The Efficiency of Binary Political Prediction Markets

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Abstract

Binary winner-takes-all prediction markets trade $>$ \$44billion annually, yet efficiency evidence rests almost entirely on continuous vote-share contracts. Using a conditional logit framework and 44 Iowa Electronic Markets U.S. election markets, we find winner-takes-all prices are well-calibrated probability forecasts across 100-day pre-election horizons. Efficiency is invariant to market size, volume, duration, and contract count. Unlike polls, prices exhibit no partisan or incumbency bias. The pervasive financial market favorite-longshot bias is absent. These results arise under four structural features: zero aggregate risk, no trading fees, an easily exploited arbitrage restriction, and a \$500 investment cap, features absent from commercial prediction markets.

Keywords: Prediction Markets, Market Efficiency, Information Aggregation, Favorite-Longshot Bias
JEL Classifications: G14, G17, D82, D84, C25, G18

The Efficiency of Binary Political Prediction Markets

Binary prediction markets have grown into a multi-billion dollar industry. Polymarket traded $21.5 billion in 2025 while Kalshi traded $17.1 billion with fee revenue of $263.5 million. Total prediction market volume recently reached $44 billion (Sobrado, 2025; O'Boyle, 2026). These commercial markets trade exclusively in binary, winner-takes-all (WTA) contracts that pay $1 if an event occurs and $0 otherwise. Under the right conditions, WTA contract prices should aggregate information and predict the probability of outcomes. The CFTC recently revised its regulatory stance on such contracts (U.S. Commodity Futures Trading Commission, 2026) based on this idea.

The commercial prediction market industry's central claim to legitimacy rests on academic evidence that prediction market prices efficiently forecast outcomes. However, the academic evidence is built almost entirely on a different contract class: continuous, vote-share contracts in political prediction markets.

Here, we fill the empirical evidence gap between continuous and binary contract efficiency using a relatively large set of WTA political markets from the oldest operating prediction market, the Iowa Electronic Markets (IEM). The IEM is ideal for this work because it is a deliberately designed laboratory for testing prediction market price efficiency. Using data from 44 U.S. election WTA markets run on the IEM since 2000, we provide the first large scale, systematic evidence on the efficiency of modern WTA political prediction markets. We find that IEM WTA prices are well-calibrated probability forecasts: they neither systematically over predict nor under predict election winning probabilities across a 100-day pre-election horizon. This efficiency is not confined to large or liquid markets—it holds regardless of the number of active traders, trading volume, market duration, or number of contracts. IEM prices also exhibit no partisan bias (favoring neither Democratic nor Republican outcomes) and no incumbency bias, in sharp contrast to the systematic polling errors documented in recent U.S. elections (American Association for Public Opinion Research, 2017, 2021; Kennedy et al., 2018). These results are robust to bootstrapped standard errors. They hold separately for presidential and congressional markets. They also hold when the data are split into pre- and post- 2014 samples to see if there have been changes resulting from increasing social media use and the rise in commercial prediction markets. Taken together, these results establish that binary political prediction markets can be efficient probability forecasters under the right structural conditions.

The structural features of prediction markets are key to interpreting our results and their implications for the commercial industry. The IEM is not merely a convenient dataset. It was specifically designed to test prediction market efficiency. Four structural features of the IEM align with the theoretical conditions under which prices should equal true probabilities (Malinvaud, 1974; Berg and Rietz, 2019). (1) The IEM's unique method of issuing contracts ensures zero aggregate risk within each market. (2) No trading fees eliminate any fee-based wedge between prices and trader beliefs. (3) A readily exploitable arbitrage restriction bounds prices within theoretically sensible ranges (Gruca and Rietz, 2026). (4) A $500 per-trader investment cap prevents any individual from persistently distorting prices through speculation or hedging. Our evaluation method can be applied to commercial prediction markets with the IEM results serving as a benchmark for assessing market efficiency in commercial markets, which have different structural features.

Commercial markets differ from the IEM with respect to each of the structural design features noted above. These differences reflect a fundamental distinction between two types of binary options markets. In a precise sense, a "prediction market" is specifically designed so that prices correspond to true probabilities. The IEM is the canonical example. An "event driven market" better describes Kalshi, Polymarket, and most commercial markets. Such markets blend forecasting, speculation and hedging. When used for hedging, the resulting *risk neutral* prices, and thus, probability forecasts, will deviate from *true* probabilities, reflecting the net hedging demand. Similarly, if traders are risk seeking (e.g., they view Kalshi or Polymarket as an alternative to casino-based gambling sites), prices deviate to reflect the net demand for risk. While deviating from probability forecasts, market prices may still reflect the natural and rational cost of transferring risk. Our results establish what prices look like when the hedging and large scale gambling motives are removed by design and there are no distortions due to trading costs. This provides the benchmark for evaluating whether, and to what degree, event driven commercial markets create efficient forecasts. Then, using our methodology, we can begin to understand why deviations arise. This market distinction is directly relevant to the CFTC's ongoing regulatory deliberations over whether commercial prediction market prices should be treated as public information goods, regulated more like insurance or derivatives products, or regulated like gambling.

Our paper connects to three active literatures in finance and economics. First, it extends the prediction market efficiency literature. Prior IEM evidence including: Forsythe, Nelson, Neumann, and Wright (1992), who find price efficiency in the first Iowa market predicting vote shares, (2) Berg, Nelson, and Rietz (2008), who show IEM prices beat polls 74% of the time, and (3) Gruca and Rietz (2025), who document election-eve vote-share prediction errors of less than 2 percentage points, among others. While, nearly all of the efficiency evidence uses vote share markets, Berg and Rietz (2019) systematically study binary WTA markets on stock prices and returns using logistic regression analysis.[1] However, their work uses repeated, homogeneous markets and their method does not generalize to elections with varying numbers of candidates and outcome categories. Here, we generalize and expand the results using a McFadden (1974) conditional logit framework that accommodates heterogeneous choice sets across elections

Second, our results connect to the behavioral finance literature on the favorite-longshot bias. Overconfidence and longshot overpricing are well documented in horse racing markets (Griffith, 1949; Thaler and Ziemba, 1988) and options markets (in the form of the volatility smile). If anything, Berg and Rietz (2019) find a transitory reverse-longshot bias reflecting some temporary overconfidence in their stock price and return markets. In contrast, we find no significant analog in IEM political WTA markets across 100 days of trading before elections.

Third, by documenting the absence of partisan and incumbency biases in prediction market prices, we contribute to a growing literature comparing prediction markets to polls as information aggregation mechanisms (e.g., Berg et al., 2008; Wolfers and Zitzewitz, 2004, among others).

In summary, this paper makes three contributions to the general finance literature. First, we provide the first large-scale, systematic evidence on the efficiency of binary, winner-takes-all (WTA) in non-repeating, non-homogeneous prediction markets, the contract type that dominates the $44 billion commercial market industry. Second, we document that WTA market efficiency is structurally robust. It is invariant to market size, trading volume, market duration, and the number of contracts. The results hold when dividing the sample by period and by election level

[1]Other exceptions include: (1) Wolfers and Zitzewitz (2004), who present a few descriptive calibration plots for some WTA markets, but not a formal analysis; and (2) Erikson and Wlezien (2012), who correlate log odds of WTA prices with vote share percentages received by parties, but not winning frequencies. To our knowledge, Berg and Rietz (2019) is the only paper that uses logistic models to determine whether prices predict payoff probabilities.

(Presidential versus Congressional). Prices exhibit no partisan bias, no incumbency bias, and no favorite–longshot bias. This contrasts with well documented polling biases and behavioral biases in other financial and betting markets. Third, we identify market design features that align the IEM with the underlying theory of efficient pricing in efficient markets, which are absent in commercial event-driven markets. Thus, our results establish a benchmark against which commercial prediction-market efficiency should be evaluated and inform ongoing regulatory debates at the CFTC about whether such markets function as information markets, derivatives markets, or gambling markets.

Methodologically, we make an additional contribution: using conditional logit models to assess price efficiency. This extends our ability to assess markets beyond the homogeneous and repeated markets that Berg and Rietz (2019) analyze. Our method can be applied to the wide range of prediction markets run today.

The remainder of the paper proceeds as follows. Section 1 describes the IEM WTA election markets and our data. Section 2 presents results, including our baseline efficiency tests, interactions with market-level characteristics, partisan and incumbency bias tests, and robustness checks based on bootstrapped standard errors, election-type subsamples, and pre- versus post-2014 subsamples. Section 3 discusses the implications of our results for commercial prediction market design and regulation, the relationship between prediction market efficiency and polling bias, and directions for future research.

1 The Iowa Electronic Markets winner-takes-all (WTA) U.S. election markets

The Iowa Electronic Markets (IEM) are relatively small scale, but real-money futures markets that trade futures and binary option contracts designed so that prices forecast future events. The Tippie College of Business (University of Iowa) operates these markets for teaching and research purposes. Traders invest their own money in the markets, bearing the real-money risks and reaping the real-money rewards of their activity.[2] The IEM market structure closely parallels naturally occurring

[2]Because IEM contracts are real futures contracts, the IEM is under the regulatory purview of the Commodity Futures Trading Commission (CFTC). The CFTC issued "no-action" letters to the IEM stating that as long as the IEM conforms to certain restrictions (related to limiting risk and conflict of interest), the CFTC will take no action

financial markets as do its price dynamics (Majumder, Diermeier, Rietz, and Amaral, 2009). It is an order-driven double-auction market accessed 24/7 through the Internet. Traders can place both limit and market orders. Price and time ordered queues hold outstanding bids and asks. The current best (highest) bid and best (lowest) ask are always publicly known.

We study all of the IEM U.S. election WTA markets run since 2000. We start with 2000 because the IEM had moved to a web platform that created a consistent trading interface and market structure for all markets since then. The specific markets we include are listed in Table 1. More specifics about each market can be found at the Iowa Electronic Markets website (https://iemweb.biz.uiowa.edu/, accessed 3/18/2026).

We use data from:

1. 7 U.S. Presidential markets, with 2, 3 or 4 contracts each, designed to forecast which party will take the majority of the popular vote and, in one case, by how much.
2. 13 Congressional Control markets, with 4 or 5 contracts each, designed to forecast the combination of majorities across the two houses of Congress.
3. 10 House markets, with 3 contracts each, designed to forecast the distribution of seats across parties.
4. 10 Senate markets, with 3 contracts each, designed to forecast the distribution of seats across parties.
5. 4 other markets, with 3 to 6 contracts each, designed to forecast state level and mayoral elections.

Overall, we have the histories of 153 contracts across 44 markets. Markets ran for 34 to 877 days before the market's associated election and had between 72 and 1,443 active traders. Individual contract volumes ranged from 10,350 to more than 1 million per market. Dollar volumes ranged from $2,911 to $360,917.

Following Berg and Rietz (2019), for each contract in each market each day, we calculate the "closing" normalized bid-ask midpoint for each contract as of 11:59 p.m. Outstanding bids and asks reflect the day's information held by market-making traders who set prices. They also reflect

against it. Under this no-action letter, IEM does not file reports that are required by regulation and therefore it is not formally regulated by, nor are its operators registered with, the CFTC.

Table 1. Summary of the Iowa Electronic Markets winner-takes-all (WTA) markets used in the paper.

