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ARE PREDICTION MARKETS POLITICALLY BIASED?

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This version of the paper is preliminary; it will be revised following the 2026 midterms to include those elections and data from Polymarket. The author would like to thank the prediction markets included in the sample for making their data available for academic research. The pre-2007 data included in the sample was collected jointly with Andrew Leigh and Justin Wolfers for a project that never led to a paper. I have traded on prediction markets, but have no financial relationship with any of the markets mentioned in this work. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

As prediction markets become more prominent, there are concerns that they will be a conduit for political bias. I analyze prediction markets returns from 1880 to 2025 and find no evidence of an overpricing of either left or right-leaning candidates, across a variety of subsamples. In recent elections, there is also no overpricing of either male or female, white or non-white, or young or old candidates. Most political prediction markets exhibit a favorite-longshot bias, and markets on near-term polling averages exhibit a very small overpricing of left-leaning outcomes (e.g., President Trump's approval falling), which is detectable only because the sample size is large. For elections, however, despite attracting participants who may not be representative of the voting population, prediction markets yield predictions without systematic bias.

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Are Prediction Markets Politically Biased?

I. Introduction

Betting on elections has been documented back to Papal elections in the 1500s (Baumgartner, 2003). Election betting was popular in the U.S. prior to World War Two, and continued to be popular in the UK and Australia. Internet-based political prediction markets have existed since 1988. But since their full legalization in the United States in 2024, prediction markets have grown unprecedently prominent. A February 2026 poll found that 17 percent of U.S. likely voters had traded on prediction markets and another 19 percent had consulted the prices.[2] Volumes are orders of magnitude higher than in the past (Table 1).

This new prominence has been accompanied by concern that prediction markets may be politically biased. This is of concern for its own sake: consumers of political prediction market prices presumably care about whether they are biased indicators of probability. But is of additional concern if biased probability estimates affect the elections themselves. Voters may prefer to back a candidate they perceive as a likely winner, as suggested by field (e.g., Granzier, Pons, and Tricaud, 2023) and lab evidence (Boukouras, et. al., 2023).

The potential for political bias arises from several sources. Prediction market participants may not be representative of the broader population. Prediction market traders are younger, more male, and of higher educational attainment than the average voter, at least based on survey evidence from the Iowa Electronic Markets (IEM) and of participants in modern commercial prediction markets.[3] At the same time, some demographics may be evolving. While the IEM attracted participants on campus, commercial prediction markets such as Kalshi and Polymarket have done so largely via advertising on social media. Whereas IEM participants were more white than the national voting population, a recent survey found that non-whites to be twice as likely as whites to have

[2] See https://www.paradigm.xyz/writing/paradigm-february-2026-poll-on-prediction-markets (last accessed 9/21/2026)
[3] See Forsythe, et. al. (1992, 1145-47), https://morningconsult.com/articles/the-dynamics-shaping-the-predictions-betting-market-category-in-2026, and https://www.gamblingnews.com/news/prediction-markets-userbase-is-exclusively-u-50/ (last accessed 9/21/2026)

traded on commercial prediction markets.[4] Regardless of their sign, demographic differences with the general population raise the potential for prices to be biased.

Another source of concern is the potential for large traders to intentionally influence prices. Rothschild and Sethi (2016) analyze proprietary data from Intrade and document a large trader who bet on Romney in the last two weeks of the 2012 election. Polymarket discloses the positions of large accounts, which allowed observers to notice a "French whale" who earned $80 million betting on a Trump victory in 2024.[5]

Working against these potential sources of bias are the incentives financial markets generate for impartiality. As the *New York Times* put it when discussing election betting outside the New York Stock Exchange in 1924: "it is a Wall Street habit, when risking a large amount of money, not to allow sentiment or partisanship to swerve judgments … any attempt to force odds in a direction unwarranted by the facts will always attract money to the opposite side." [6]

Consistent with this, Forsythe, et. al. (1992) find that while Bush and Dukakis-favoring participants tended to bet on their favorite candidate, there were also "marginal traders" who appeared to trade based on news that affected outcome probabilities. These marginal traders were sufficient to keep the Republican-leaning trader population from producing a bias in prices.[7] Hanson and Oprea (2009) predict that manipulation will attract trading by such marginal traders, pushing prices back towards their efficient level and, in some circumstances, leading to higher market accuracy than would have existed without the manipulation.

Academics have run experiments to test whether manipulation can affect prediction markets. Rhode and Strumpf (2006), ran a field experiment in which they made random trades in the 2000 IEM Presidential election markets. They found that their trades moved prices initially, but that full mean reversion occurred within a few hours (their Figure 10). Rasooly and Rozzi (2025) report on an analogous experiment in Manifold Markets, a play-money exchange. They found their manipulative trades had longer lived effects, albeit in play-money markets with limited volume. Current real-money prediction markets, at least on the highest-interest topics, are so liquid that

[4] https://www.paradigm.xyz/writing/paradigm-february-2026-poll-on-prediction-markets (last accessed 9/21/2026)
[5] https://www.cbsnews.com/news/french-whale-made-over-80-million-on-polymarket-betting-on-trump-election-win-60-minutes/ (last accessed 9/21/2026)
[6] *New York Times*, 10/10/1924, p. E9. Cited in Strumpf and Rhode (2004, p. 134).
[7] Forsythe, et. al. (1998) and Forsythe, Rietz, and Ross (1999) report similar findings for IEM markets on Canadian elections.

manipulation is presumably beyond the budget of academics, if not the "whales." So our ability to resolve this question using experiments may be limited, at least in the most important current settings.

Therefore the question remains whether the extant mixture of participant characteristics and trading motivations is sufficient to yield unbiased predictions, especially given the dramatic changes in scale and participation over the years. Assessing bias requires a large sample of both elections and election cycles. In any given cycle, one party can outperform expectations, which is ex post indistinguishable from a pricing bias in favor of the other party.

Accordingly, in this paper, I assemble as large a sample of political prediction markets as possible. I include pre-prediction market election betting on U.S. Presidential elections from 1880-1988, as well as the primary U.S.-facing prediction market from each election cycle. Across many different subsamples of this dataset (eras, offices, countries) there is no evidence of a systematic political bias. Given the evidence that prediction markets traders are disproportionately male and young, and that evidence on their racial background is mixed, I also test for gender, age, and racial biases, finding no evidence of pricing biases in any direction.

