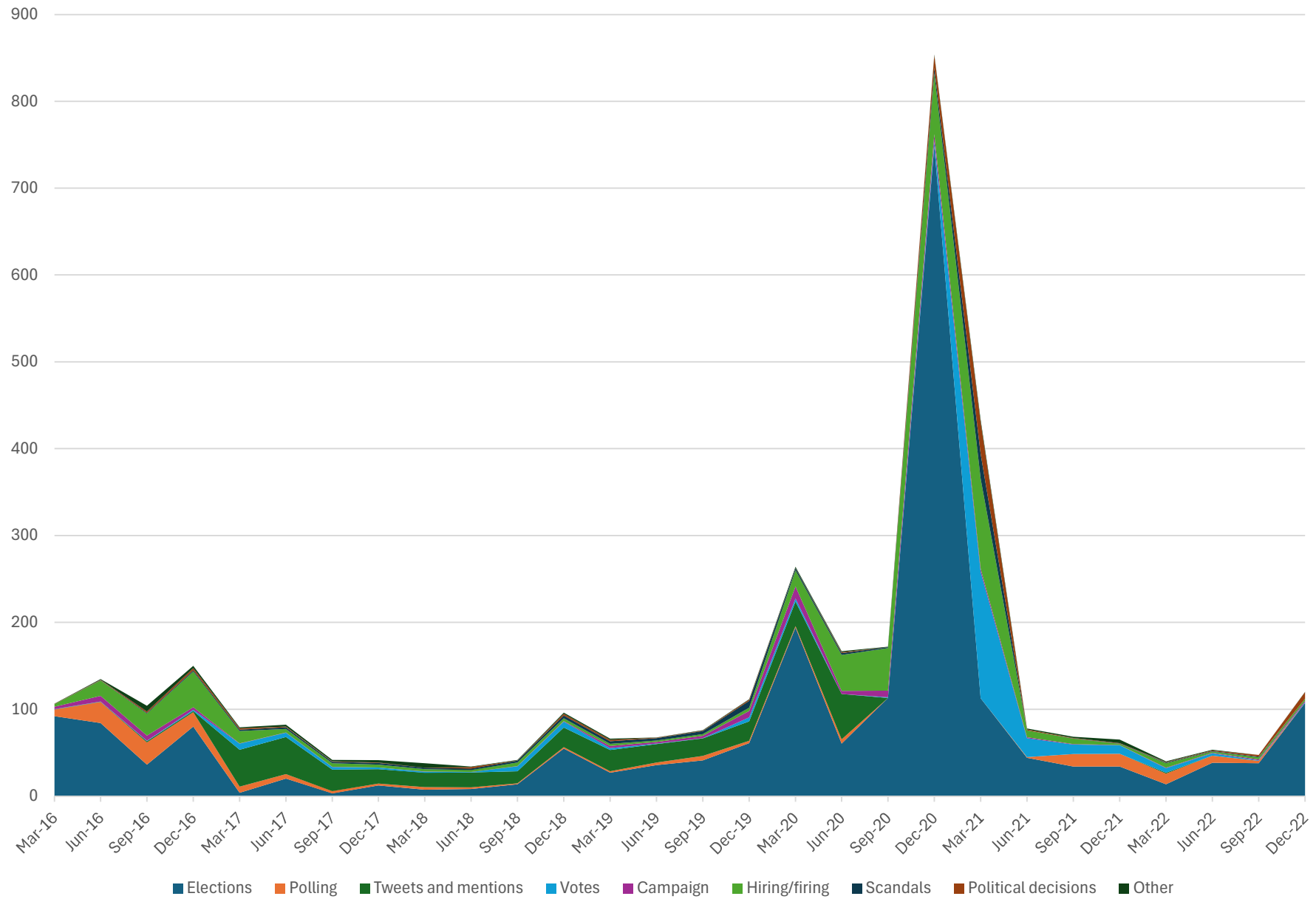


Figure 2. Volume shares by category and calendar quarter

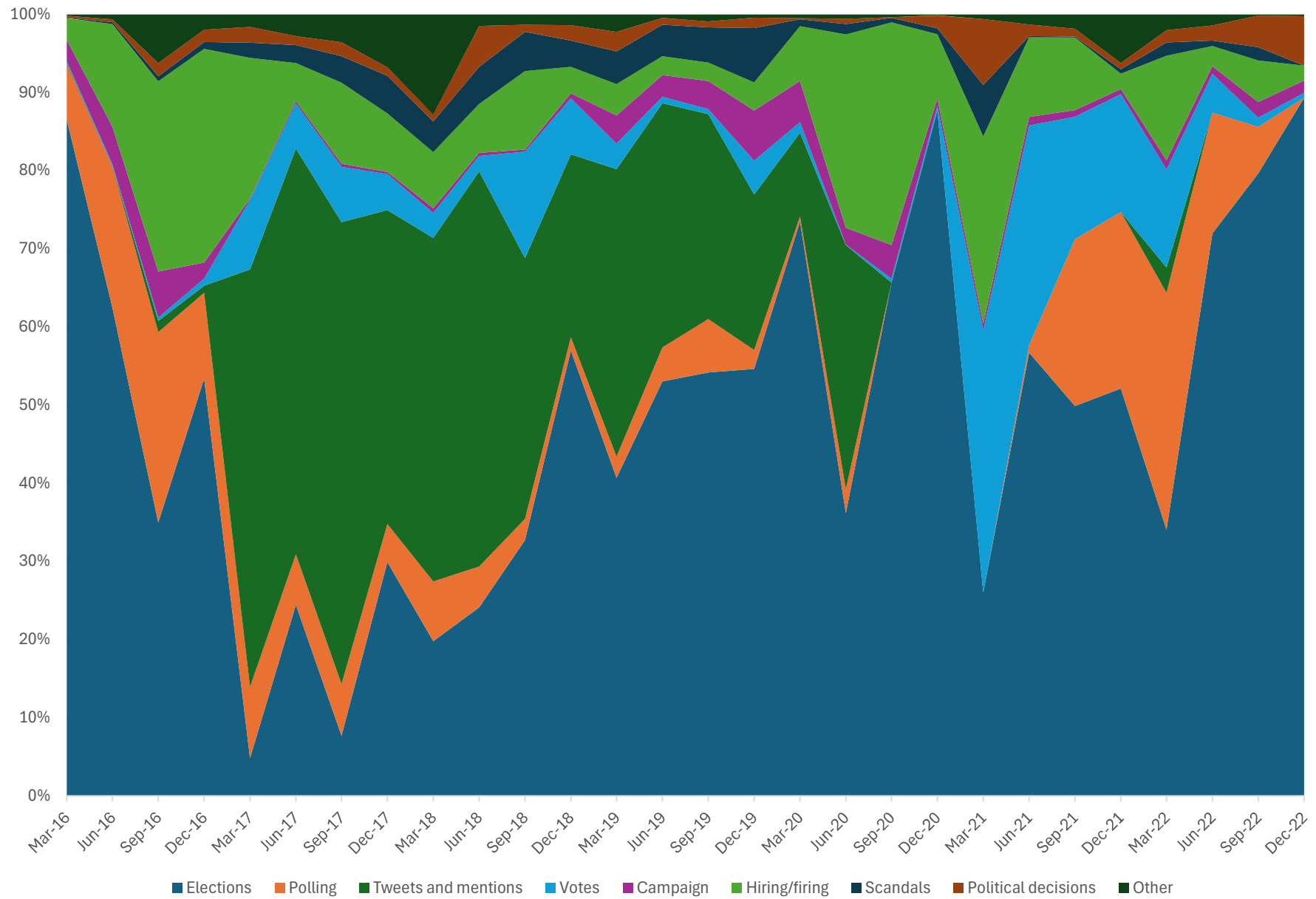


Figure 3. Who will win the 2020 Democratic presidential nomination?