Market Name	Number of Active Traders	Number of Contracts	Days Open Before Election	Volume Contracts	Volume Dollars
2000 Presidential WTA	977	3	190	473,202	$ 185,107
2004 Presidential WTA	1159	2 split to 4	154	1,069,635	$ 360,917
2008 Presidential WTA	1101	2	887	493,733	$ 255,006
2012 Presidential WTA	765	2	494	504,882	$ 299,705
2016 Presidential WTA	653	2	720	464,706	$ 232,326
2020 Presidential WTA	355	2	635	158,387	$ 82,064
2024 Presidential WTA	177	2	535	82,652	$ 42,392
2000 Congressional Control	1063	4	648	105,883	$ 25,821
2002 Congressional Control	254	4	110	110,366	$ 27,788
2004 Congressional Control	215	4	137	44,510	$ 11,790
2006 Congressional Control	280	4	159	90,214	$ 28,534
2008 Congressional Control	104	4	73	13,217	$ 5,473
2010 Congressional Control	269	4	342	76,893	$ 22,270
2012 Congressional Control	220	5	480	70,302	$ 17,820
2014 Congressional Control	239	5	678	93,756	$ 24,425
2016 Congressional Control	281	5	720	104,711	$ 23,981
2018 Congressional Control	147	5	686	95,780	$ 21,209
2020 Congressional Control	243	5	635	143,085	$ 32,811
2022 Congressional Control	93	5	620	44,706	$ 9,514
2024 Congressional Control	97	5	546	40,443	$ 8,151
2004 House Control	200	3	137	29,307	$ 10,086
2006 House Control	264	3	159	66,228	$ 27,451
2008 House Control	117	3	73	14,057	$ 6,000
2010 House Control	237	3	342	49,801	$ 16,884
2012 House Control	169	3	480	22,741	$ 8,455
2014 House Control	160	3	678	15,549	$ 5,884
2018 House Control	139	3	686	56,101	$ 17,701
2020 House Control	116	3	386	12,792	$ 4,348
2022 House Control	73	3	620	19,533	$ 10,252
2024 House Control	74	3	546	12,407	$ 3,233
2004 Senate Control	270	3	137	36,328	$ 13,062
2006 Senate Control	231	3	159	43,697	$ 15,945
2008 Senate Control	115	3	73	10,350	$ 4,655
2010 Senate Control	230	3	342	39,419	$ 12,878
2012 Senate Control	203	3	480	32,675	$ 10,945
2014 Senate Control	193	3	678	33,209	$ 13,542
2018 Senate Control	124	3	686	32,987	$ 11,435
2020 Senate Control	168	3	386	24,885	$ 9,955
2022 Senate Control	82	3	620	40,029	$ 10,799
2024 Senate Control	79	3	546	15,433	$ 4,534
2000 New York Senate	1443	6	512	278,211	$ 69,300
2001 New York City Mayor	257	3	34	22,071	$ 7,692
2008 Minnesota Senate	183	3	75	23,199	$ 10,403
2010 Florida Senate	72	4	148	12,025	$ 2,911

limit values after price-taking traders are no longer willing to trade. So, in that sense, outstanding bids and asks represent an end-of-day market consensus.[3] Specifically, for contract j on date t, the best bid and best ask are denoted bb_t^j and ba_t^j. The midpoint is $mp_t^j = ba_t^j - bb_t^j$. Asymmetries or stale quotes in the bids and asks may result in midpoints that do not add up to \$1. Again, we follow Berg and Rietz (2019) normalizing them by dividing by the sum of contract midpoints in the market. We will define this as the daily market "price" or forecast as follows:

$$p_t^j = \frac{mp_t^j}{\sum_{i=1}^{n} mp_t^i}, \quad (1)$$

where n is the number of contracts in the market. As shown in Berg and Rietz (2019), a minor extension to Malinvaud (1974) implies that p_t^j should equal q_t^j, the probability that the contract will pay off \$1 as a result of the ensuing election. Thus, prices become forecasts of winning probabilities for associated candidates or parties in the ensuing elections.[4]

2 Results

Each day before an election, we have a forecast probability of each contract paying off \$1 in the form of the normalized bid/ask midpoint "price," p_t^j, where t is the number of days until the election and j denotes a contract associated with an outcome. In each election, we have 2 to 6 contracts and, thus, forecasts. Between 39 and 44 markets were open across the 100 day horizon with 138 to 154 contracts trading. The exact numbers change for two reasons: (1) some markets run less than 100 days and (2) there was a contract split in the 2004 Presidential WTA market that converted 2 contracts into 4 contracts.

[3] Using bid-ask midpoints is standard in the prediction market literature and goes back at least to Demsetz (1968) for other financial markets. Concerns about asymmetric effects of bids and asks are mitigated here because there is no cost for carrying inventory (as in Glosten and Milgrom, 1985). We use 11:59 p.m. because, unless changed, bids and asks expire beginning at 11:59 two days after they are submitted. This mass expiration may widen the queues and shift midpoints just after 11:59.

[4] The extension is that there is no aggregate risk. The way the IEM issues contracts assures this is true within the market. We note that Malinvaud (1974) assumes risk neutral or risk averse traders. This result continues to hold so long as the marginal traders are risk neutral or risk averse. Sufficiently many risk seeking traders or those with sufficient resources can destabilize the market and drive prices away from forecasts. The extension essentially amounts to assuming that the markets are not used for significant hedging purposes. Significant hedging will drive the "risk neutral" prices away from forecasts of true probabilities. With a \$500 budget constraint, it is unlikely that a few risk seeking or hedging traders will affect prices in IEM markets. This may not be the case in markets designed to attract either risk seeking traders (speculators) or large hedgers.

2.1 Forecasts vs frequencies of outcomes

While it ignores the correlation structure of contracts within a given election, directly comparing forecasts to frequencies of outcomes provides a first look at market efficiency. Each day between 1 and 100 days before an election, we divide the contracts into quintiles according to their prices. Then, for each quintile, we find the average forecast price and the average frequencies of election winners for contracts in that quintile. We compare the average price with the frequency across quintiles. Roughly speaking, the average prices should approximate the average frequencies within each quintile each day.

Figure 1 shows examples from 1, 3, 7, 30, 60 and 90 days before each election. In each panel, across that day's quintiles, we graph the frequency of actual payoffs relative to the average forecast probability of payoffs.

Throughout the horizons, the high and low quintiles show similar forecast probabilities and frequencies of payoffs. However, 90 and 60 days before the elections, the middle quintiles show average forecast probabilities that do not align well with payoff frequencies. At 30 days and fewer before an election, forecast probabilities and actual payoff frequencies align quite well.

To give a sense of how far the quintile forecast probabilities deviate from the realized frequencies across quintiles (i.e., how far they deviate from the 45 degree line in Figure 1), we define a goodness of fit measure as:

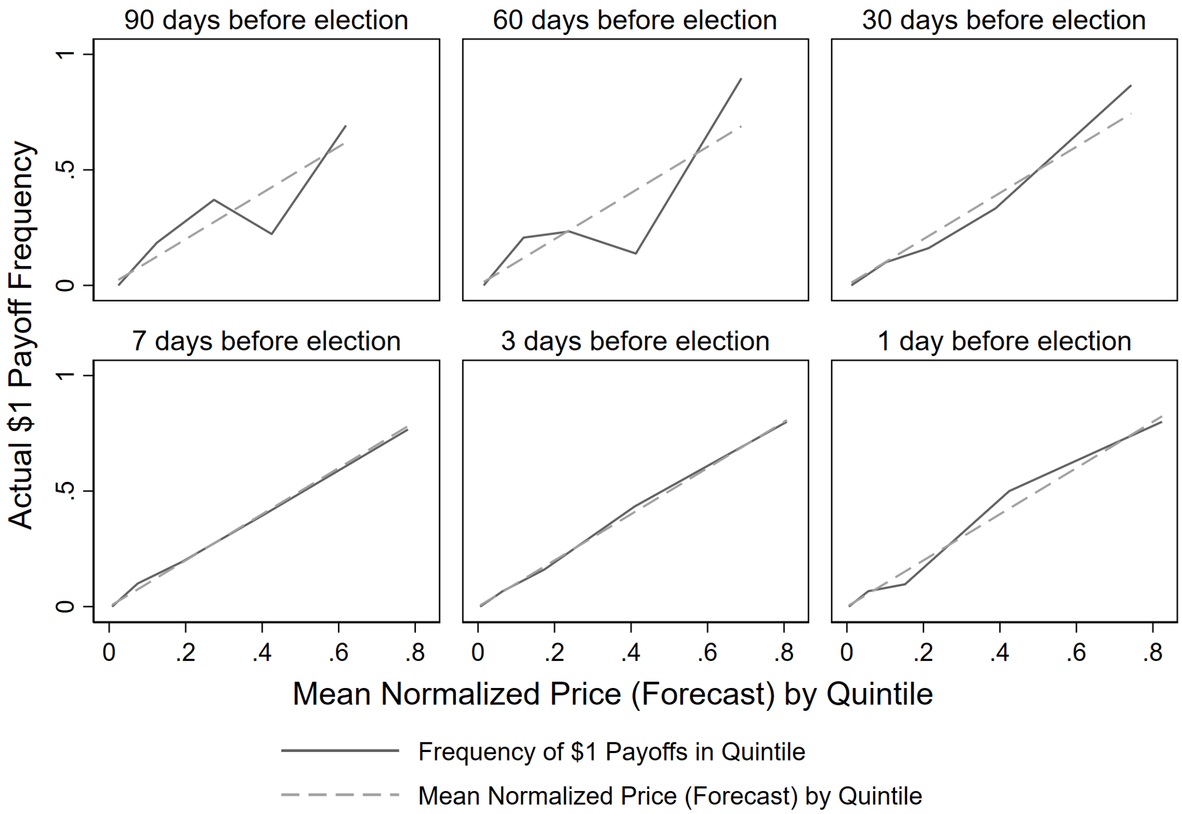
$$G^2 := \sum_{q=1}^{5} \frac{(w_q - \hat{n_q \widehat{p_q}})^2}{n_q \widehat{p_q}(1-\widehat{p_q})} \tag{2}$$

where q indexes the quintiles, w_q is the number of winners out of the contracts in quintile q, n_q is the number of contracts in quintile q, and $\widehat{p_q}$ is the average price of contracts in quintile q. This statistic equals 0 if the average price in each quintile equals the fraction of winning contracts in that quintile. Deviations from this make G^2 larger, with a weighting that is proportional to how close the forecast probabilities are to 0 and 1.[5]

Figure 2 shows how the G^2 measure of fit evolves over time. The dates shown in Figure 1 are

[5]The savvy reader will note that this is mathematically the same as a χ^2 statistic for actual versus predicted frequencies. However, the independence assumption underlying χ^2 tests is violated here because only one contract will win in each market. The regression analysis we run next controls for this intra-market interdependence. To avoid confusion with χ^2 tests, we label this statistic G^2 here.

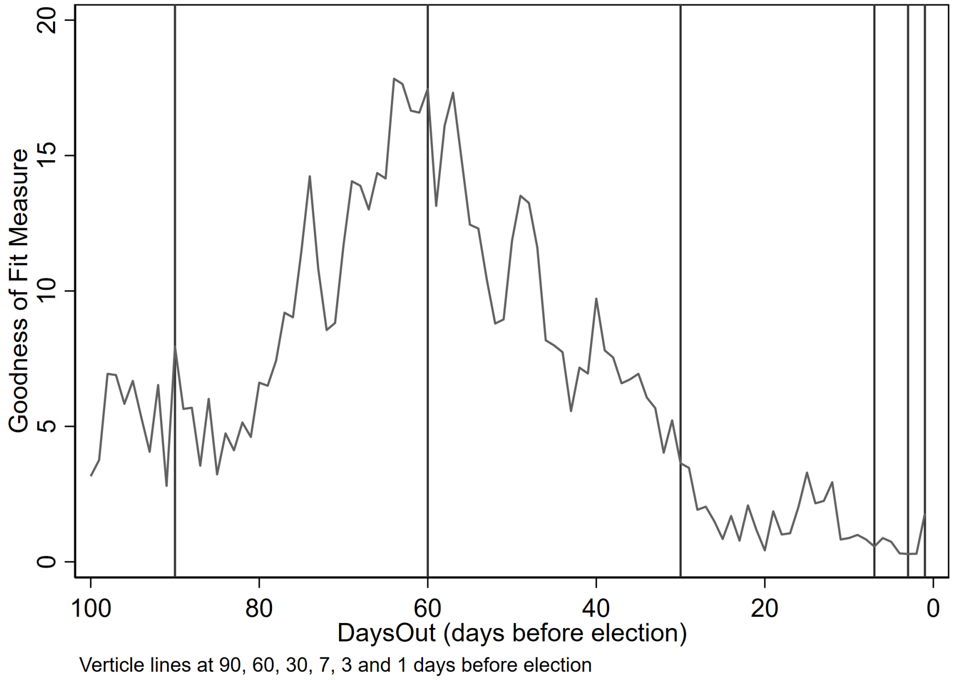
Figure 1. Average forecast probabilities that contracts will pay off \$1 versus average frequency of paying off \$1 by quintile of forecast probabilities 1, 3, 7, 30, 60 and 90 days before each election.



marked by vertical lines. The fit is relatively good early in the 100 day horizon and deteriorates steadily, peaking around 60 days, then falls through election eve.

While Figures 1 and 2 suggests patterns that merit formal testing, they do not show whether these deviations are significant. Comparing prices and frequencies suffers from three issues. Combining data within quintile introduces noise. It throws away information by blending individual forecasts and outcomes into a category. It also ignores completely the intra-election correlation of outcomes: Only one outcome in an election can occur. We test for significance in the next section without blending forecasts and outcomes, using all the available information and accounting specifically for the intra-election correlation.

Figure 2. G^2 goodness of fit measures for quintiles of prices across 100 to 1 days before elections.



2.2 Regression models

To test for significant differences, we extend Berg and Rietz' (2019) use of binary logistic and multinomial logistic regression models to the more general case of election markets. Studying repeated markets with the same contracts allows Berg and Rietz to use these simpler models. However, no two elections are the same. Therefore, we use McFadden's (1974) conditional logit choice model. This model does not require the same choices, nor even the same number of choices, across choice sets ("cases" or, here, elections). For each election on each day, we use the normalized contract prices (based on bid/ask midpoints as discussed above) to estimate β in the following relationship:

$$Pr(LV_0^j = 1|Election) = \frac{e^{\beta \ln p_t^j}}{\sum_{i=1}^{n} e^{\beta \ln p_t^i}}, \tag{3}$$

where LV_0^j is the liquidation value, or payoff, of contract j as a result of the election (day 0), p_t^j is the normalized price of contract j on t days before the election, and the summation is across all contracts in the market for the election.[6] An estimated β equal to 1 implies that the normalized prices are well calibrated in forecasting the probabilities of winning. An estimated β significantly less than or greater than 1 implies overconfidence and underconfidence, respectively.