I do find evidence of a favorite-longshot bias in most political prediction markets, consistent with prior work (Page and Clemen, 2013; Zitzewitz, 2026). I also find evidence of an overpricing of left-leaning outcomes (e.g., President Biden's approval rating rising, or President Trump's falling) in markets tracking largely short-term polling outcomes. The overpricing is modest in magnitude – the average left-leaning is overpriced by about one percentage point and the average right-leaning outcome is underpriced by the same amount, but it is relatively consistent throughout the 2015-26 sample period and across polling sources and subjects.

II. Background and Data

In this paper, I combine data from many different eras. I focus on the primary U.S.-facing prediction markets in their time periods: pre-prediction market election betting (1880-1988), the Iowa Electronic Market (1988-2024), Intrade (2004-12), PredictIt (2014-26), and Kalshi (2024-26).[8] I also include data from UK and Australia-facing Betfair from 2019-23, most of which consists of

[8] I plan to add Polymarket data and data from the 2026 midterm elections to a later version.

individual-seat races from the 2019 UK general election and Australian general and state-level elections.

II.A Election betting before prediction markets

Betting on elections predates prediction markets. Between the Civil War and World War Two, betting on elections occurred outside the New York Stock Exchange, and major newspapers reported on the odds. Rhode and Strumpf (2004) describe these data, and Snowberg, Wolfers, and Zitzewitz (2007a) use them to examine stock market reactions to electoral surprises in U.S. Presidential elections. For the period between the end of the Wall Street betting in 1940 and the beginning of the Iowa Electronic Markets in 1988, Snowberg, Wolfers, and Zitzewitz supplement these data with odds from London bookmakers.

For most of the sample period, I only have betting market odds on one outcome every four years: the U.S. Presidential election. The data also include a few of the highest profile non-US elections in the 1990s (e.g., France in 1995, Russia in 1996).

II.B. The Iowa Electronic Markets

The Iowa Electronic Markets (IEM) began in 1988 with a single market, limited to University of Iowa affiliates, that predicted the vote share in the U.S. Presidential election. In 1990, it obtained a No Action Letter from the Commodity Futures Trading Commission (CFTC) allowing it to open its markets to the public.[9] Since then, the IEM has run markets on the highest profile elections: the U.S. Presidential election, Presidential nominations, Congressional control, and a few high-profile non-US and individual Senate and Governor races.[10]

The IEM runs both winner-take-all and vote share markets. Winner-take-all markets offer securities that pay $1 if the specified candidate wins; vote share securities pay 1 cent for each percentage point of the popular vote the specified candidate receives. Given that vote share

[9] 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).
[10] Forsythe, et. al. (1992) describe the original 1988 market. Berg, Forsythe, Nelson, and Rietz (2008) find that forecasts from the IEM's vote share market price from immediately before elections are better predictors of election results than the final political polls. Berg, Nelson, and Rietz (2008) reach the same conclusion at longer time horizons.

securities are almost unique to the IEM,[11] I include only the winner-take-all securities in the sample for this paper.

II.C. Betfair and Intrade

Commercial prediction markets Betfair and Intrade emerged in 2000 and 2002, respectively.

Intrade was initially known as Tradesports and operated in Ireland. It was reportedly willing to serve U.S. clients, and its sports and political contract offerings were consistent with a more U.S.-heavy mix of contracts. Intrade offered a wider range of U.S. political contracts than the IEM or Betfair, including markets on all Senate and Governors races, along with high-profile U.S. House, foreign mayoral elections. In 2008 it stopped offering sports contracts; most of its non-political volume came from financial contracts. The CFTC sued Intrade in late November 2012 for offering prediction market contracts to U.S. customers, prompting its closure in early 2013.[12]

Betfair operated in the UK and other countries in which online betting was legal, like Australia. It reportedly aggressively refused accounts from U.S. individuals. Most of Betfair's contracts were on sports. Its political contract offerings were limited to the highest profile U.S. races, but were more extensive for UK and Australian races. For Betfair, I only have data from mid 2019 until mid 2023. My sample includes elections that were not covered in US-facing prediction markets, such as seat-level races in the 2019 UK general election, the 2021 Australian general election, and several state-level Australian elections.

II.D. PredictIt

In 2014, the CFTC granted a No Action Letter to Predictit, which was a partnership between Victoria University in Wellington, New Zealand and Aristotle International, a political consulting firm.[13] The No Action Letter was based on the No Action relief granted to the IEM, but extended it by allowing more traders, larger investments, and advertising. While not provided for explicitly in

[11] Beers (2010) describes "majority" securities with payoffs linearly linked to the size of UK parliamentary majorities in seats. In 2004, Intrade offered a security that paid $1 for every electoral vote received by President Bush in the 2004 election.
[12] See https://www.cftc.gov/PressRoom/PressReleases/6423-12 (last accessed July 31, 2026).
[13] See https://www.cftc.gov/csl/14-130/download (last accessed July 31, 2026).

the 2014 No Action Letter, PredictIt offered a much wider range of contracts than the IEM or Intrade, including markets on political polling averages, the number of messages politicians like Donald Trump would tweet, and whether specific words would be mentioned in speeches.

PredictIt is arguably a hybrid between an academic and a commercial prediction market. Stakes on PredictIt were limited by regulation. Yet it charged fees, advertised, and offered markets on topics that were arguably of more entertainment value than academic interest (e.g., numbers of tweets).

PredictIt was successful in attracting liquidity to markets on topics that Intrade had tried unsuccessfully. For example, while Intrade only offered markets on a few of the highest profile U.S. House general election outcomes, PredictIt was able to attract liquidity to markets on the *margin of victory* in *primaries* for House races. PredictIt also attracted liquidity to markets on a broader range of non-U.S. elections than Intrade had been able to.

On the other hand, as discussed in detail in Zitzewitz (2026), PredictIt's markets suffered from overpricing and longshot biases which were likely the result of the exchange's popularity with small traders and the limited ability of sophisticated investors to trade against pricing biases. Longshot biases have also been noted on Intrade and pre-prediction market betting (Page and Clemen, 2013 and Rhode and Strumpf, 2004, respectively). In this paper I construct measures of prices that correct for overpricing, and check confirm that my estimates of political and gender, age, and racial biases in prediction market prices are robust to controlling for overpricing and longshot biases.

The CFTC revoked its 2014 No Action Letter in August 2022, alleging that PredictIt had not observed its terms. PredictIt challenged the CFTC order that it shut down in early 2023, and it operated through the 2024 election. Its contract offerings were extremely limited, likely due to the dispute.