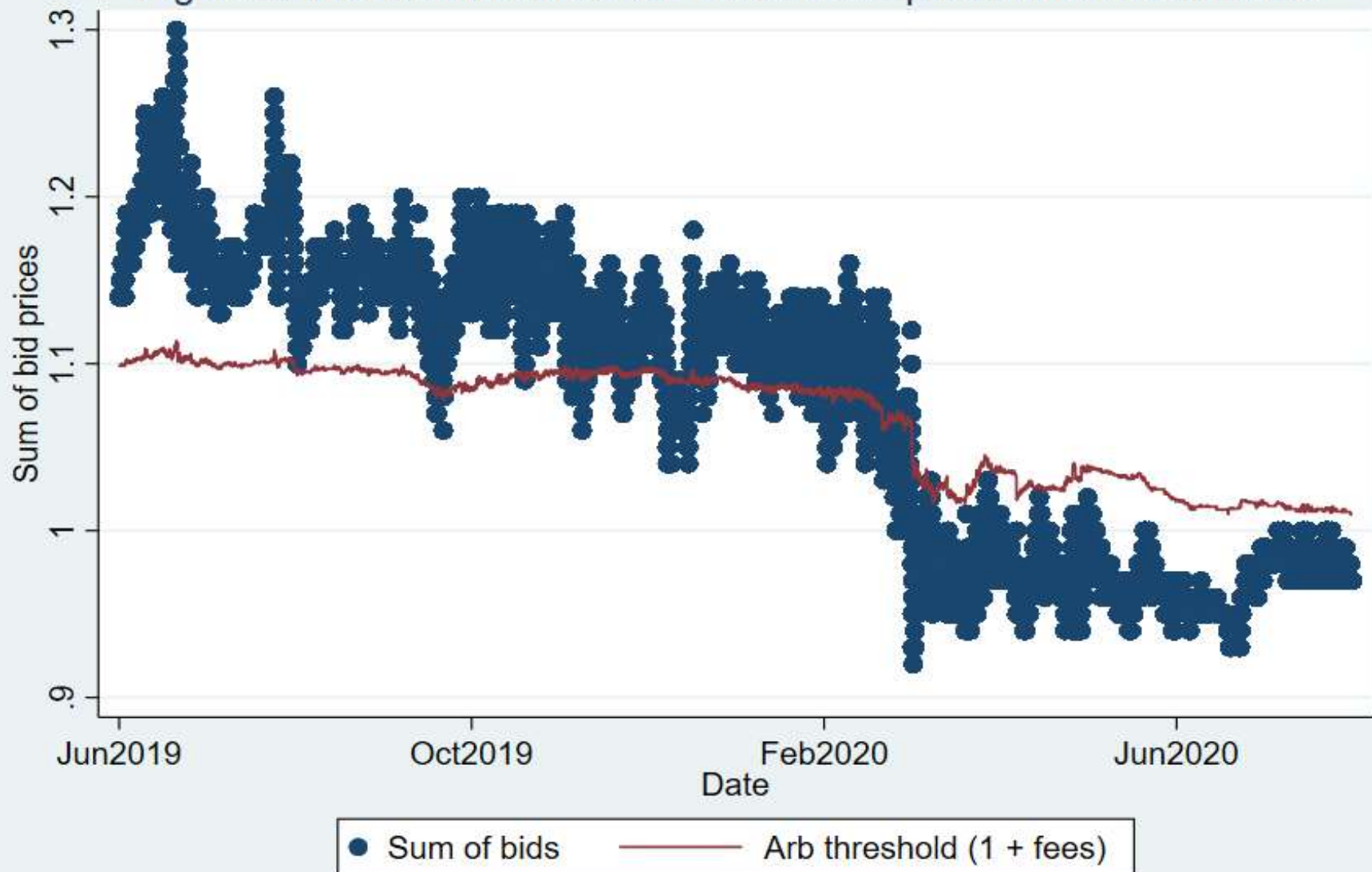


Figure 4. Who will win the 2020 U.S. presidential election?