Figure 3 maps out the relationship between β coefficients and whether the market prices efficiently forecast the probabilities of a particular contract winning. For a single contract (i.e, contract j), we vary the normalized price from 0 to 1. For illustrative purposes, we assume that the prices of the remaining contracts are all equal (i.e., $p_t^i = p_t^k \; \forall i, k \neq j$) and, since they are normalized, the sum of all prices equals 1 (i.e., $\sum_{i=1}^{n} p_t^i = 1$). Panels show mappings from the price of contract j to the estimated true probabilities of payoff given beta equal to 0.5, 1 and 2 and for 2, 3, 4, and 5 contract markets.

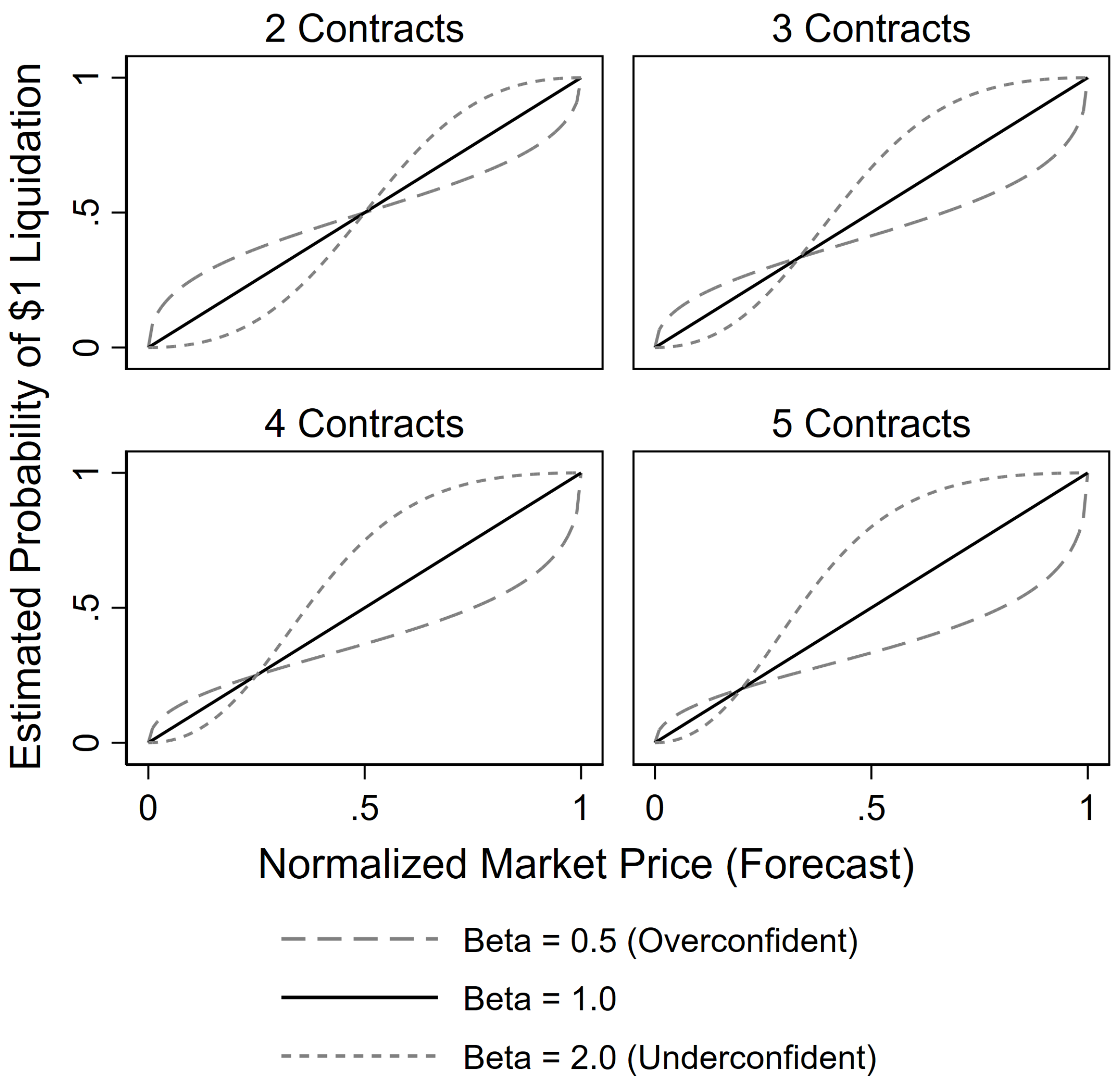
Figure 3 shows that, regardless of the number of contracts, $\beta = 1$ directly maps the normalized price (x-axis) of a contract to a winning probability (y-axis) equal to that price. Thus, prices equal estimated probabilities of payoffs in the data. Thus $\beta = 1$ correspond to well calibrated (i.e., price efficient) markets.

For $\beta > 1$ (short dashed line), prices of relatively high priced contracts map to probabilities that are even higher than the price implies. In contrast, prices of lower priced contracts map to probabilities that are even lower than the price implies. The market's prices are under predicting the probabilities of both \$1 and \$0 payoffs and, in that sense, are under confident. $\beta > 1$ corresponds to a favorite-longshot bias as observed in racetrack odds and elsewhere (Griffith, 1949; Thaler and Ziemba, 1988). Favorites are under priced, giving a higher relative expected return, while longshots are overpriced, giving a lower relative expected return. An alternative interpretation of the graph is to reverse the interpretation of causality and consider the price reaction to the probability of winning. For $\beta > 1$, probabilities of winning move along the short dashed line. However, prices move along the solid line. Thus, over the majority of the range, price movements under react to probability movements. So, in this alternative reaction based sense, the market prices are typically underconfident in reacting to changing probabilities.[7]

[6] On a technical note, the IEM prices as defined conform very closely to the model's assumptions. They represent probabilities of mutually exclusive and exhaustive choices which, by definition, add up to 1. Any additional concerns about independence of irrelevant alternative are mitigated because the alternatives are not close substitute in any behavioral sense. Further, the number of contracts in a market has no significant effect empirically. In the estimation we use robust standard errors, but do not cluster because each election is an independent observation.

[7] The probability mapping and price reaction interpretations are mathematically equivalent but emphasize different intuitions.

Figure 3. Graphs of the relationship between normalized prices (forecasts) and estimated actual outcome probabilities using McFadden's (1974) conditional logit choice models for coefficients in equation (3) of 0.5, 1.0 and 2.0. In each panel, the price of a single contract ranges from \$0 to \$1. We assume all other contracts are priced the same as each other and that the overall prices sum to \$1. Panels change the number of contracts across 2, 3, 4 and 5, which match the numbers of contracts in all but one of our election markets.



For $\beta < 1$ (long dashed lines), prices of relatively high priced contracts map to probabilities that are lower than the price implies. In contrast, prices of lower priced contracts map to probabilities that are higher than the price implies. The market's prices are over predicting the probabilities of both \$1 and \$0 payoffs and, in that sense, are overconfident. Thus, $\beta < 1$ corresponds to a reverse favorite-longshot bias. Shifting to the alternative interpretation, for $\beta < 1$, probabilities of winning move along the long dashed line. However, prices move along the solid line. Thus, over the majority of the range, price movements over react to probability movements. So, the market prices are typically overconfident in reacting to changing probabilities.

The number of contracts and the actual prices of the contracts only shift the crossing point, not whether the prices over or under predict relatively high or low probabilities.

2.2.1 Do IEM markets appear overconfident, underconfident, or well calibrated overall?. Figure 4 shows estimated β coefficients using daily cross-sectional regressions across all markets running for each of 100 days before each election along with 95% confidence intervals.[8] It shows that estimated β coefficients do vary from 1, but never significantly. Judging from the point estimates alone, one might conclude that the markets are well calibrated early, become somewhat underconfident a little over six weeks before the election, returning to well calibrated about three weeks before the election. However, none of the estimated coefficients deviate significantly from 1. The average p-value from χ^2 tests that the β coefficient equals one is 0.6136.

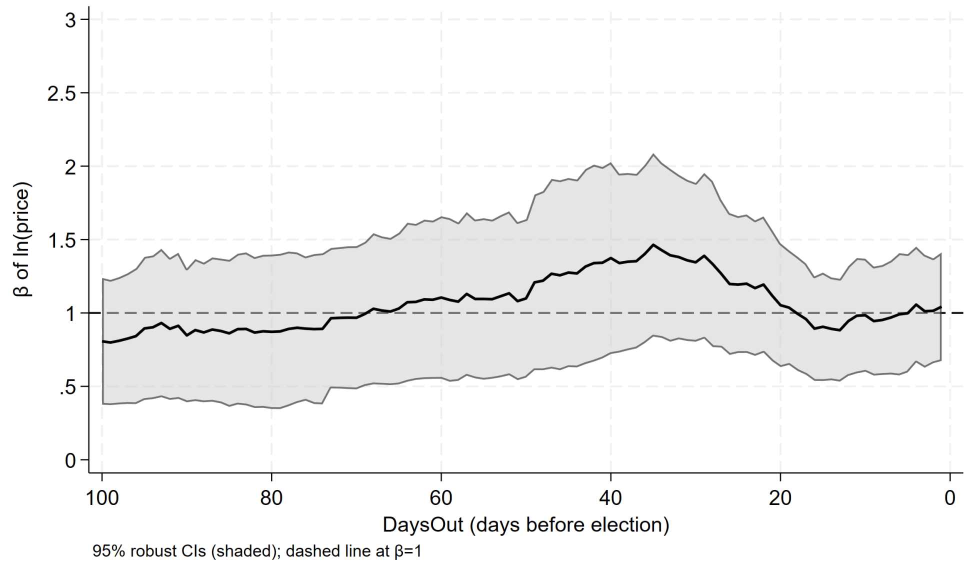
This leads to the following result:

Result 1. *IEM political winner-takes-all markets appear well calibrated (price efficient), neither significantly over predicting probabilities of winning and losing (overconfidence) nor under predicting them (underconfidence).*

2.2.2 Robustness Checks. Here, we show the results of three robustness checks on the baseline estimation: (1) we bootstrap standard errors, (2) we divide the data up by election level and run separate regressions for Presidential and Congressional elections, and (3) we divide the data into

[8] We use cross sectional regressions instead of panel regressions because we are interested in whether prices accurately forecast outcomes on any given day, not how they evolve across time. All the statistics are listed in Table A.1 in the Appendix.

Figure 4. β coefficients estimated using McFadden's (1974) conditional logit choice model (equation (3)) for 100 through 1 days before elections. 95% confidence intervals are shown by the shaded region.



early and later markets (before and including 2014 and after 2014).[9]

Bootstrapped standard errors. We bootstrap the standard errors to the main regression shown in Figure 4 each of 1 to 100 days before the election by resampling 1,000 times randomly from the markets operating that day with replacement. Then, we build confidence intervals based on the standard deviation of the β coefficients. Figure 5 compares the bootstrapped confidence intervals to the robust confidence intervals.

As with the robust standard errors, we never reject efficiency. The bootstrapped confidence intervals average 11% wider than the robust confidence intervals. Because rejecting efficiency would mean the market is inefficient, the more conservative approach is to use the narrower robust confidence intervals. Thus, we use robust confidence intervals for the rest of the paper.

Presidential versus Congressional markets. One might think our results are driven by our most popular and active Presidential markets. To consider this possibility, we split the data into the election levels of Presidential and Congressional. The low number of state level and mayoral elections (4) make reasonable regressions impossible in this subset of data.

[9] 2016 was the first year with a large scale alternative prediction market (PredictIt) running on U.S. elections, potentially pulling active traders from the IEM.

Figure 5. β coefficients estimated using McFadden's (1974) conditional logit choice model (equation (3)) for 100 through 1 days before elections. The upper panel shows 95% confidence intervals based on robust standard errors. The lower panel shows 95% confidence intervals based on bootstrapped standard errors.

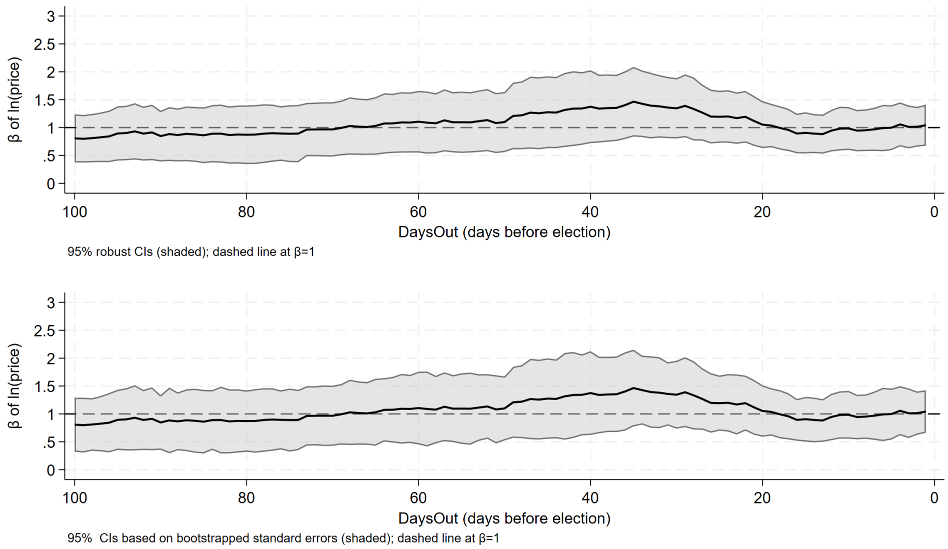


Figure 6. β coefficients estimated using McFadden's (1974) conditional logit choice model (equation (3)) for 100 through 1 days before elections. The upper panel shows 95% confidence intervals for Presidential markets (truncated at 0 and 3). The lower panel shows 95% confidence intervals for Congressional markets.