After the change in the partisan control of the CFTC after the 2024 Presidential election, the CFTC issued a new No Action Letter that approved of the broader range of contract offerings, eliminated the limit on the number of traders, and increased the limit on the size of stakes.[14] PredictIt relaunched its platform following this new No Action relief, and as of the spring of 2026 it

[14] See https://www.cftc.gov/csl/25-20/download (last accessed July 31, 2026).

was offering slightly more contracts as it had four years earlier (before the CFTC action). Volumes were less than 10% of what they were four years earlier though, presumably because of emerging competition from Kalshi and Polymarket.

Any analysis of PredictIt should distinguish between three eras: 1) 2014-2022, when it was the only US-facing prediction market and less constrained by regulation, 2) 2023-24, when its offerings were severely limited, and 3) 2025-6, when it is again less constrained by regulation, but struggling to compete with the new entrants. Given the constrained offerings and low volume in the 2023-4 and 2025-6 periods, respectively, I include PredictIt in the elections sample only through the end of 2022. I may revisit this in a revised version of this paper after the 2026 midterm elections, when more 2025-26 election markets will be available. In the polling market analysis, I do include markets from 2025-26, since they are able to meaningfully add to the sample size.

II.E. Kalshi and Polymarket

Kalshi launched in 2021; Polymarket in late 2020. Both remained small until 2024, for different reasons.

Kalshi is onshore, a CFTC-regulated designated contract market. Initially, this limited them to offering contracts on topics such as the weather and macroeconomic variables, but these contracts attracted little volume. They applied to the CFTC asking to offer election contracts, and sued when their request was denied. On September 6, 2024 a U.S. District Court ruled in Kalshi's favor, and on October 2, 2024, the DC Circuit upheld the ruling. [15] Kalshi launched its election markets on October 7. Regulatory pressure from the CFTC abated after the change in administration, and Kalshi introduced sports markets in late January 2025. Their volumes in both election and other markets have grown rapidly since.

Polymarket began offshore, as a decentralized cryptocurrency-based platform that might have been hoping to limit its legal liability by taking this approach. Polymarket ran a few markets on the 2020 elections and other outcomes. In early 2022, the CFTC charged Polymarket with having

[15] https://www.dwt.com/blogs/financial-services-law-advisor/2024/10/cftc-election-trading-event-contracts-ban-in-court and https://law.justia.com/cases/federal/appellate-courts/cadc/24-5205/24-5205-2024-10-02.html (last accessed, July 31, 2026).

offered prediction markets to U.S. customers.[16] Polymarket paid a penalty, and began blocking access to U.S. customers. Trading volumes on the 2024 elections were high nonetheless, and on November 13, 2024, after the election, the Federal Bureau of Investigations raided Polymarket CEO Shayne Coplan's apartment, seeking evidence that he had allowed U.S. customers on his exchange. In late 2025, Polymarket launched a U.S. version of their exchange, which allows U.S.-based clients to trade the subset of Polymarket contracts allowed by the CFTC (contracts on war and terrorism are excluded).

Kalshi and Polymarket currently co-exist, despite the pressures towards monopolization driven by traders' desire to trade where there is the most liquidity. Presumably, Kalshi's primary onshore and Polymarket's primary offshore customer base explains the coexistence, in a manner since to that of Intrade and Betfair in the 2002-12 period.

Kalshi and Polymarket each offer a broad range of contracts. Most of their volume is on sports and financial contracts on short term movements in cryptocurrencies, traditional currencies, equity indices, and individual stocks. Kalshi offers contracts on macroeconomics and Polymarket offers contracts on corporate earnings that early analyses have found to be well-calibrated.[17] Polymarket also has an extensive range of contracts on geopolitical events, such as events in the wars in the Ukraine and Iran.

The range of election contracts offered by each exchange is similar to that offered by PredictIt; volumes in these markets are higher than achieved by PredictIt, which is understandable given the limited stakes on PredictIt. Given that Kalshi did not offer election contracts until October 2024 and Polymarket was very small until the summer of 2024, I include Kalshi and will include Polymarket beginning with the 2024 U.S. general election.

II.F. Sample overview

Table 2 reports the types of events covered by each market. I limit the election sample to general elections, for which the political orientation of candidates is most easily determined. For the U.S., the Republican candidate is considered to be the right-leaning candidate throughout the sample;

[16] https://www.cftc.gov/PressRoom/PressReleases/8478-22 (last accessed July 31, 2026).
[17] See Diercks, Katz, and Wright (2026) on Kalshi's economic markets and Rabetti, Shao, and Zhang (2026) on Polymarket's earnings markets.

independents are generally treated as centrist.[18] European political parties are assigned based on European parliamentary alliances, and political parties in other countries are assigned when it can be done with reasonable confidence.[19]

The scale and scope of prediction markets have increased steadily since the Iowa Electronic Markets. Returns in election markets can be correlated within an election cycle, so the number of elections and the number of unique election dates are both indicative of the true sample size. There is overlap between the PredictIt and Betfair samples and the Kalshi and Polymarket samples, and this provides an opportunity to compare pricing across platforms with different trader populations.

For most markets I have both trading and quote data. Bid-ask midpoints are generally more predictive of both future market prices and outcomes, and sophisticated users of market prices might be expected to rely on them more heavily for forecasting. For multi-outcome markets, I use a bid-ask midpoint that is weighted so that it sums to one across all outcomes.[20]

For many markets, quote data is available for a more limited sample period than trade data, so analyzing trade data allows for a larger sample. I will analyze both trade and quote data for the sample in which both are available, as well as trade data for the larger sample. Bid ask spreads can often be quite wide; this is particularly an issue in Intrade and Betfair's markets.[21]

I will analyze prices at three time horizons: 1 day before the election, 3 weeks before the election, and 4 months before the election. The three-week time horizon captures the approximate time at which apparent attempted price manipulations in 2012 and 2024 occurred and seems an intuitive time to expect price manipulation to influence perceptions about probabilities in a way that may influence voting. Page and Clemen (2013) find a longshot bias in Intrade prices at a four-month time horizon that disappears as the election approaches. If this result reflects long-run arbitrage

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[18] The exception is Bernie Sanders, who I treat as a left-leaning candidate throughout his career.