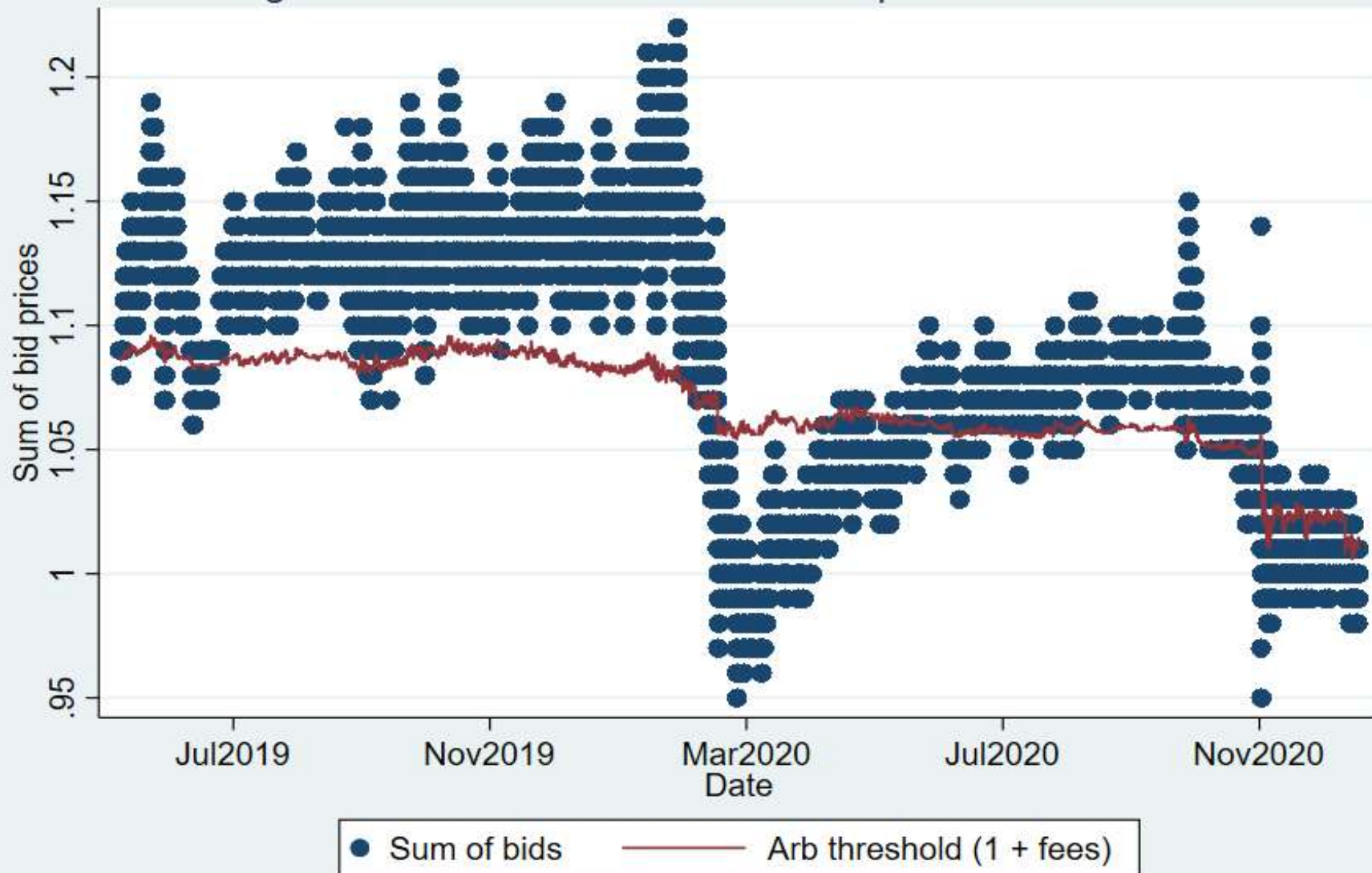


Figure 5A. Prices and probabilities for single-outcome (yes/no) markets

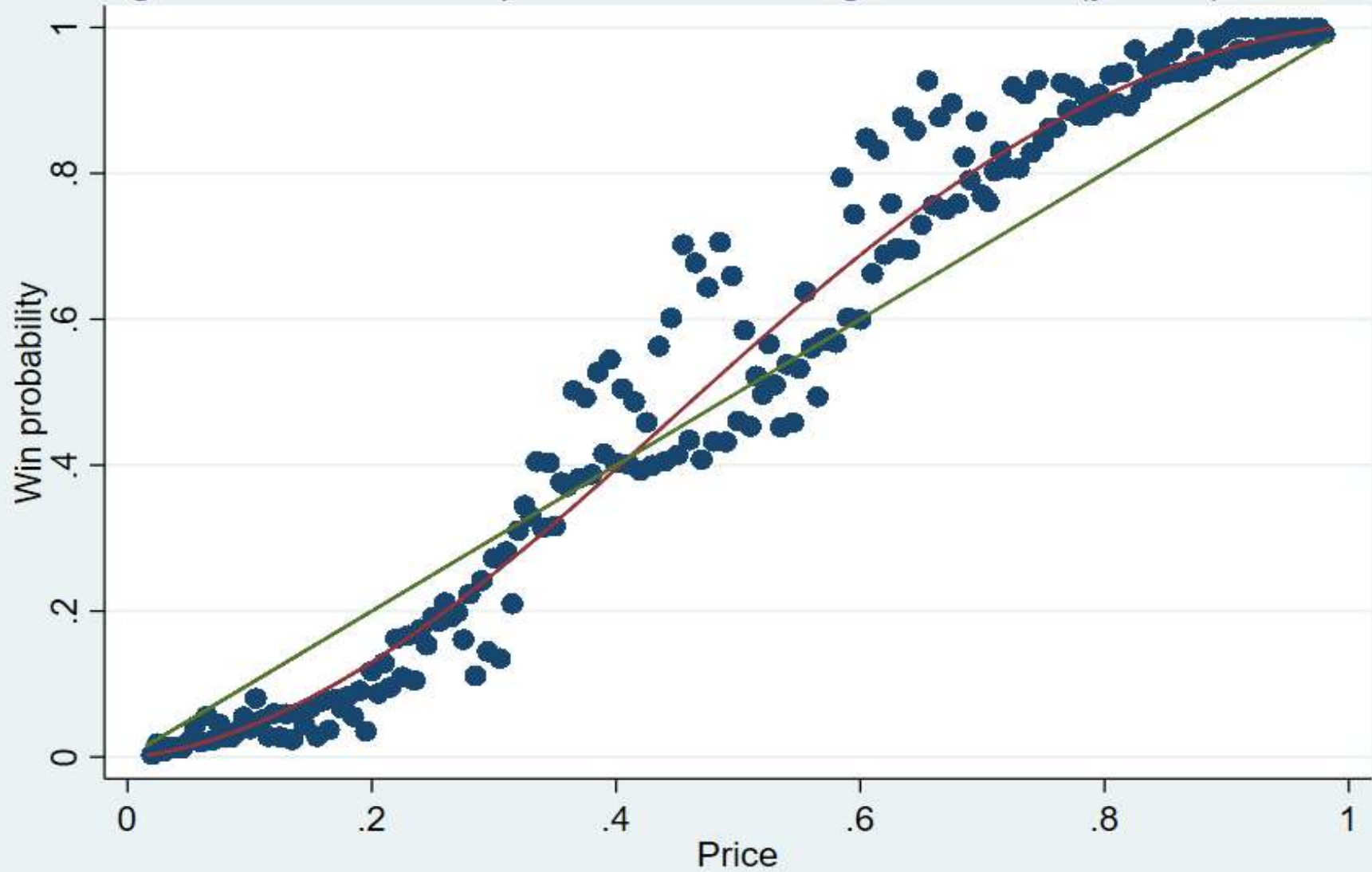