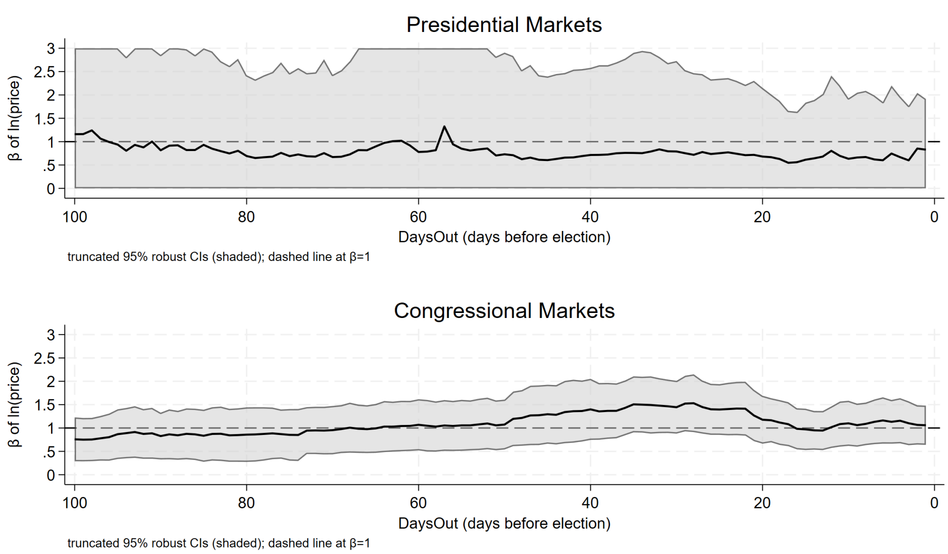


Figure 7. β coefficients estimated using McFadden's (1974) conditional logit choice model (equation (3)) for 100 through 1 days before elections. The upper panel shows 95% confidence intervals for pre-2014 and 2014 elections. The lower panel shows 95% confidence intervals for post 2014 elections.

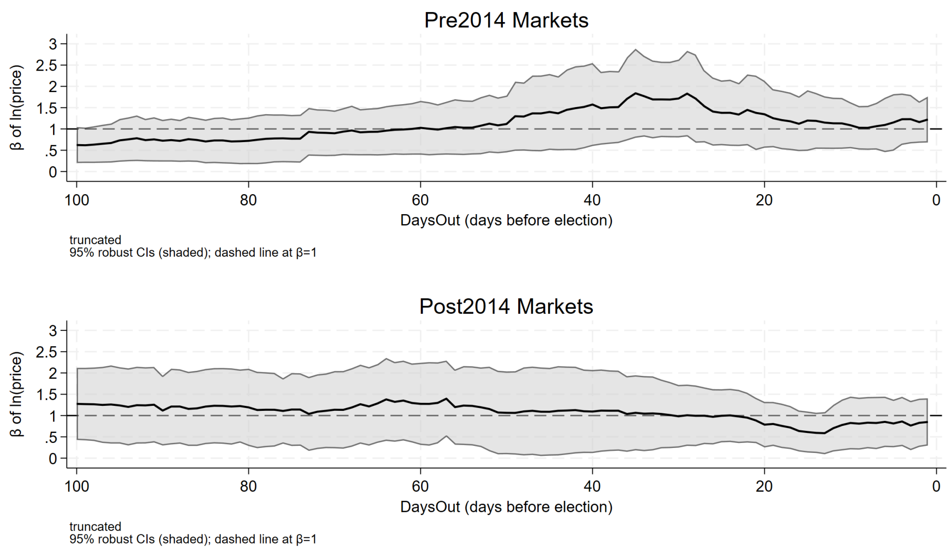


Figure 6 shows the results. The upper panel shows Presidential election results. With only 7 markets and 15 to 17 contracts, the confidence intervals are very wide. But, the point estimates are quite close to 1. the lower panel shows Congressional election results. With 33 markets and 119 contracts, the confidence intervals are much narrower, but we still never reject the null that the markets are efficient.

Earlier versus later markets. Over time, commercial prediction markets have become available and information sources have become more complex with the rise in social media, the proliferation of polls, and other information aggregators such as Nate Silver's fivethirtyeight.com. To investigate whether the efficiency of the markets have evolved over time, we split the data into elections through 2014 and elections after 2014. Why 2014? 2016 was the first US election with commercial prediction markets hosted by PredictIt (which was launched on Nov 3, 2014 and first ran on a U.S. election in 2016).

Figure 7 shows the results. As with the other cases, we never reject the null that the markets are efficient.

2.2.3 Do market level characteristics affect the efficiency of IEM political winner–takes-all markets?.

Market level characteristics may make some markets more overconfident or underconfident than other markets. We investigate the following characteristics:

1. The number of active traders in the market.
2. The contract trading volume in the market.
3. The number of days that the market was run.
4. The number of different contracts in the market.

Because each market is a unique case in the McFadden regressions, we cannot run market level characteristics in the regression outright.[10] But, we can interact the market level characteristics with the individual contracts. Thus, we estimate the following regression:

$$Pr(LV_0^j = 1|Election_e) = \frac{e^{\beta \ln p_t^j + \gamma MC_e \ln p_t^j}}{\sum_{i=1}^n e^{\beta \ln p_t^i + \gamma MC_e \ln p_t^i}}, \quad (4)$$

where LV_0^j is the liquidation value, or payoff, of contract j as a result of the election (day 0), p_t^j is the normalized price of contract j on t days before the election, MC_e is the market-level characteristic for election market c, and the summation is across all contracts in the market for the election.[11] Thus, equation (4) shows how much the market level characteristic changes the level of overconfidence or underconfidence in the market.

First, we ask about the number of active traders. We normalize the number of active traders in a market by subtracting the mean and dividing by the standard deviation (both across markets). Then, we run the regression shown in equation (4) for each of the 100 days preceding the elections.

Figure 8a shows the impact of the number of active traders in a market (NoActiveTraders). It shows the γ coefficient from equation (4) which represents the shift in the β coefficient as the number of traders changes across markets.[12] While the point estimates seem to indicate that more traders shift the forecasts away from underconfident and towards overconfident, the shift is never significantly different from 0 at the 95% confidence level. The average p-value from χ^2 tests that the γ coefficient equals zero is 0.3724.

[10] The market characteristics are constant within each case (election), creating a colinearity.

[11] To make coefficients comparable, we normalize each market level statistic by subtracting its mean and dividing by its standard deviation.

[12] All the statistics are listed in Table A.2 in the Appendix.

Figure 8b gives a different perspective. It shows the summed overall model coefficients and 95% confidence intervals for (1) the mean normalized number of active traders and (2) the mean plus 1 standard deviation of the normalized number of active traders. It shows very little impact resulting from the number of traders across markets.

Second, we ask about the level of trading activity. We normalize the total contract trading volume by subtracting the mean and dividing by the standard deviation (both across markets).[13] Then, we run the regression shown in equation (4) for each of the 100 days preceding the elections.

Figure 9a shows the impact of trading volume in a market. It shows the γ coefficient from equation (4) which represents the shift in the $\beta|$ coefficient as the trading volume changes across markets.[14] Point estimates seem to indicate that more trading volume shift the forecast away from overconfidence and towards underconfidence. However, again the shift is never significantly different from 0 at the 95% confidence level. The average p-value from χ^2 tests that the γ coefficient equals zero is 0.6079.

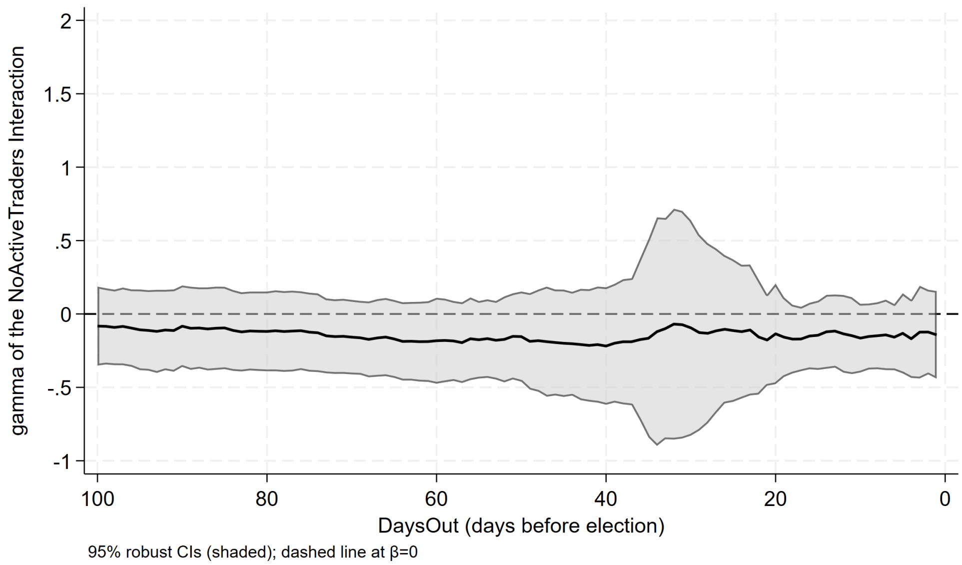
Again, figure 9b gives a different perspective. It shows the overall model β and 95% confidence intervals for (1) the mean normalized total contract volume and (2) the mean plus 1 standard deviation of the normalized total contract volume. Again, it shows very little impact resulting from the total contract volume in the market.

Third, we ask about the lengths of the market in days that the market was running before the election (DaysRun). We normalize the market length by subtracting the mean and dividing by the standard deviation (both across markets). Then, we run the regression shown in equation (4) for each of the 100 days preceding the elections.

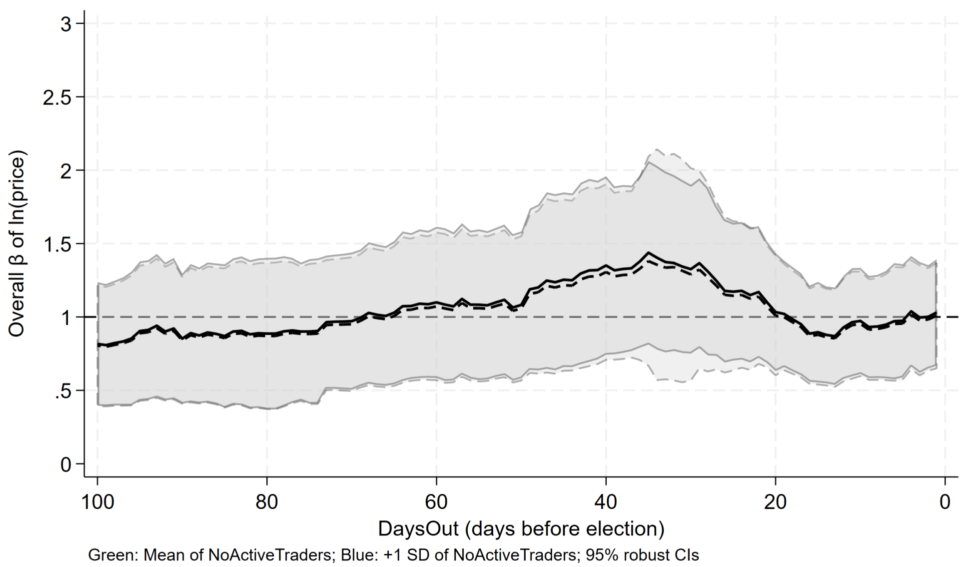
Figure 10a shows the impact of market length in terms of days run in a market.[15] It shows the γ coefficient from equation (4) which represents the shift in the $\beta|$ coefficient as the market length changes across markets. As with our other market level statistics, the shift is never significantly different from 0 at the 95% confidence level. The average p-value from χ^2 tests that the γ coefficient equals zero is 0.6821.

Figure 10b shows the overall model β and 95% confidence intervals for (1) the mean normalized market length and (2) the mean plus 1 standard deviation of market length. Again, the figure

[13]Here we use contract volume. Dollar volume gives nearly identical results.
[14]All the statistics are listed in Table A.3 in the Appendix.
[15]All the statistics are listed in Table A.4 in the Appendix.