[19] European political parties that are allied with the German Left, Greens, or Social Democratic parties are treated as left-leaning. Allies of the Christian Democrats and Alliance for Germany are treated as right-leaning. Allies of the Free Democrats are treated as Centrist. For the UK, I treat Labor, the Greens, and the SNP as left-leaning, the Conservatives and Reform as right-leaning, and the Liberal Democrats as centrist. Australia, Canada, New Zealand have analogous party systems. In this version of the paper, I have not classified parties in most other countries, but plan to do so in the revised version.

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

[21] In my main sample, I prioritize quote data where both trades and quotes are available, so long as quotes are sufficiently narrow. Specifically, I require that multi-outcome markets have bid prices that sum to at least 0.8 and ask prices that sum to no more than 1.5. Results are robust to prioritizing trade data instead, as well as to requiring narrower spreads for sample inclusion (Table A2).

being more costly, we might expect other biases to be larger in long-dated prediction market prices. Moreover, the four-month time horizon might also be plausibly attractive for manipulation, given lower liquidity, and the opportunity to influence longer-run narratives.

III. Political bias in election markets

Table 3 presents tests of whether the returns to prediction market securities of right-leaning candidates are higher than those of left-leaning candidates. The tests are conducted by regressing the returns to expiry in percentage points on a variable that is equal to -1 for left-leaning, 0 for centrist, and +1 for right-leaning candidates. A positive coefficient indicates higher average returns for right-leaning candidates, implying a historical overpricing of left-leaning candidates.

The point estimate for the full sample is almost exactly zero. The standard error is narrow enough that mispricings of roughly five percentage points in either direction can be rejected with 95 percent statistical confidence. At the one-day time horizon the confidence interval is narrower, and we can reject a left-leaning bias of about 4.5 percentage points and a right-leaning bias of about 3.0 percentage points or more. The bulk of the sample comes from the commercial prediction markets (Intrade, PredictIt, Betfair, and Kalshi) and from 2003 or later; results for these subsample are similar to the overall results.

Standard errors allow for the correlation of returns between securities linked to elections occurring on the same day. They therefore allow for correlation of returns within a given election – the negative correlation between securities on different candidates to win the same election and the positive correlation between the returns to purchases of the same candidate at the same time. They also allow for the correlation of different elections in the same electoral cycle (e.g., Trump to win Wisconsin and Trump to win Michigan). These correlations are important, as evidenced by the fact that falling to account for them would lead to an underestimate of standard errors by a factor of more than 2.75 (Table A1).[22] Given the importance of these correlations, our true sample size is in a sense limited by the number of election dates included. This motivates extending the sample as far back into history as possible, even if the number of elections added is small.

[22] In contrast, allowing additionally for correlations of returns between contracts on elections on different dates within the same calendar quarter, or different dates within the same year, would make almost no difference.

Table 3 also reports results separately for different prediction markets and different time horizons. While some of the point estimates are large, the estimates for any one prediction market are typically imprecise.[23] This reinforces the need for a meta-analysis of multiple prediction markets to draw questions about political bias.

Table 4 disaggregates the same sample by the level of office at stake and whether the election is for the U.S. or not. The U.S. accounts for 60 percent of the combined sample; the UK (16 percent) and Australia (13 percent) account for much of the remainder, most of which is accounted for by the seat-level markets in the Betfair sample. Canada (3.4 percent), Germany (2.4 percent), and France (1.0 percent) are the next most important.

The results for individual cells in Table 4 are less precisely estimated than for the full sample. Beyond this, there a few clear patterns. Point estimates are generally negative outside the U.S. and positive for the U.S. The negative non-US coefficient largely reflects the importance in the sample of the 2022 Australia federal election and, to a lesser extent, the 2023 New South Wales state election, and the fact that Labor outperformed expectations in both.

One potential reason for predictable non-zero expected returns in political prediction markets is hedging. Past research has found that asset prices rise after right-leaning parties unexpectedly win the U.S. Presidency (Snowberg, Wolfers, and Zitzewitz, 2007a).[24] Asset price reactions to surprise changes in Congressional control are smaller (Snowberg, Wolfers, and Zitzewitz, 2007b). The often more gradual release of electoral news outside the U.S. makes sharp evidence for other countries harder to come by, although the 2007 French Presidential election (e.g., Coulomb and Sangnier, 2014) and the Brexit referendum (Breinlich, et. al., 2018) provide exceptions.

If asset prices rise when the right-leaning candidate wins, a prediction market security linked to a left-leaning candidate should provide hedging value, should trade at a premium to its true probability, and should therefore have negative expected returns. Thus we might expect more

[23] Standard errors for most individual prediction markets are also likely downwardly biased due to the small number of cluster groups and the fact that they are unequally sized (due to the large number of markets lnked to U.S. general elections). Thus estimates for individual markets are likely less precise than they appear in Table 3.

[24] The 2016 U.S. Presidential election is a partial exception to this statement. Markets dropped sharply when Trump won the 2016 U.S. Presidential election, consistent with their reaction to pre-election news about electoral probabilities (Wolfers and Zitzewitz, 2018). But they rallied afterwards and closed up by the day after the election, consistent with how they have responded to Republican wins historically.

positive coefficients in Table 4 for higher offices and for U.S. elections, given that they are likely more consequential for asset prices. We see little evidence of this in Table 4, although unfortunately even in this sample the statistical power with which one can distinguish between the returns of right-leaning securities tied to national leadership and other right-leaning securities is limited.

I also conducted some robustness checks, which are outlined in Table A1. As mentioned earlier, adjusting standard errors for return correlations only within each election, rather than within all elections on the same date, leads to an underestimate of the standard error by a factor of about 2.75 (line 2). Allowing for correlations between elections in the same calendar quarter (line 3) or year (line 4) makes little difference, however.

The main results used a variable that classified political parties into three categories: left-leaning (-1), right-leaning (+1), and centrist (0). As an alternative, I tried a specification that treated far left (-2) and far right parties (+2) as more extreme. This made little difference (line 5).

In the main results, I used bid-ask midpoints as the indicator of price where available and last trade prices only when quotes were not available. Favoring trades over quotes makes little difference (line 6). If I limited the sample to observations for which both quotes and trades are available the choice again makes little difference (line 7 vs. 8), but that sample has returns for right-leaning securities that are about 1.5 percentage points below those of the full sample (lines 7, 8, and 9 vs. others). Requiring quote data for inclusion excludes the pre-IEM, IEM, and part of the Intrade (2003-6) and PredictIt (2016-19) samples. This difference is far from statistically significant, and presumably reflects the fact that right-leaning parties happened to perform slightly better during the excluded cycles.