Figure 5B. Prices and return to expiry for single-outcome (yes/no) markets

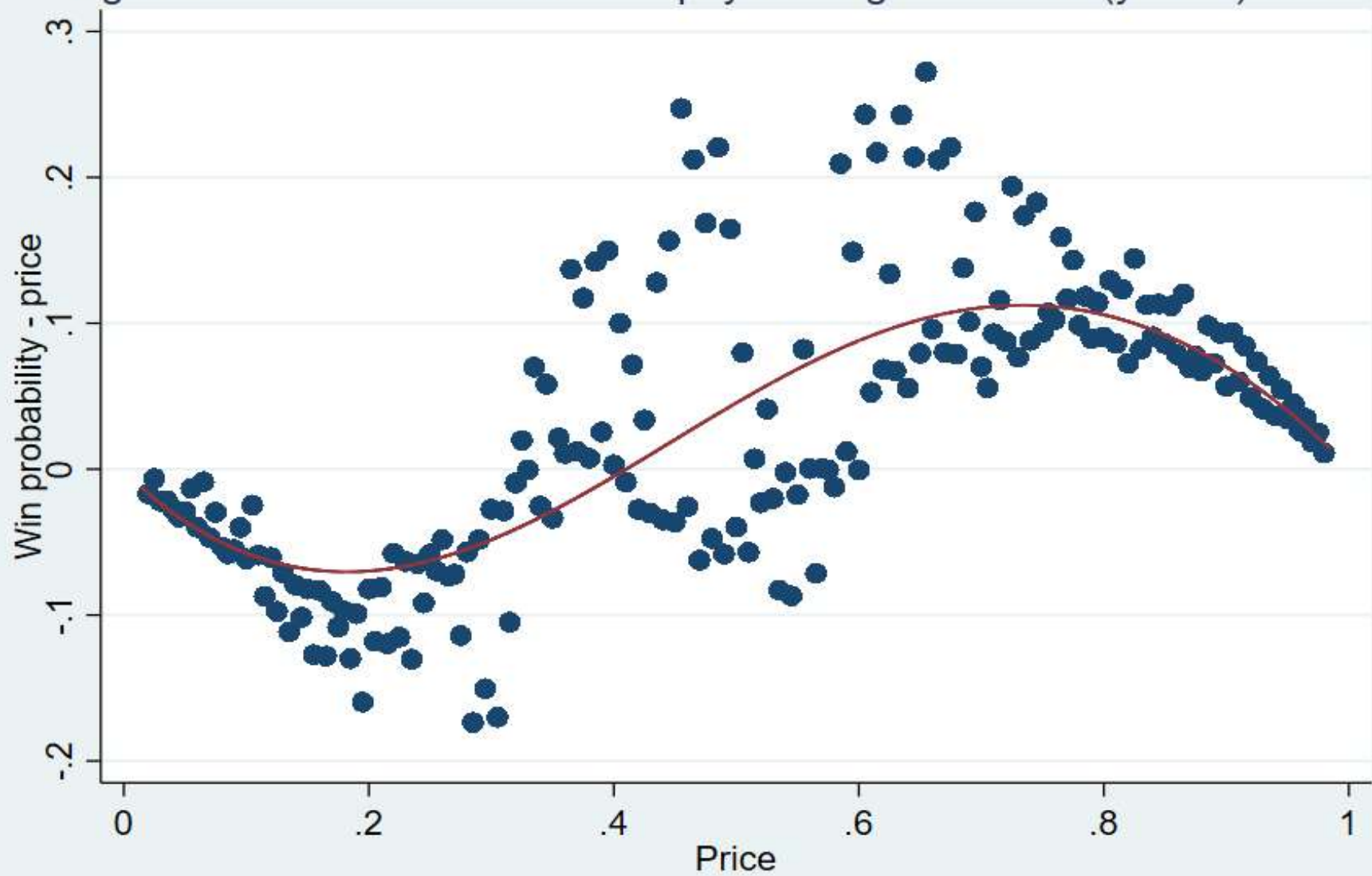