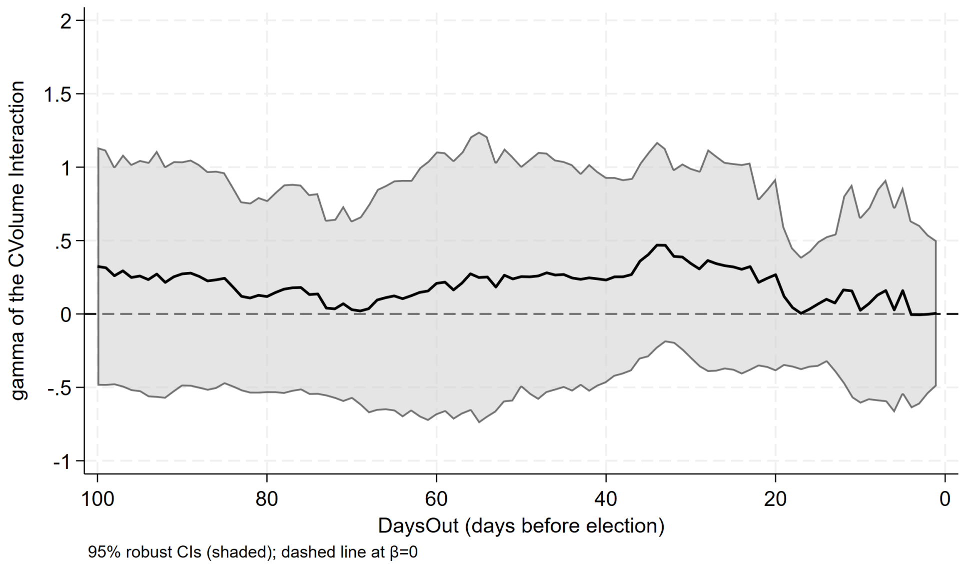


(a) Estimated γ coefficients (i.e., shift in β coefficients) from equation (4) using McFadden's (1974) conditional logit choice model interactions with the normalized number of active traders (NoActiveTraders) across markets. 95% confidence intervals are shown by the shaded region.

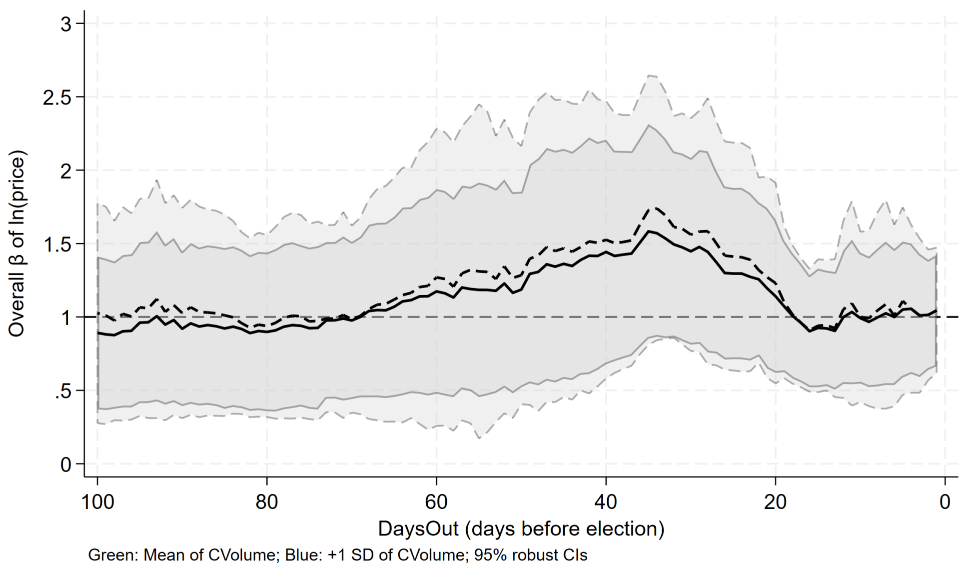


(b) Overall coefficients estimated using McFadden's (1974) conditional logit choice model for 100 to 1 days before the elections. The coefficients (shown by a heavy solid line) and 95% confidence intervals (outlined by a solid line) correspond to the mean number of active traders across markets and the coefficients (shown by a heavy dashed line) and 95% confidence intervals (outlined by a dashed line) correspond to +1 standard deviation in the number of active traders.

Figure 8. The impact of the overall number of active traders in the market on the level of overconfidence or underconfidence in the market.



(a) Estimated γ coefficients (i.e., shift in β coefficients) from equation (4) using McFadden's (1974) conditional logit choice model interactions with the normalized trading volume (CVolume) across markets. 95% confidence intervals are shown by the shaded region.



(b) Overall coefficients estimated using McFadden's (1974) conditional logit choice model for 100 to 1 days before the elections. The coefficients (shown by a heavy solid line) and 95% confidence intervals (outlined by a solid line) correspond to the mean trading volume across markets and the coefficients (shown by a heavy dashed line) and 95% confidence intervals (outlined by a dashed line) correspond to +1 standard deviation in trading volume.

Figure 9. The impact of the total trading volume in the market on the level of overconfidence or underconfidence in the market.

shows very little impact resulting from market length.

Fourth, we ask about the number of different contracts offered in the market (NoContracts). We normalize the number of contracts by subtracting the mean and dividing by the standard deviation (both across markets). Then, we run the regression shown in equation (4) for each of the 100 days preceding the elections.

Figure 11a shows the impact of the number of contracts in the market.[16] It shows the γ coefficient from equation (4) which represents the shift in the β coefficient as the number of contracts changes across markets. Again, the shift is never significantly different from 0 at the 95% confidence level. The average p-value from χ^2 tests that the γ coefficient equals zero is 0.7889.

Figure 11b shows the overall model β and 95% confidence intervals for (1) the mean normalized number of contracts and (2) the mean plus 1 standard deviation of the number of contracts. Again, it shows very little impact resulting from the number of different contracts offered.

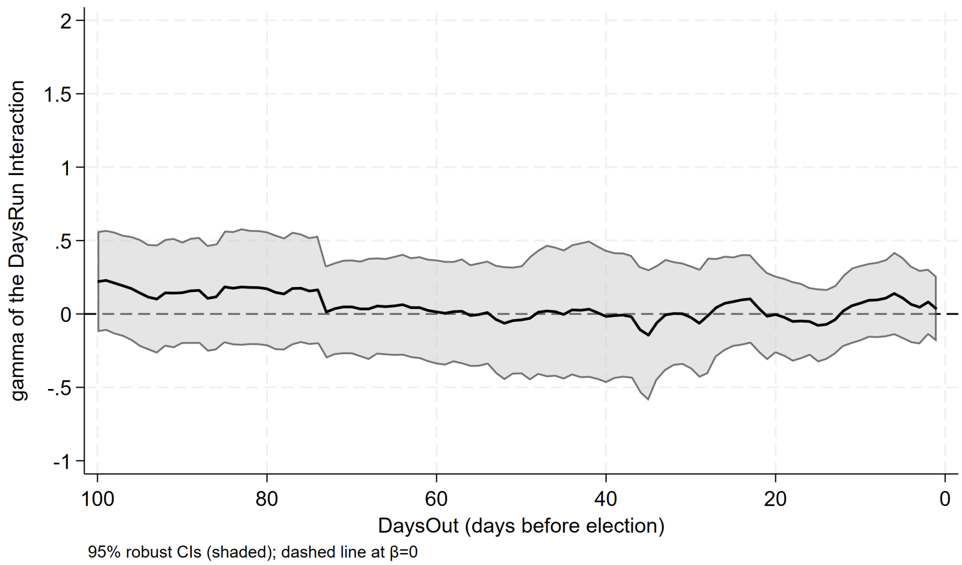
This leads to the following result:

Result 2. *The size of IEM political winner-takes-all markets, in terms of the total number of active traders, the length of the market, the total market volume, and the number of different contracts offered in the market, has little impact on the efficiency of the markets in forecasting winning probabilities.*

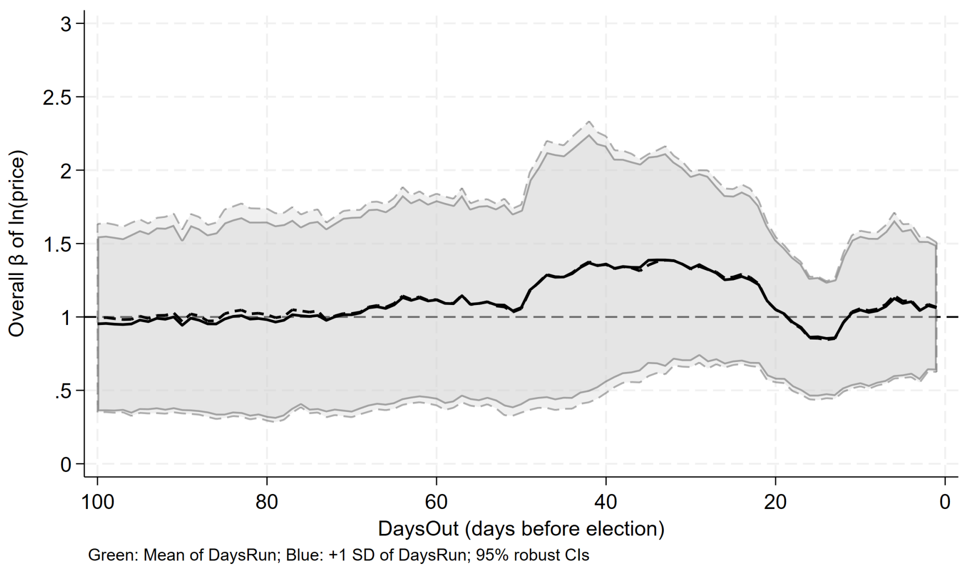
2.2.4 Do individual contract characteristic affect the efficiency of IEM political winner-takes-all contract prices?.

Research comparing recent polls to outcomes in U.S. Presidential elections suggests both an incumbency bias (understating the incumbent party vote shares) and a partisan Democratic bias in polls (overstating the Democratic vote share). Mattei (1998) first documents that pro-incumbent poll responses exceed the pro-incumbent actual voting behavior, which already gives incumbents an advantage. The American Association of Public Opinion Research (AAPOR) post-election evaluations for both the 2016 and 2020 elections concluded that polls consistently underestimated Republican support, producing a pro-Democratic bias largely attributable to non-response bias and failures in education weighting (AAPOR 2017, 2021). This finding is supported by academic research (see the survey articles in Kennedy et al., 2018, for

[16] All the statistics are listed in Table A.5 in the Appendix.

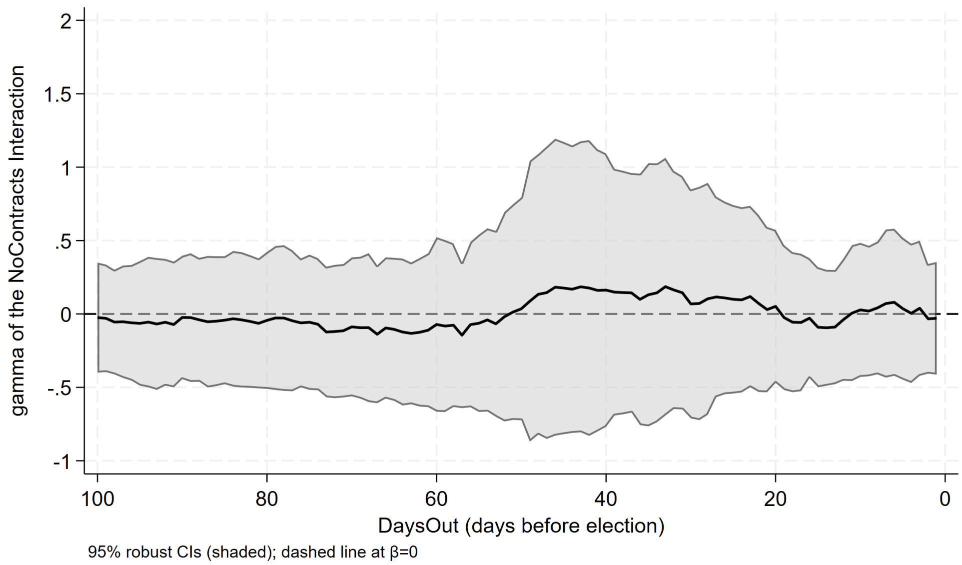


(a) Estimated γ coefficients (i.e., shift in β coefficients) from equation (4) using McFadden's (1974) conditional logit choice model interactions with the normalized market length (DaysOpen) across markets. 95% confidence intervals are shown by the shaded region.