The main results weight long-lived election prediction markets more heavily, since markets that begin more than 120 days before the election can be included in the sample three times. Weighting each election equally improves the performance of right-leaning securities slightly (line 12). The results also weight more recent election cycles more heavily, since there are predictions markets on more elections that in the past. Election cycles with more included elections (recent U.S. elections, the UK and Australian elections mentioned above) get weighted more heavily for the same reason. Weighting the sample equally by election date reduces the performance of right-leaning securities by just over one percentage point, partly because it reduces the weight given U.S. elections (line 13). On the other hand, weighting the sample equally by election year sharply increases the

weight of the pre-2003 election years, which increases the performance of right-leaning securities (line 14).

In none of these approaches is there statistically significant evidence of political bias; indeed the highest t statistic in Table A1 in absolute value is 0.6. The absence of political bias in prediction markets over the long run appears quite robust.

IV. Demographic bias in election markets

What survey and anecdotal evidence that we have suggests that prediction market participants are disproportionately young and male, while evidence on their race composition is both mixed and more sparse. This raises the question of whether prediction market pricing is biased in favor of the young and male, and how it relates to race.

Table 5 presents regressions that test for bias in the same way as those in Tables 3 and 4. The returns to expiry to prediction market securities is regressed on indicator variables for whether the candidate is female, non-white, or black, and a continuous variable for their age on election day. Regressions include fixed effects for election*pricing date combinations, so candidates are being compared against their competitor(s).

The univariate results suggest that female and nonwhite candidates have historically been overpriced by about one percentage point, compared with white and male candidates. A candidate who is nine years younger has likewise historically been overpriced by a percentage point. None of these differences are close to statistically significant (highest t-statistic is about 0.85).

Demographic data for the above analysis was gathered using Google Gemini, a large language model (LLM). Basically, the LLM was asked to do what a human RA could have been tasked with: Googling each candidate and collecting their demographics, making judgments as necessary. The LLM appeared quite confident about sex and race, and provided more detail than requested (it unbiddenly identified which white candidates were of Jewish or Middle Eastern descent, and often also identified European ethnicities such as Irish or Italian). When candidates were listed as mixed race (e.g., Kamala Harris was listed as Black / South Asian), I used the first-listed race. Races were not always listed alphabetically, so presumably the LLM was making a judgment about which racial identity was primary for the candidate in question.

The LLM was able to provide age for about 80 percent of candidates. For about half of these, it provided an exact birthdate. For the others it provided an integer age or a range (e.g., 56-57, 60s). In these cases, I used the birthdate consistent with being at the midpoint of the age range on the date of the search. The LLM often offered an explanation for its age estimate, such as a college graduation year or a date of passing a bar exam. Spot checks largely confirmed its findings, albeit with a couple odd errors that were corrected.[25]

The sample for the analysis in Table 5 currently includes PredictIt and Kalshi markets on US elections where the candidate was named in the contract name. Most general election contracts are currently excluded, since these usually had contracts named "Democratic" or "Republican." I hope to expand the sample in the revised version of the paper, which should help increase the precision of the estimates. That said, based on the current sample, there is clearly no statistically significant evidence of a bias for or against young, white, or male candidates.

V. Polling markets

Prediction markets on elections are the focus of this paper because they are the prediction markets where political or other biases would be most concerning, particularly to the extent that these biases might affect elections themselves. The problem with elections is that we only have so many of them, even in a 145-year sample.

One of the type of markets PredictIt ran to keep its users engaged between elections was on weekly changes in polling averages, such as the job approval rating of the President, the approval rating of the President in specific areas (the economy, foreign policy) or specific policies (the 2017 travel ban, impeachment, the current Iran war). During election campaigns, markets were also run on the favorability ratings of the candidates and on the margin in head-to-head or Congressional generic ballot polls. Most polling markets were settled based on the polling average published by a major polling aggregator (Real Clear Politics and 538 were the most commonly used) at 11 AM ET on the day of expiry. Most markets were settled a week after they were launched, with a new market replacing the old. A few markets were on longer-term polling outcomes, such as the Presidential job

[25] For example, the 2017 Detroit mayoral candidate Coleman Young II was confused with his father, who was mayor of Detroit from 1973-93 and died in 1994. Currently active Australian politician Ian Winton Smith was confused with Ian Douglas Smith, the former Prime Minister of Rhodesia, who died in 2007.

approval rating at the end of a month or calendar year. Markets typically traded securities that divided the range of possible polling outcomes into 7-10 mutually exclusive bins, each one security paying off $1 if the polling average fell into its bin at expiry.

PredictIt ran more of these markets than any other prediction market, by a wide margin. Perhaps this was because they were not allowed to run markets on other short-term topics, such as sporting events or financial market movements. Regardless of the reason, these markets presumably attracted participation from traders who were politically engaged and had opinions about how polling would evolve in response to events. They therefore seem an excellent place to learn about political bias in prediction markets.

Table 6 reports regressions to expiry in percentage points of polling prediction market securities on a variable ranking them on a left-to-right scale. The most favorable polling outcome for a Democrat (high approval for a Democratic president, low approval for Trump, a large lead for a Democratic candidate) was scaled as -1, the most favorable outcome for a Republican as +1.

The sample of polling markets runs from late 2015 to early 2026, with a gap from mid-2022 until early 2025, during the legal conflict between PredictIt and the CFTC. It therefore covers roughly 7 years. Markets ran continuously, so there are 351 unique weeks (Sunday-Saturday) in which a polling market expired.

For the full sample, the most left-leaning securities are overpriced by 1.4 percentage points, and the most right-leaning securities are underpriced by the same amount. The standard errors, which allow for correlated returns for markets expiring in the same week, are much tighter than for the election markets, reflecting the larger sample size. The overpricing of left-leaning outcomes is statistically significant at convention levels; we can reject overpricing outside the 0.3 to 2.5 percentage point range with 95% confidence.

The left-leaning pricing bias of 1.4 percentage points is remarkably consistent in different subsamples. The bias is 1-1.5 percentage points during each of the Obama, Trump I, Biden, and Trump II Presidencies. Overpricing is roughly similar for both election and approval polling. It is roughly similar for polling that does and does not involve Trump. It is roughly similar for markets based on Real Clear Politics and 538 polling averages. The estimated pricing bias does not change when controlling the price of the contract, the ordering of the bins, or the extremeness of the outcomes.