Figure 6A. Prices and probabilities for two-outcome markets

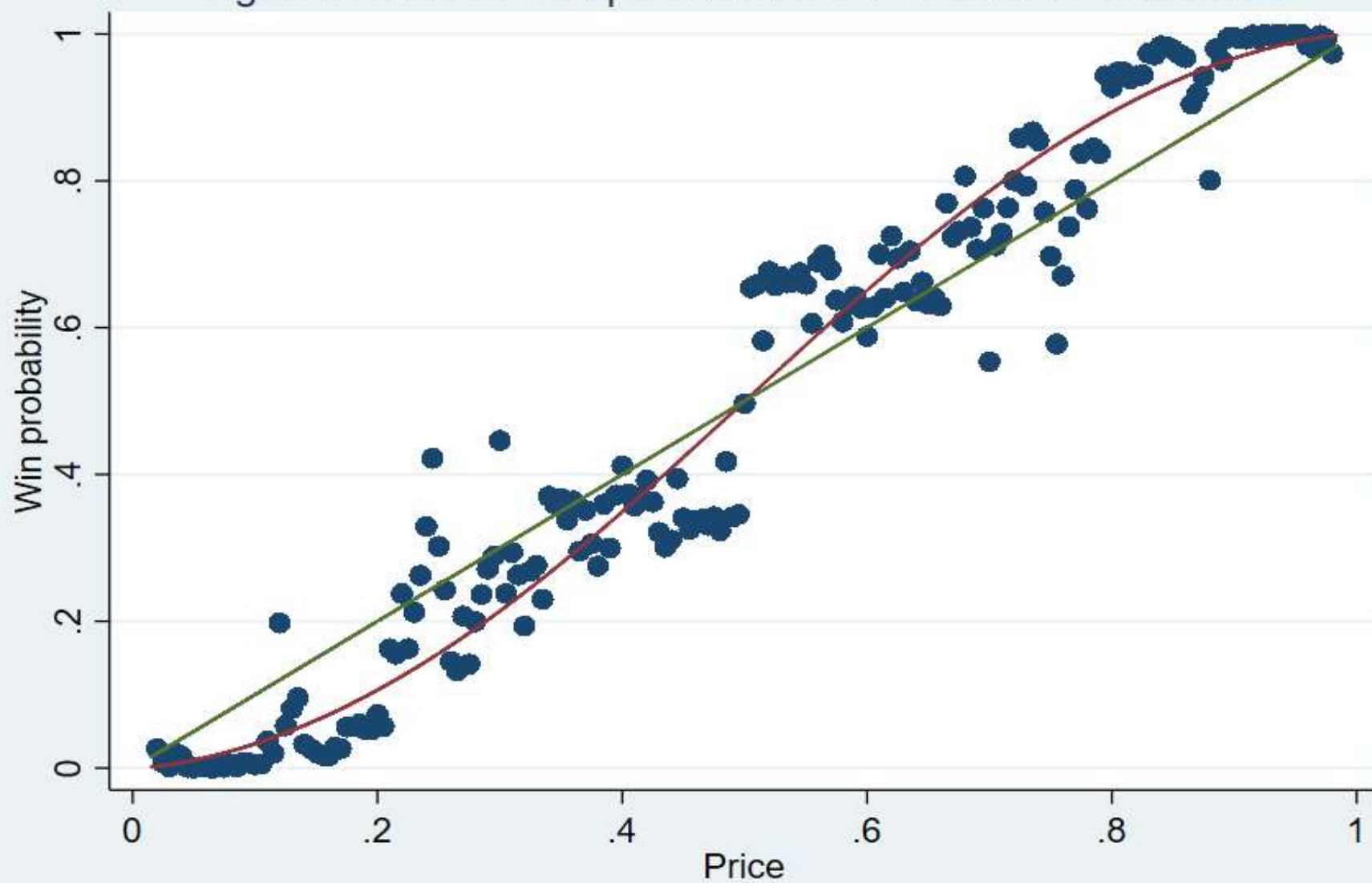


Figure 6B. Prices and return to expiry for two-outcome markets