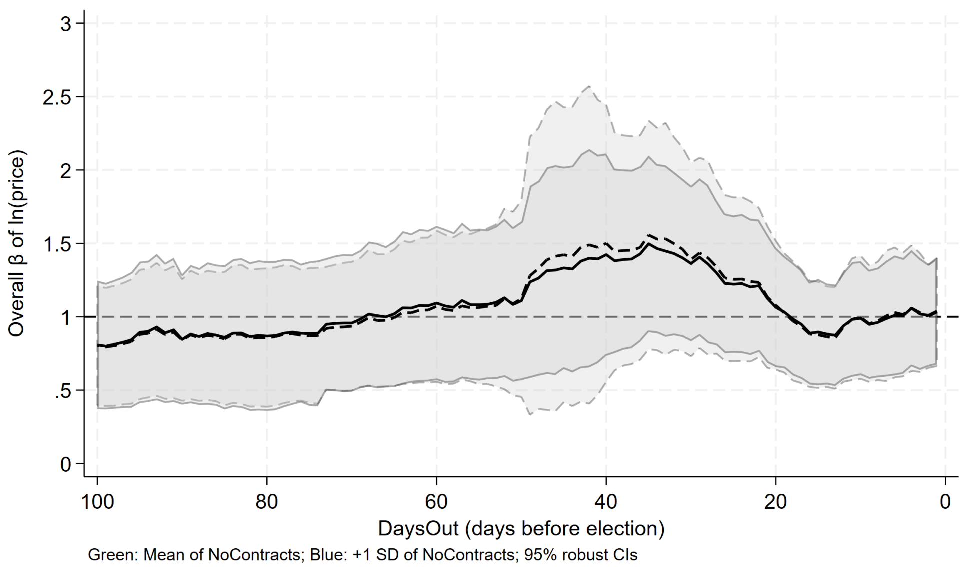


(b) Overall coefficients estimated using McFadden's (1974) conditional logit choice model for 100 to 1 days before the elections. The coefficients (shown by a heavy solid line) and 95% confidence intervals (outlined by a solid line) correspond to the mean number of active traders across markets and the coefficients (shown by a heavy dashed line) and 95% confidence intervals (outlined by a dashed line) correspond to +1 standard deviation in the number of active traders.

Figure 10. The impact of the market length on the level of overconfidence or underconfidence in the market.



(a) Estimated γ coefficients (i.e., shift in β coefficients) from equation (4) using McFadden's (1974) conditional logit choice model interactions with the normalized number of different contracts offered in a market (NoContracts). 95% confidence intervals are shown by the shaded region.



(b) Overall coefficients estimated using McFadden's (1974) conditional logit choice model for 100 to 1 days before the elections. The coefficients (shown by a heavy solid line) and 95% confidence intervals (outlined by a solid line) correspond to the mean number of active traders across markets and the coefficients (shown by a heavy dashed line) and 95% confidence intervals (outlined by a dashed line) correspond to +1 standard deviation in the number of active traders.

Figure 11. The impact of the number of different contracts offered in the market on the level of overconfidence or underconfidence in the market.

examples). At first glance, the biases persisted through the 2024 election (e.g. Montanaro, 2024).[17]

For individual contracts, we can create dummy variables that represent individual contract characteristics to test for such effects. We investigate whether the IEM has a partisan bias and/or an incumbency bias by creating dummy variables associated with the contract's party.

We define a Democratic dummy variable, D, as:

1. D=1 if the contract pays $1 if the Democratic party wins the popular vote in individual election markets; D=0 otherwise.
2. D=1 if the contract pays $1 if the Democratic party gains seats in the House and Senate election markets; D=0 otherwise.[18]
3. D=1 if the contract pays $1 if the Democratic party controls both the House and Senate in congressional control markets; D=0.5 if the contract pays $1 if the Democratic party controls one chamber and the Republican party controls the other; D=0 otherwise.

We define an Incumbent (or more properly a "status quo") dummy variable, I, as:

1. I=1 if the contract pays $1 if the current incumbent party wins the popular vote in individual election markets; I=0 otherwise.
2. I=1 if the contract pays $1 if the current controlling party gains seats in the House and Senate election markets; I=0.5 if the current party loses seats but retains control; I=0 otherwise.
3. I=1 if the contract pays $1 if the current control configuration remains the same in congressional control markets; I=0 otherwise.

We then assess whether the IEM systematically over or under predicts probabilities of Democratic or incumbent related outcomes by running a regression to estimate the following equation:

$$Pr(LV_0^j = 1|Election_e) = \frac{e^{\beta \ln p_t^j + \tau DV}}{\sum_{i=1}^{n} e^{\beta \ln p_t^i + \tau DV}}, \tag{5}$$

where DV is the dummy variable, either D or I. While significant γ estimates in equation (4) move the price forecast to probability mapping in opposite directions for high and low price forecasts,

[17] In contrast, analyzing exit polls in the 2008 election, Mokrzycki, Keeter, and Kennedy (2009) find that polls that do not poll households that only have cell phones may result in an anti-Democratic party poll bias.

[18] We could set D=1 if, when in the majority, Democrats lose seats but remain in control, but it results in little difference in the regressions estimates and confidence intervals.

significant τ estimates in equation (5) move the mapping in one direction across the entire range of price forecasts.[19]

Figure 12 shows the mapping from market prices to probabilities of outcomes for τ coefficients of -0.5, 0.0 and 0.5 assuming $\beta = 1$ in equation (5). For $\tau = 0.0$ (solid line), the prices map directly to probabilities, indicating no bias. For $\tau = -0.5$ (short dashed line), the markets underprice the contracts associated with the dummy variable since the forecast price maps into a higher probability of winning across the board. At the same time, the markets are over pricing the other contracts because the sum of prices must equal 1. For $\tau = 0.5$ (long dashed line), the markets over price the contracts associated with a dummy variable since the forecast price maps into a lower probability of winning across the board. Similarly, the markets are underpricing the other contracts. This shift is independent of the number of contracts. Further, the direction of the shift is the same when $\beta \neq 0$.

First, do prices display an absolute partisan bias for or against Democratic associated contracts (and the opposite against or for non-Democratic, generally Republican, candidates)? Figure 13 shows the estimated τ coefficient in equation (5).[20] This represents and overall shift up or down in the estimated versus actual probability of winning for Democratic contracts versus other contracts. There is little difference between Democratic and non-Democratic contracts. The average p-value from χ^2 tests that the τ coefficient equals zero is 0.7000.

Figure 13 leads to the following result:

Result 3. *IEM political winner-takes-all markets do not have a partisan bias,*

Second, do IEM prices display a status quo or incumbency bias for or against the incumbent party associated contracts? Figure 14 shows the estimated τ coefficient in equation(5).[21] This represents and overall shift up or down in the estimated versus actual probability of winning for incumbent party contracts versus other contracts. There are no significant differences between incumbent and non-incumbent party contracts. The average p-value from χ^2 tests that the τ coefficient equals zero is 0.2230.

[19] It makes little sense to run these as interactions. Consider a two-contract market. Because the contract prices add to 1, the Democratic contract cannot display and overconfidence or underconfidence bias without the Republican candidate displaying the same bias. Thus, we only run the absolute bias of over versus under pricing for contract level variables.

[20] All the statistics are listed in Table A.6 in the Appendix.

[21] All the statistics are listed in Table A.7 in the Appendix.

Figure 12. The relationship between normalized prices (forecasts) and estimated actual outcome probabilities using McFadden's (1974) conditional logit choice model for τ coefficients of -0.5, 0.0 and +0.5 and $\beta = 1$ in equation (5) .

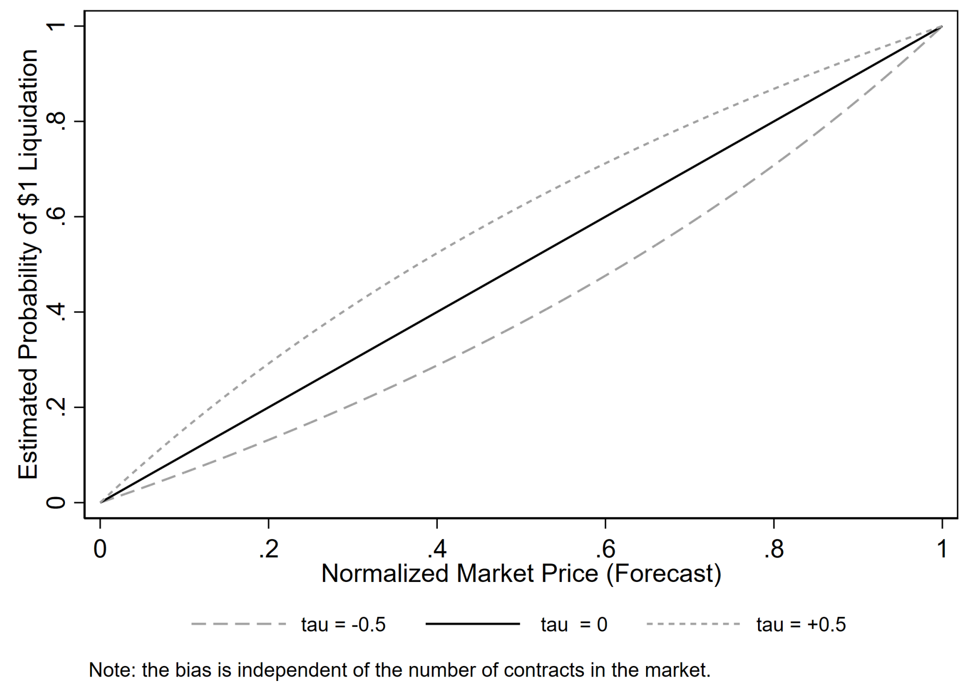


Figure 13. τ coefficients on the Democratic contract dummy variable estimated using McFadden's (1974) conditional logit choice model (equation 5) for 100 through 1 days before elections. 95% confidence intervals are shown by the shaded region.

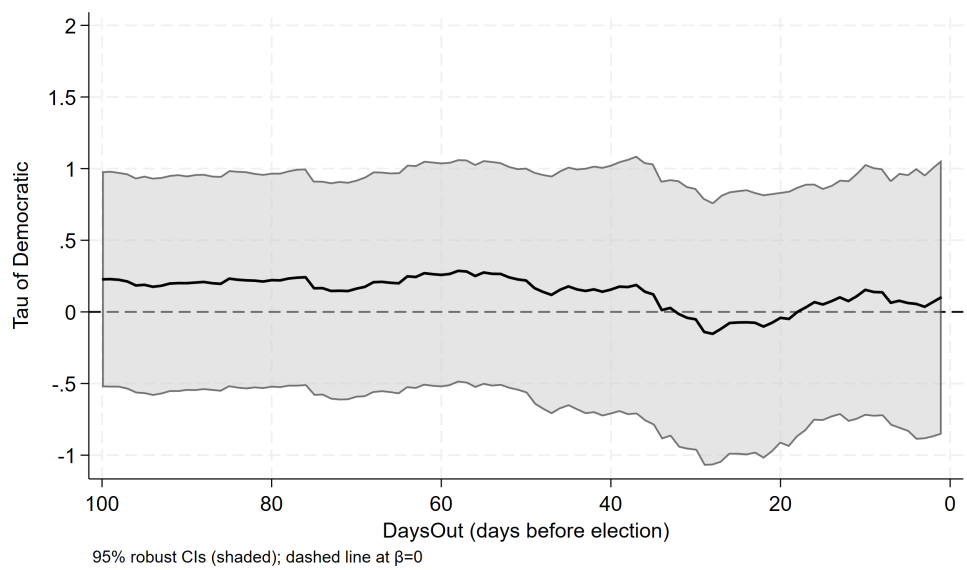


Figure 14. τ coefficients on the incumbent party contract dummy variable estimated using McFadden's (1974) conditional logit choice model (equation 5) for 100 through 1 days before elections. 95% confidence intervals are shown by the shaded region.

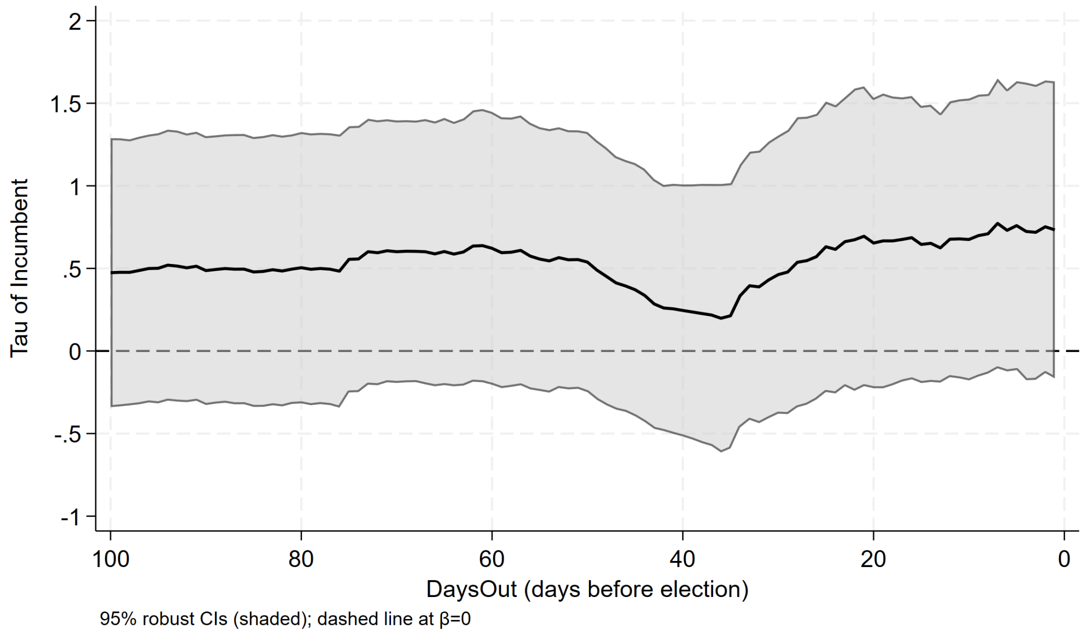


Figure 14 leads to the following result:

Result 4. *IEM political winner-takes-all markets do not have an incumbency bias,*

However, while there is no significant incumbency bias, this is the closest the IEM comes to having a bias (with the average p-value = 0.2230). Thus, if there is any bias at all in IEM WTA political markets, it is a very weak tendency to underforecast the probability that incumbent associated contracts will payoff $1.