The left-leaning bias in polling markets begs the question of whether we would observe a similar bias in election prediction markets, were our estimates precise enough to detect a bias of that size. As the sample of election prediction markets grows, and expands to more countries and therefore more unique election dates, it may soon be possible to answer that question.

VI. Favorite-longshot bias

The favorite-longshot bias is one of the more frequently observed pricing biases in betting and prediction markets. The bias involves high-probability outcomes (favorites) being overpriced, and low probability outcomes (longshots) being underpriced. It is thought to arise from probability misperceptions among traders (Kahneman and Tversky, 1979), combined with costly or limited arbitrage. Arbitrage that involves buying underpriced favorites may be more costly due to the capital requirements (Ali, 1977; Manski, 2006), and these costs matter more for events that are further from expiry (Page and Clemen, 2013). Elections have less repetition of similar events than domains such as sports, and so might allow more scope for miscalibration.

In this section, I test for political and demographic bias in election markets while also controlling for the favorite-longshot bias. I model favorite-longshot bias using an approach that allows for linear-in-log-odds probability misperceptions (Lattimore, Baker, and White, 1992). Suppose the marginal trader misperceives the true probability π as $p(\pi)$, given by the following functional form:

$$p(\pi) = \frac{\alpha \cdot \pi^{\beta}}{\alpha \cdot \pi^{\beta} + (1-\pi)^{\beta}}$$

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. Unbiased probabilities result when $\alpha = \beta = 1$. If the market prices a security at $p(\pi)$ when the true probability is π, the log odds ratios of the price and probability will be related linearly:

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

A logit regression of outcomes on log price ratios will yield a slope of β^{-1} and the constant an estimate of $\frac{-\ln(\alpha)}{\beta}$. Thus a slope > 1 in this regression is consistent with a favorite-longshot bias.

This approach can be extended to events with more than 2 possible outcomes using a multinomial logit (Berg and Rietz, 2019). One simply includes the log of price as the key independent variable in the multinomial logit, along with any variables that might linearly affect the log odds. This approach is convenient, because given that a multinomial logit model will also accommodate settings with two outcomes, markets with 2 and 3 or more outcomes can be combined in the same sample.

As I discuss in Zitzewitz (2026), the model has a latent variables interpretation in which the regression slope captures the factor by which traders overestimate the spread of future political shocks. A slope > 1 implies pricing consistent with traders expecting more future political news than will eventually arrive.[26] A positive coefficient on a demographic variable would imply that traders underestimate the political strength of candidates in that demographic.

Table 7 presents estimates of the slope from the model for the full sample, and for specific prediction markets and time horizons. As mentioned, a favorite-longshot bias is indicated by a coefficient larger than one, and indications of statistical significance in the table are relative to a null hypothesis of slope = 1. Statistically significant evidence of a bias is present at all or most time horizons for Intrade, PredictIt, and Betfair, as well as for the full sample.

The results do not exactly match Page and Clemen (2013), who find larger pricing biases for Intrade at long time horizons. PredictIt also appears as less of a large-bias outlier than in Zitzewitz (2026). This may reflect the sample, as it is limited to general elections.

Tables 8 and 9 report estimates of political bias than control for the favorite-longshot bias using this multinomial logit approach. The logit coefficients on political and demographic variables are expressed in percentage points and divided by 5 to approximate marginal effects. This makes coefficients the tables roughly comparable to those in Tables 3 and 5.

[26] This conception of the favorite-longshot bias makes clear its link with the overpricing of volatility in options markets (e.g., Jackwerth and Rubenstein).

Results are generally similar. A few more individual coefficients are statistically significant in Table 8 than in Table 3, but they are mostly marginally significant, and in prediction markets for which the number of clusters is small enough that the standard errors may be downwardly biased.

In Table 9, we now conclude that female candidates have been overpriced, at least when controlling for the (still statistically insignificant) overpricing of older candidates and the overpricing of longshot (also statistically insignificant in this sample). This fits with the fact that male candidates are older in this sample, and with the fact that longshot candidates are more likely to be male. But given that it is the one significant coefficient out of 18 in the table, it likely should not be overinterpreted.

VI. Conclusions

This paper assembles what I believe is the largest sample of election prediction markets ever analyzed together. Working with such a large sample increases the precision with which we can measure biases in pricing. Despite this, I find no systematic evidence of either political or demographic bias in election prediction markets. Prediction market traders may not be representative of the voting population, but we do not see evidence that this affects the electoral probabilities they produce.

Election prediction markets are not free of all biases, however. Historically, most election prediction markets have exhibited an underpricing of favorites and an overpricing of longshots. My current sample of Kalshi prediction markets is too small to confirm that this bias is present in their markets, but the sample will grow substantially after the 2026 midterms.

For markets on changes in polling averages, I do find evidence of a 1.4 percentage point overpricing of left-leaning outcomes that is remarkably consist throughout the 2015-26 sample period. A bias of this size would be too small to detect even in my 145-year election sample. Biases this subtle are also presumably not what observers who worry about prediction markets adversely affecting electoral outcomes have in mind.

Taken together, the results are broadly consistent with past work on prediction markets (as surveyed, e.g., in Wolfers and Zitzewitz, 2004). Prediction markets prices may exhibit some small biases, but they are simultaneously well-calibrated on many important dimensions.

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Table 1. Prediction market volume in October and November of U.S. Presidential Election years

Thousands of current US$

Year	Iowa Elec. Mkt.	Intrade	Predictit	Kalshi	Polymarket	Total
1988	39					39
1992	173					173
1996	245					245
2000	401					401
2004	801	14,277				15,078
2008	231	25,115				25,347
2012	306	69,576				69,881
2016	308		115,531			115,839
2020	133		650,187			650,320
2024	83		69,438	1,386,483	7,732,139	9,188,144

Notes: Volumes are notional values (i.e., they reflect the maximum possible value of the traded contract on expiry: $1 per contract for all exchanges except Intrade which was $10). Intrade, Kalshi, and Polymarket data include only election and political outcomes.