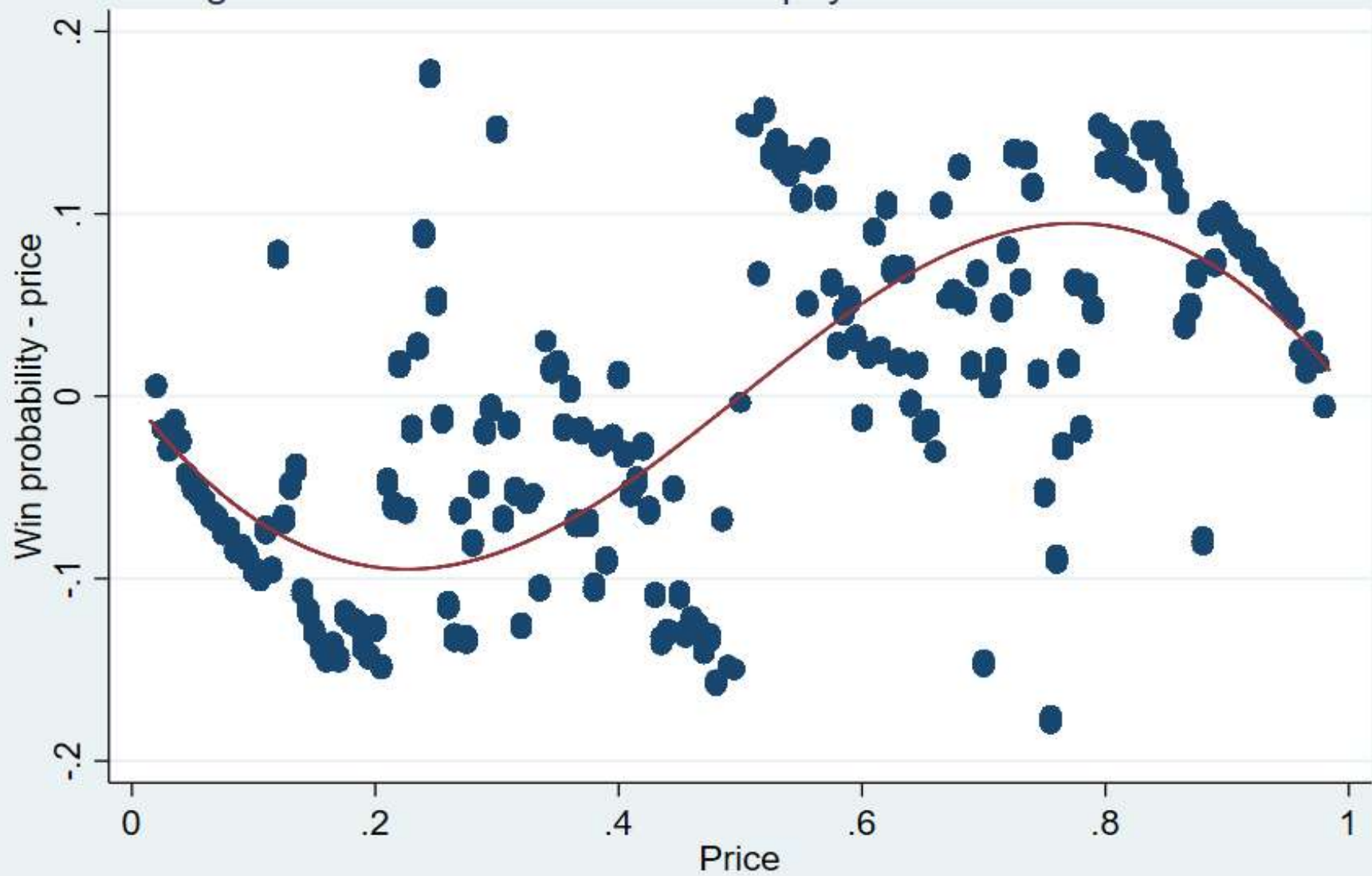


Figure 7. Differences between Betfair and PredictIt prices for 1-2 outcome markets