3 Discussion

We make two primary contributions in this paper. We provide the first large scale evidence on the efficiency of IEM binary winner-takes-all (WTA) political prediction markets. This extends prior IEM literature beyond continuous vote-share markets. More broadly, we establish a clean empirical benchmark for binary prediction market efficiency under near-ideal structural conditions. This benchmark takes on new importance as commercial prediction markets have grown into a multi-billion dollar industry.

3.1 What the results do and do not say

All of our main results are unified: IEM WTA political markets are well-calibrated probability forecasts. Prices neither systematically over predict nor under predict winning probabilities, and this holds across the full 100-day pre-election horizon we study. Critically, this efficiency is not confined to large, liquid, or long-running markets. Market size (trader count, trading volume, duration, and number of contracts) has no significant effect on calibration. Nor do we find the partisan or incumbency biases that pervade polls (American Association for Public Opinion Research, 2017, 2021; Kennedy et al., 2018; Mattei, 1998). IEM prices appear to aggregate information about election probabilities efficiently and without systematic distortion.

One finding deserves special attention. The behavioral finance literature documents a pervasive favorite-longshot bias across a wide range of betting and financial markets— favorites are systematically under priced and longshots over priced (Griffith, 1949; Thaler and Ziemba, 1988; Jullien and Salanié, 2000; Snowberg and Wolfers, 2010). Similarly, the "volatility smile" in options markets results from systematic over pricing of out-of-the-money contracts. While our β estimates occasionally drift away from 1, they never significantly differ from 1 at conventional confidence levels. The average p-value across all 100 days is 0.61 in the baseline regression. This non-finding is itself informative: it suggests that the IEM's structural design is capable of suppressing the overconfidence and longshot-pricing distortions that characterize many other markets. In particular, the IEM limits both channels for the longshot bias described by Wolfers and Zitzewitz (2004): The $500 investment cap limits the impact of risk seeking ("risk love") and the most biased traders ("misperception") while arbitrage restriction limits overall mis-pricing (Gruca and Rietz, 2026). Whether the same is true of commercial prediction markets, where incentive structures differ substantially, is an open and important question.

3.2 The IEM as an efficiency laboratory

Because commercial prediction market structures differ considerably from the IEM, will the IEM's documented efficiency extend to them? While this is a concern, as with experimental laboratory markets, the structural features of the IEM give it an advantage for testing the possibility of prediction market efficiency. They allow us to isolate price efficiency from confounding frictions that may arise in other markets.

Four features of the IEM are particularly important for making it an ideal testing ground for prediction market efficiency. First, the IEM's contract design ensures zero aggregate risk within each market, which is important for the expected value pricing theory to hold. Because a complete set of contingent claims is issued simultaneously, the market has no net supply of risk. This means the theoretical prediction is clean: under risk neutral or risk averse marginal traders with no net hedging demand, prices should equal true probabilities (Malinvaud, 1974; Berg and Rietz, 2019). Our results are consistent with this prediction. Second, the IEM charges no trading fees, which creates a wedge between prices and beliefs in markets that charge fees. Third, an easily exploited arbitrage restriction prevents contract bundles from trading away from their $1 value, bounding prices within a theoretically sensible range (Gruca and Rietz, 2026). Fourth, the $500 maximum investment cap limits the ability of any individual trader to persistently push prices away from fundamental probability assessments even if they are risk seeking or hedging.

The IEM's features deliberately create a market designed so that prices correspond as closely as possible to true probabilities. In part, this is why IEM evidence has been cited by the CFTC and by commercial market operators to argue for the legitimacy of prediction markets as probability forecasting tools (Tower Research Capital, 2026; U.S. Commodity Futures Trading Commission, 2026). Our results validate this particular legitimacy claim, at least for binary political markets under the IEM's structural conditions.

3.3 Implications for commercial prediction markets

The rise of large scale commercial prediction markets raises a natural question: do our results generalize to these markets? Not necessarily, for specific and theoretically important reasons.

Commercial platforms differ from the IEM along each of the four structural dimensions identified above. First, commercial platforms charge transaction fees, creating a direct friction between prices and trader beliefs. Second, budget constraints are typically absent or much larger, enabling well-capitalized participants to move prices substantially. Third, and perhaps most importantly, commercial prediction markets attract two types of traders who may violate the theoretical connection between prices and forecast probabilities: (1) risk seeking speculators, who may drive prices to extreme values independently of probability assessments, and (2) large hedgers, who may drive risk neutral prices away from true probabilities because of their net hedging demand. Under these conditions, deviations of prices from probabilities are not necessarily irrational. Instead, the deviations can result from the market efficiently pricing risk transfers.

This distinction matters enormously for how we interpret commercial prediction market prices. A commercial market price of $0.72 on a candidate winning an election means something different if the market is primarily an information aggregation mechanism for forecasting versus a hedging mechanism or a gambling mechanism. If substantial net hedging demand exists (e.g., from politically exposed businesses or media organizations managing reputation risk), the price reflects a risk adjusted measure rather than a consensus probability. Our IEM results show that prices can be effective forecasts when the hedging motive is essentially removed by design.

This suggests a research agenda of direct relevance to regulators and market designers. The CFTC has recently revisited its stance on event driven contracts (U.S. Commodity Futures Trading Commission, 2026). A central regulatory question is whether commercial prediction market prices are efficient probability forecasts or risk transfer prices since the former interpretation supports treating them as public information goods, while the latter implies they should be regulated more like insurance products or hedging options markets. Our paper provides the necessary benchmark: IEM binary political markets are efficient under clean conditions. Whether efficiency survives the introduction of fees, uncapped positions, hedging demand and/or gambling demand is an empirical question that we can now address with the methods outlined in this paper.

3.4 Efficiency without bias

A separate contribution is the absence of partisan and incumbency bias. Survey research consistently finds that pre-election polls overstate Democratic support and understate the incumbent party's disadvantage (American Association for Public Opinion Research, 2017, 2021; Kennedy et al., 2018). These biases appear to reflect structural features of survey methodology (i.e., differential nonresponse, social desirability effects, and difficulties in likely-voter modeling) that prediction markets are not subject to by design.

Our finding of no significant Democratic bias and no significant incumbency bias is consistent with earlier evidence from IEM vote-share markets (Berg et al., 2008) but extends it to the binary probability domain. More broadly, the contrast between prediction market efficiency and polling bias has direct implications for how practitioners, journalists, and policymakers should weight these information sources. Poll aggregators have become sophisticated, but they remain downstream of the survey methodology problems that generate the biases. IEM prices, and perhaps commercial prediction market prices subject to the caveats above, aggregate information through a mechanism that appears neutral with respect to party and incumbency. Our results suggest this structural neutrality translates into calibration efficiency in the binary probability domain.

3.5 Limitations and future research

Three limitations of our study are worth acknowledging explicitly. First, our sample of 44 markets, while the largest available for IEM binary political markets, spans a single market platform with fixed structural features. Testing whether efficiency holds on Kalshi or Polymarket using the same McFadden conditional logit framework developed here is a natural and high-value extension. Second, our efficiency tests are unconditional. We test whether prices are calibrated on average. We do not test dynamic efficiency (i.e., whether prices update appropriately in response to specific information events such as debate performances, polling releases, or candidate announcements). Dynamic efficiency testing in binary markets requires different methods and is an important open question. Third, our results cover the period 2000–2024. Changes in the information environment such as social media, prediction market visibility, increased participation in commercial markets, etc., may alter efficiency properties over time. While a splitting our sample across two time periods shows no significant effects, changes in the future information environment may affect future market performance in unanticipated ways.

These limitations notwithstanding, we view our results as establishing a strong prior for binary political prediction market efficiency under well-designed conditions. The theoretical framework is clear, the empirical method is appropriate to the data structure, and the results are consistent across multiple specifications and horizons. As the commercial prediction market industry matures and data accumulate, the methods and benchmark results developed here provide a natural foundation for the next generation of research on this rapidly growing class of financial markets.

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Online Appendix

A Regression Tables

Table A.1. Baseline regressions. Estimates of the β coefficients in McFadden (1974) choice models with logged IEM forecasts as the independent variable for 1 to 100 days before the associated elections. The null hypothesis in the χ^2 test is that $\beta = 1$.

Days Before Election	β **Est.**	**Std. Error**	$\chi^2(1)$	$p > \chi^2$
1	1.0428	0.1885	0.0516	0.8202
2	1.0146	0.1822	0.0065	0.9359
3	1.0118	0.1964	0.0036	0.9520
4	1.0572	0.2014	0.0805	0.7766
5	0.9980	0.2053	0.0001	0.9924
6	0.9908	0.2123	0.0019	0.9656
7	0.9687	0.1978	0.0251	0.8741
8	0.9523	0.1909	0.0625	0.8025
9	0.9446	0.1893	0.0856	0.7698
10	0.9846	0.1963	0.0062	0.9374
11	0.9812	0.2003	0.0088	0.9254
12	0.9449	0.1907	0.0835	0.7726
13	0.8825	0.1786	0.4325	0.5108
14	0.8918	0.1786	0.3673	0.5445
15	0.9058	0.1883	0.2501	0.6170
16	0.8933	0.1815	0.3455	0.5567
17	0.9582	0.1935	0.0466	0.8290
18	0.9949	0.1985	0.0007	0.9797
19	1.0368	0.1991	0.0341	0.8535
20	1.0529	0.2152	0.0604	0.8059
21	1.1193	0.2284	0.2729	0.6014
22	1.1936	0.2367	0.6690	0.4134
23	1.1692	0.2353	0.5169	0.4722
24	1.1994	0.2405	0.6874	0.4071
25	1.1935	0.2376	0.6631	0.4155
26	1.1971	0.2464	0.6401	0.4237
27	1.2682	0.2570	1.0888	0.2967
28	1.3332	0.2883	1.3357	0.2478
29	1.3894	0.2878	1.8299	0.1761
30	1.3450	0.2758	1.5645	0.2110
31	1.3585	0.2800	1.6384	0.2005
32	1.3810	0.2859	1.7752	0.1827
33	1.3929	0.3005	1.7096	0.1910
34	1.4271	0.3046	1.9656	0.1609
35	1.4643	0.3188	2.1213	0.1453
36	1.4019	0.3098	1.6828	0.1946
37	1.3526	0.3032	1.3521	0.2449

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Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
38	1.3494	0.3080	1.2865	0.2567
39	1.3398	0.3107	1.1960	0.2741
40	1.3740	0.3333	1.2589	0.2619
41	1.3422	0.3326	1.0584	0.3036
42	1.3397	0.3421	0.9858	0.3208
43	1.3160	0.3387	0.8702	0.3509
44	1.2692	0.3263	0.6805	0.4094
45	1.2753	0.3285	0.7023	0.4020
46	1.2567	0.3299	0.6054	0.4365
47	1.2674	0.3295	0.6584	0.4171
48	1.2199	0.3110	0.5001	0.4794
49	1.2084	0.3051	0.4665	0.4946
50	1.0991	0.2752	0.1296	0.7188
51	1.0807	0.2746	0.0863	0.7690
52	1.1341	0.2847	0.2218	0.6377
53	1.1140	0.2815	0.1640	0.6855
54	1.0937	0.2762	0.1152	0.7343
55	1.0955	0.2805	0.1159	0.7335
56	1.0952	0.2759	0.1191	0.7300
57	1.1298	0.2844	0.2082	0.6482
58	1.0770	0.2752	0.0783	0.7796
59	1.0886	0.2843	0.0972	0.7552
60	1.1052	0.2823	0.1388	0.7095
61	1.0901	0.2749	0.1073	0.7432
62	1.0926	0.2769	0.1119	0.7380
63	1.0753	0.2709	0.0773	0.7810
64	1.0732	0.2761	0.0703	0.7909
65	1.0300	0.2633	0.0130	0.9092
66	1.0097	0.2557	0.0014	0.9697
67	1.0167	0.2576	0.0042	0.9484
68	1.0287	0.2625	0.0119	0.9130
69	0.9935	0.2505	0.0007	0.9793
70	0.9673	0.2487	0.0173	0.8955
71	0.9679	0.2480	0.0167	0.8971
72	0.9668	0.2456	0.0183	0.8923
73	0.9642	0.2439	0.0215	0.8834
74	0.8917	0.2624	0.1702	0.6800
75	0.8901	0.2603	0.1781	0.6730
76	0.8935	0.2505	0.1808	0.6707
77	0.8994	0.2616	0.1479	0.7005
78	0.8913	0.2688	0.1635	0.6860
79	0.8742	0.2696	0.2178	0.6407
80	0.8716	0.2683	0.2289	0.6323
81	0.8752	0.2658	0.2207	0.6385
82	0.8664	0.2622	0.2597	0.6103
83	0.8911	0.2658	0.1678	0.6821
84	0.8899	0.2618	0.1768	0.6741
85	0.8612	0.2554	0.2955	0.5867
86	0.8774	0.2514	0.2378	0.6258

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Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
87	0.8871	0.2506	0.2031	0.6522
88	0.8672	0.2425	0.2999	0.5839
89	0.8835	0.2467	0.2230	0.6368
90	0.8474	0.2323	0.4316	0.5112
91	0.9127	0.2539	0.1182	0.7310
92	0.8918	0.2469	0.1921	0.6612
93	0.9317	0.2579	0.0702	0.7910
94	0.9025	0.2495	0.1528	0.6959
95	0.8946	0.2484	0.1800	0.6714
96	0.8421	0.2361	0.4469	0.5038
97	0.8252	0.2268	0.5941	0.4408
98	0.8105	0.2210	0.7357	0.3910
99	0.7989	0.2175	0.8552	0.3551
100	0.8070	0.2202	0.7683	0.3807

Table A.2. Impact of the number of active traders. Estimates of the β and γ coefficients in McFadden (1974) choice models with logged IEM forecasts and the interaction with the normalized number of active traders as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\gamma = 0$.