Table 2. Election prediction markets Included

		Races included (● = all/many; ○ = a few)									
Years	Market	Pres	State	Control	Senate	House	Gov	Other	Non-US	Polls	Trades/quotes
1884-1940	Wall Street Curb	●									Trades
1944-2001	London bookmakers	●							○		Trades
1992-2024	Iowa Electonic Markets	●		●	○	○	○		○		Trades
2002-2012	Intrade	●	●	●	●	○	●	○	○	○	Trades (quotes 2007-12)
2014-2022	PredictIt	●	●	●	●	●	●	●	●	●	Trades (quotes 2019-22)
2019-2022	Betfair	●	●	●	●	○	●	○	●		Trades and quotes
2024-25	Kalshi	●	●	●	●	●	●	●	●	●	Trades and quotes
2024-25	Polymarket (to come)	●	●	●	●	●	●	●	●	●	Trades and quotes

Key:

Pres	U.S. Presidential election winner (popular vote winner for IEM)
State	U.S. Presidential state-level vote
Control	U.S. House/Senate partisan control
Senate	Individual U.S. Senate races
House	Individual U.S. House races
Gov	U.S. Governors
Other	Lower offices, state legislature control
Non-US	Other non-U.S. elections
Polls	Approval and electoral polling

Polymarket data will be added to the post-midterms version of this paper

Table 3. Returns to right-leaning candidates -- by market and time horizon

			Days to election			
Market	Observations	Election dates	All	1 day	3 weeks	4 months
All	9,642	216	0.03	0.76	0.74	-3.63
			(2.66)	(1.90)	(2.91)	(5.06)
Pre-IEM (1880-1988)	124	35	2.87	6.39	4.73	
			(12.47)	(12.20)	(14.81)	
IEM (1992-2024)	350	20	10.34	9.55	12.83	
			(8.42)	(7.59)	(7.58)	
Intrade (2003-12)	2,412	20	-5.53	-4.64	-4.12	-8.23
			(3.32)	(2.73)	(3.84)	(4.67)
PredictIt (2016-22)	2,884	114	2.07	1.61	3.33	0.93
			(6.17)	(4.99)	(7.27)	(6.84)
Betfair (2019-23)	3,037	29	-1.72	-0.44	-2.38*	
			(1.19)	(0.83)	(1.21)	
Kalshi (2024-25)	835	16	4.72	6.11**	5.27	
			(3.85)	(2.50)	(3.77)	
Commercial prediction markets	9,168	175	-0.43	0.39	0.20	-4.26
(Intrade, PredictIt, Betfair, Kalshi)			(2.61)	(1.87)	(2.89)	(5.05)

Each cell is the coefficient from a univariate regression of the returns to expiry in percentage points of a contract on an indicator for whether the candidate is left (-1) or right (+1) of center or centrist (0). Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election. Regressions include fixed effects for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks. Estimates for the 120-day horizons are not reported for markets with fewer than 100 observations.

Table 4. Returns to right-leaning candidates -- by office and US/non-US

Market	Observations	Election dates	Country		
			All	Non-US	US
All	9,642	216	0.03	-1.42	0.84
			(2.66)	(1.30)	(4.39)
National leader	2,352	76	-0.49	-6.82*	1.10
(President, PM)			(4.26)	(3.86)	(5.36)
National legislative partisan control	480	34	1.98	-11.02	4.75
(Parliament, US House, US Senate)			(6.64)	(6.68)	(8.07)
Individual seats	4,994	67	0.12	-0.99	1.05
(Parliament, US House, US Senate)			(2.95)	(0.81)	(5.92)
State/provincial governor	849	36	0.41	-3.95	1.15
			(6.04)	(7.06)	(7.35)
Other elections	967	64	-0.66	3.84	-7.77
(Referenda, other elective offices)			(4.72)	(3.02)	(6.96)

Each cell is the coefficient from a univariate regression of the returns to expiry in percentage points of a contract on an indicator for whether the candidate is left (-1) or right (+1) of center or centrist (0). Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election. Regressions include fixed effects for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks.

Table 5. Returns by candidate demographics

	Mean	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.31	-0.95			-0.79		-5.17
		(3.84)			(3.53)		(4.54)
Nonwhite	0.37		-0.85	-0.40	-0.27		1.75
			(4.02)	(4.67)	(4.53)		(6.16)
Black	0.21			-0.69	-0.56		-2.20
				(4.17)	(4.09)		(6.37)
Age / 10	5.58					1.17	0.92
						(1.40)	(1.35)
Election*horizon FEs		X	X	X	X	X	X
Observations		3,126	3,126	3,126	3,126	2,322	2,322
Election dates		112	112	112	112	112	112

Each column is a regression of the returns to expiry in percentage points of a contract on candidate demographics. Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election. Regressions include fixed effects for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks.

Table 6. Overpricing of left-leaning outcomes in polling markets

	Observations	Expiry weeks	Coeff.	S.E.
Baseline	62,256	351	1.41***	(0.53)
Obama (12/15 - 1/17)	8,950	90	0.85	(1.44)
Trump I (1/17 - 1/21)	37,828	175	1.58**	(0.72)
Biden (1/21 - 1/25)	11,804	59	1.48*	(0.81)
Trump II (1/25 - 4/26)	3,674	27	0.95	(1.99)
Election polling	11,051	135	1.21	(0.80)
Approval/favorability polling	51,205	351	1.46**	(0.59)
Involves Trump	37,007	210	1.47**	(0.73)
Does not involve Trump	25,249	229	1.32*	(0.69)
Source = Real Clear Politics average	38,357	342	1.54**	(0.72)
Source = 538 average	21,592	191	1.09**	(0.54)
Source = Other (e.g., DDHQ, Rasmussen, Gallup)	2,307	36	2.25	(2.77)
7 or fewer days to expiry	44,646	351	1.14***	(0.41)
8-28 days to expiry	8,051	262	1.24	(1.09)
29+ days to expiry	9,559	29	2.76	(1.91)
Controls: price (linear), bin number, extremeness	62,256	351	1.44***	(0.51)

Each row reports the coefficient from a regression. The dependent variable is the returns to expiry in percentage points of a contract on whether a polling average at the end of a specific time period (typically a week) falls into a specific bin. The independent variable is the ranking of the bin on a scale where -1 is the most favorable outcome for the Democratic party and +1 is the most favorable outcome for the Republican party. Each contract is included once per day of its life, which is typically 7 days. Regressions include fixed effects for polling average*day combinations. Standard errors (in parentheses) adjust for clustering at the expiry week level. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks.