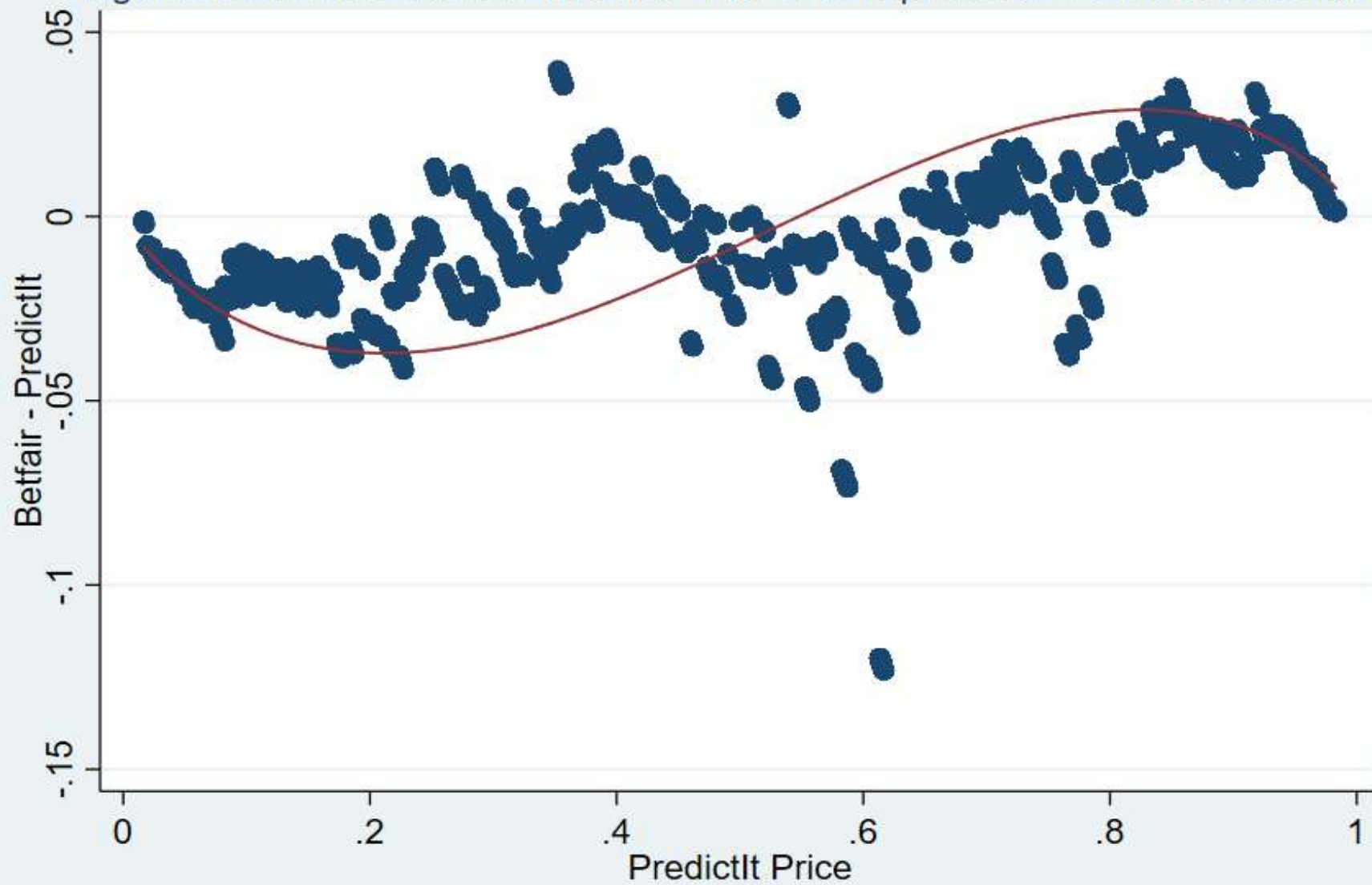


Fig A1. Trump win probabilities after 2020 election

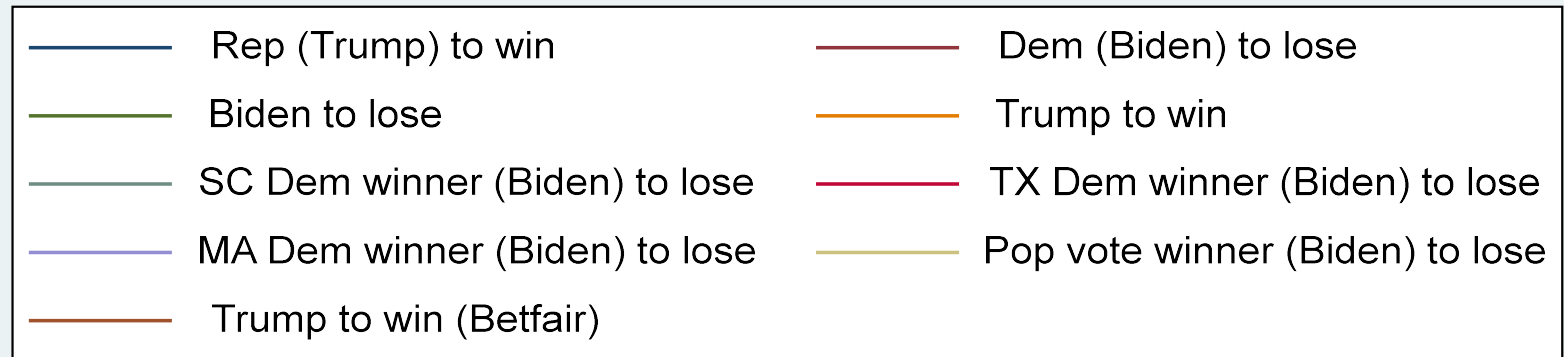