Table 7. Tests for favorite-longshot bias by market and time horizon

			Days to election			
Market	Observations	Election dates	All	1 day	3 weeks	4 months
All	8,778	193	1.40***	1.48***	1.50***	1.15
			(0.10)	(0.12)	(0.12)	(0.15)
Pre-IEM (1880-1988)	124	35	1.57	1.32	4.55**	
			(0.49)	(0.45)	(1.66)	
IEM (1992-2024)	338	20	1.00	1.15	1.37	
			(0.22)	(0.24)	(0.26)	
Intrade (2003-12)	2,008	16	1.62***	2.00***	1.79***	1.35*
			(0.17)	(0.36)	(0.25)	(0.19)
PredictIt (2016-22)	2,541	96	1.39*	1.46**	1.26	1.51*
			(0.20)	(0.20)	(0.19)	(0.28)
Betfair (2019-23)	2,941	29	1.47**	1.47*	1.76***	
			(0.22)	(0.27)	(0.18)	
Kalshi (2024-25)	826	13	1.44	1.52	1.81	
			(0.34)	(0.32)	(0.56)	
Commercial prediction markets	8,316	150	1.43***	1.51***	1.51***	1.21
			(0.11)	(0.13)	(0.12)	(0.15)

Each cell is the coefficient on log price from a fixed effects logit regression of contract payoff, controlling for an indicator for whether the candidate is left (-1) or right (+1) of center or centrist (0). Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election.Fixed effects are for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Coefficients statistically significantly different from one at the 10, 5, and 1 percent level are indicated with 1, 2, and 3 asterisks. Estimates for the 120-day horizons are not reported for markets with fewer than 100 observations.

Table 8. Tests for overpricing of left-leaning candidates, controlling for favorite-longshot bias

			Days to election			
Market	Observations	Election dates	All	1 day	3 weeks	4 months
All	8,778	193	0.62	1.82	1.75	-2.64
			(2.54)	(2.17)	(2.89)	(3.00)
Pre-IEM (1880-1988)	124	35	-0.48	3.23	-12.63	
			(6.43)	(6.15)	(15.60)	
IEM (1992-2024)	338	20	6.76	8.20*	10.01**	
			(4.26)	(4.89)	(4.70)	
Intrade (2003-12)	2,008	16	-7.65**	-10.71**	-5.02	-8.37**
			(3.84)	(5.37)	(4.39)	(4.16)
PredictIt (2016-22)	2,541	96	2.49	2.26	3.27	1.85
			(3.98)	(3.69)	(4.44)	(4.10)
Betfair (2019-23)	2,941	29	-2.19	0.31	-3.23	
			(2.03)	(1.80)	(2.09)	
Kalshi (2024-25)	826	13	7.58	9.56***	10.83	
			(4.94)	(2.71)	(7.53)	
Commercial prediction markets	8,316	150	0.15	1.43	1.18	-3.26
			(2.63)	(2.23)	(3.00)	(3.24)

Each cell is the coefficient on an indicator for whether the candidate is left (-1) or right (+1) of center or centrist (0) in the fixed effects log regression in Table 5. Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election. Regressions include fixed effects for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Coefficients and standard errors expressed in percentage points and are divided by 5 in order to approximate marginal effects and thereby be comparable to Table 3. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks. Estimates for the 120-day horizons are not reported for markets with fewer than 100 observations.

Table 9. Multinomial logit regressions testing for demographic biases while controlling for favorite-longshot bias

	(1)	(2)	(3)	(4)	(5)	(6)
Ln(price)	1.14	1.13	1.13	1.14	1.15	1.20
	(0.09)	(0.08)	(0.08)	(0.09)	(0.12)	(0.14)
Female	-2.95			-2.47		-10.76**
	(6.00)			(5.49)		(5.35)
Nonwhite		-2.99	-2.08	-1.88		1.21
		(6.62)	(8.13)	(8.06)		(9.69)
Black			-1.37	-0.71		-2.45
			(7.11)	(7.07)		(9.29)
Age / 10					1.97	1.60
					(2.18)	(2.22)
Election*horizon FEs	X	X	X	X	X	X
Observations	2,791	2,791	2,791	2,791	1,832	1,832
Election dates	100	100	100	100	92	92

Each column is a multinomial logit regression predicting which candidate's security will pay off $1 as a function of the log of the price of the security and candidate demographics. Each election is included in the sample up to three times: with pricing from 1 day, 21 days, and 120 days before the election. Regressions include fixed effects for election*time horizon combinations. Standard errors (in parentheses) adjust for clustering at the election date level. Coefficients and standard errors for demographic varaibles are expressed in percentage points and are divided by 5 in order to approximate marginal effects and thereby be comparable to Table 5. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks.

Table A1. Robustness of full-sample political bias results

	Observations	Clusters*	Coeff.	S.E.
1. Baseline (Table 3)	9,642	216	0.03	(2.66)
2. Standard errors clustered by election	9,642	1770	0.03	(0.96)
3. Standard errors clustered by election quarter	9,642	98	0.03	(2.67)
4. Standard errors clustered by election year	9,642	56	0.03	(2.74)
5. Right-leaning ranges from -2 to +2	9,642	216	-0.01	(1.90)
6. Favor last trade over quotes	9,642	216	-0.03	(2.65)
7. Subsample with both: use quotes	4,215	92	-1.54	(4.18)
8. Subsample with both: use trades	4,215	92	-1.66	(4.14)
9. Only use quotes	6,533	94	-0.97	(2.53)
10. Only use trades	7,317	214	-0.08	(3.76)
11. Require tighter spreads when using quotes	4,743	86	-1.20	(3.24)
12. Equal-weight elections	9,642	216	1.25	(2.80)
13. Equal-weight election dates	9,642	216	-1.17	(3.35)
14. Equal-weight election years	9,642	216	3.75	(6.04)

* Clusters = election dates, unless otherwise indicated (in lines 2-4)

Each row reports the coefficient from a regression. The dependent variable is the returns to expiry in percentage points of a contract. The independent variable is the ranking of the bin on a scale where -1 is the most favorable outcome for the Democratic party and +1 is the most favorable outcome for the Republican party. Each contract is included once per day of its life, which is typically 7 days. Regressions include fixed effects for polling average*day combinations. Standard errors (in parentheses) adjust for clustering at the election date level, except for lines 2-4, where they adjust for clustering at the election, election quarter, and election year level, respectively. Statistical significance at the 10, 5, and 1 percent level is indicated with 1, 2, and 3 asterisks.