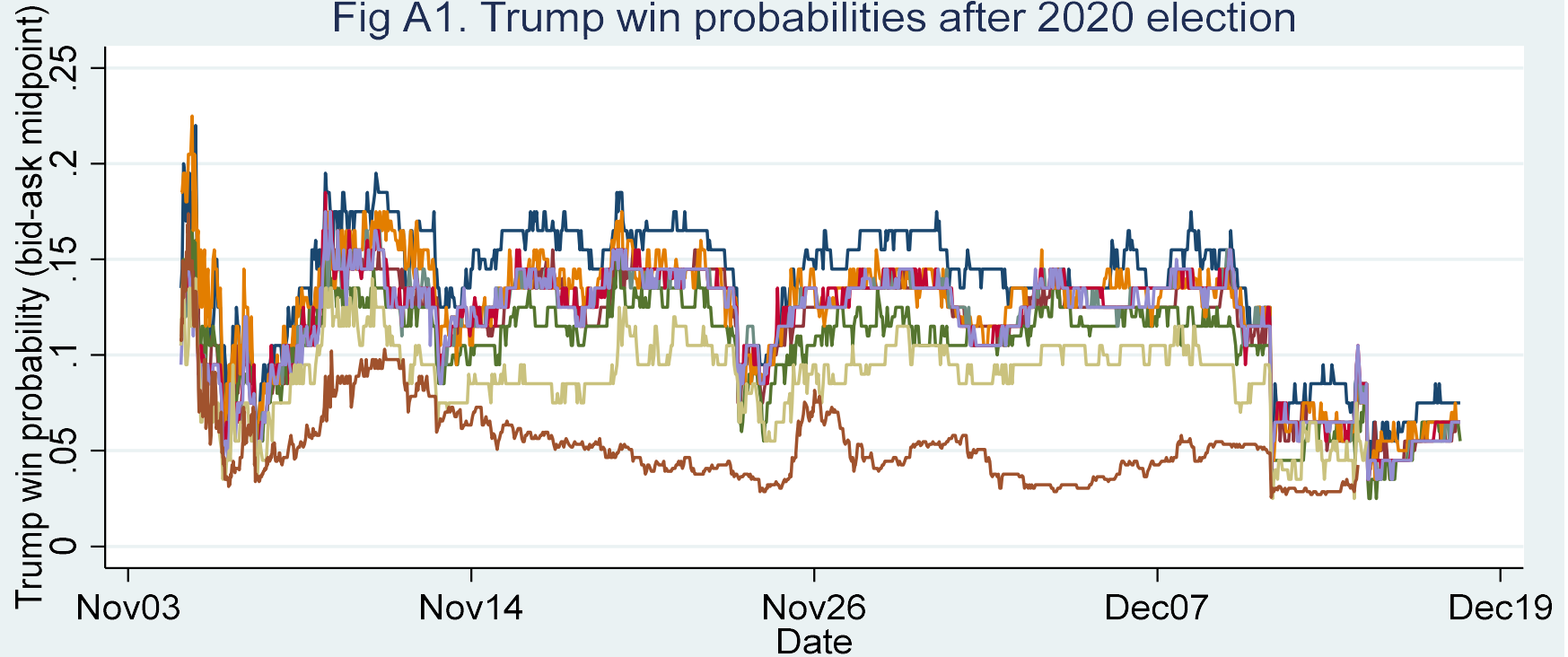


Fig A2. Trump win probabilities after 2020 election (Betfair)