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
1	1.0304	0.1850	0.0270	0.8694	-0.1424	0.1524	0.8734	0.3500
2	1.0010	0.1795	0.0000	0.9955	-0.1232	0.1472	0.7006	0.4026
3	0.9964	0.1927	0.0004	0.9850	-0.1235	0.1611	0.5880	0.4432
4	1.0386	0.1922	0.0403	0.8409	-0.1690	0.1362	1.5400	0.2146
5	0.9739	0.1965	0.0176	0.8943	-0.1320	0.1393	0.8975	0.3435
6	0.9711	0.2019	0.0205	0.8863	-0.1580	0.1150	1.8882	0.1694
7	0.9475	0.1865	0.0793	0.7783	-0.1426	0.1224	1.3578	0.2439
8	0.9352	0.1790	0.1309	0.7175	-0.1483	0.1162	1.6284	0.2019
9	0.9314	0.1778	0.1487	0.6998	-0.1534	0.1146	1.7906	0.1809
10	0.9734	0.1845	0.0208	0.8854	-0.1647	0.1193	1.9056	0.1675
11	0.9638	0.1879	0.0371	0.8472	-0.1478	0.1335	1.2261	0.2682
12	0.9285	0.1789	0.1596	0.6895	-0.1352	0.1349	1.0042	0.3163
13	0.8690	0.1692	0.5990	0.4390	-0.1165	0.1270	0.8416	0.3590
14	0.8778	0.1683	0.5274	0.4677	-0.1215	0.1283	0.8967	0.3437
15	0.8961	0.1747	0.3537	0.5520	-0.1450	0.1203	1.4544	0.2278
16	0.8864	0.1671	0.4620	0.4967	-0.1502	0.1154	1.6952	0.1929
17	0.9505	0.1777	0.0775	0.7807	-0.1706	0.1119	2.3236	0.1274
18	0.9847	0.1811	0.0071	0.9327	-0.1712	0.1195	2.0524	0.1520
19	1.0210	0.1848	0.0129	0.9097	-0.1582	0.1383	1.3090	0.2526
20	1.0331	0.2052	0.0260	0.8718	-0.1354	0.1747	0.6006	0.4384
21	1.0992	0.2113	0.2206	0.6386	-0.1774	0.1589	1.2460	0.2643
22	1.1700	0.2288	0.5519	0.4575	-0.1569	0.1999	0.6165	0.4324
23	1.1491	0.2341	0.4056	0.5242	-0.1091	0.2273	0.2301	0.6314
24	1.1782	0.2390	0.5560	0.4559	-0.1204	0.2324	0.2686	0.6043

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
25	1.1723	0.2394	0.5178	0.4718	-0.1131	0.2474	0.2091	0.6475
26	1.1776	0.2489	0.5092	0.4755	-0.1043	0.2577	0.1640	0.6855
27	1.2474	0.2613	0.8961	0.3438	-0.1147	0.2860	0.1609	0.6884
28	1.3101	0.2918	1.1299	0.2878	-0.1316	0.3130	0.1769	0.6741
29	1.3665	0.2951	1.5422	0.2143	-0.1270	0.3408	0.1388	0.7095
30	1.3255	0.2933	1.2313	0.2671	-0.0946	0.3746	0.0638	0.8007
31	1.3434	0.3004	1.3072	0.2529	-0.0733	0.3953	0.0344	0.8529
32	1.3674	0.3054	1.4473	0.2290	-0.0691	0.4011	0.0296	0.8633
33	1.3744	0.3144	1.4182	0.2337	-0.0996	0.3845	0.0671	0.7956
34	1.4039	0.3192	1.6014	0.2057	-0.1206	0.3971	0.0922	0.7613
35	1.4376	0.3189	1.8829	0.1700	-0.1655	0.3447	0.2307	0.6310
36	1.3788	0.2998	1.5958	0.2065	-0.1746	0.2819	0.3836	0.5357
37	1.3315	0.2874	1.3306	0.2487	-0.1893	0.2208	0.7346	0.3914
38	1.3272	0.2917	1.2589	0.2619	-0.1894	0.2174	0.7585	0.3838
39	1.3177	0.2917	1.1859	0.2762	-0.1991	0.2063	0.9312	0.3345
40	1.3508	0.3102	1.2791	0.2581	-0.2183	0.2041	1.1448	0.2846
41	1.3196	0.3105	1.0596	0.3033	-0.2086	0.2016	1.0707	0.3008
42	1.3171	0.3179	0.9948	0.3186	-0.2143	0.1954	1.2029	0.2727
43	1.2959	0.3152	0.8807	0.3480	-0.2081	0.1934	1.1586	0.2818
44	1.2499	0.3017	0.6857	0.4076	-0.2027	0.1804	1.2615	0.2614
45	1.2538	0.3033	0.7003	0.4027	-0.1996	0.1865	1.1454	0.2845
46	1.2364	0.3060	0.5971	0.4397	-0.1943	0.1841	1.1137	0.2913
47	1.2480	0.3067	0.6540	0.4187	-0.1887	0.1912	0.9737	0.3238
48	1.2010	0.2883	0.4862	0.4856	-0.1818	0.1775	1.0488	0.3058
49	1.1884	0.2802	0.4522	0.5013	-0.1865	0.1674	1.2405	0.2654
50	1.0822	0.2553	0.1037	0.7475	-0.1543	0.1567	0.9698	0.3247
51	1.0647	0.2548	0.0646	0.7994	-0.1526	0.1496	1.0399	0.3078
52	1.1168	0.2616	0.1994	0.6552	-0.1731	0.1494	1.3429	0.2465
53	1.0991	0.2589	0.1464	0.7020	-0.1790	0.1364	1.7229	0.1893
54	1.0793	0.2577	0.0947	0.7583	-0.1679	0.1363	1.5157	0.2183
55	1.0835	0.2618	0.1017	0.7498	-0.1757	0.1347	1.7019	0.1920
56	1.0838	0.2572	0.1061	0.7447	-0.1688	0.1436	1.3815	0.2398
57	1.1230	0.2631	0.2186	0.6401	-0.1954	0.1402	1.9433	0.1633
58	1.0721	0.2573	0.0786	0.7793	-0.1837	0.1388	1.7511	0.1857
59	1.0840	0.2654	0.1001	0.7517	-0.1803	0.1451	1.5433	0.2141
60	1.0994	0.2629	0.1430	0.7053	-0.1824	0.1492	1.4935	0.2217
61	1.0866	0.2553	0.1152	0.7343	-0.1879	0.1400	1.8006	0.1796
62	1.0903	0.2585	0.1221	0.7267	-0.1887	0.1385	1.8563	0.1731
63	1.0745	0.2532	0.0866	0.7685	-0.1860	0.1364	1.8598	0.1726
64	1.0731	0.2600	0.0792	0.7784	-0.1869	0.1359	1.8894	0.1693
65	1.0291	0.2491	0.0137	0.9070	-0.1700	0.1353	1.5788	0.2089
66	1.0069	0.2425	0.0008	0.9774	-0.1574	0.1357	1.3450	0.2462
67	1.0146	0.2441	0.0036	0.9521	-0.1633	0.1346	1.4729	0.2249
68	1.0276	0.2458	0.0127	0.9104	-0.1732	0.1317	1.7284	0.1886
69	0.9936	0.2373	0.0007	0.9785	-0.1623	0.1283	1.6014	0.2057
70	0.9715	0.2385	0.0143	0.9049	-0.1580	0.1293	1.4915	0.2220
71	0.9688	0.2354	0.0176	0.8945	-0.1522	0.1302	1.3666	0.2424
72	0.9679	0.2331	0.0190	0.8903	-0.1541	0.1295	1.4161	0.2340
73	0.9645	0.2313	0.0235	0.8781	-0.1492	0.1301	1.3143	0.2516
74	0.9046	0.2524	0.1430	0.7054	-0.1280	0.1367	0.8769	0.3491

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
75	0.9011	0.2512	0.1550	0.6938	-0.1240	0.1371	0.8187	0.3656
76	0.9008	0.2396	0.1715	0.6788	-0.1138	0.1367	0.6931	0.4051
77	0.9083	0.2519	0.1325	0.7158	-0.1164	0.1403	0.6880	0.4069
78	0.9021	0.2610	0.1406	0.7076	-0.1193	0.1402	0.7243	0.3947
79	0.8868	0.2639	0.1838	0.6681	-0.1145	0.1405	0.6643	0.4150
80	0.8866	0.2632	0.1856	0.6666	-0.1188	0.1386	0.7352	0.3912
81	0.8895	0.2601	0.1807	0.6708	-0.1178	0.1378	0.7310	0.3926
82	0.8816	0.2575	0.2113	0.6457	-0.1160	0.1370	0.7164	0.3973
83	0.9055	0.2587	0.1335	0.7149	-0.1221	0.1375	0.7881	0.3747
84	0.9007	0.2541	0.1529	0.6958	-0.1122	0.1405	0.6384	0.4243
85	0.8697	0.2495	0.2729	0.6014	-0.0952	0.1431	0.4424	0.5060
86	0.8848	0.2449	0.2212	0.6381	-0.0971	0.1445	0.4522	0.5013
87	0.8945	0.2433	0.1878	0.6648	-0.1018	0.1443	0.4981	0.4804
88	0.8739	0.2360	0.2854	0.5932	-0.0955	0.1410	0.4582	0.4984
89	0.8899	0.2402	0.2100	0.6468	-0.0974	0.1444	0.4551	0.4999
90	0.8521	0.2259	0.4288	0.5126	-0.0833	0.1416	0.3462	0.5563
91	0.9214	0.2456	0.1023	0.7491	-0.1130	0.1429	0.6250	0.4292
92	0.9009	0.2393	0.1714	0.6788	-0.1094	0.1397	0.6132	0.4336
93	0.9406	0.2493	0.0568	0.8116	-0.1185	0.1443	0.6745	0.4115
94	0.9117	0.2428	0.1322	0.7162	-0.1121	0.1398	0.6428	0.4227
95	0.9042	0.2421	0.1566	0.6923	-0.1079	0.1401	0.5932	0.4412
96	0.8528	0.2325	0.4006	0.5268	-0.0960	0.1345	0.5101	0.4751
97	0.8328	0.2227	0.5640	0.4527	-0.0848	0.1350	0.3944	0.5300
98	0.8217	0.2166	0.6776	0.4104	-0.0915	0.1312	0.4868	0.4854
99	0.8084	0.2123	0.8146	0.3668	-0.0843	0.1324	0.4055	0.5243
100	0.8164	0.2146	0.7317	0.3923	-0.0826	0.1372	0.3620	0.5474

Table A.3. Impact of the total contract volume in the market. Estimates of the β and γ coefficients in McFadden (1974) choice models with logged IEM forecasts and the interaction with the normalized total contract volume in the market as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\gamma = 0$.

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
1	1.0439	0.1937	0.0513	0.8208	0.0047	0.2526	0.0003	0.9851
2	1.0142	0.1913	0.0055	0.9410	-0.0020	0.2764	0.0000	0.9944
3	1.0105	0.2143	0.0024	0.9609	-0.0052	0.3112	0.0003	0.9868
4	1.0560	0.2265	0.0612	0.8047	-0.0043	0.3262	0.0002	0.9895
5	1.0507	0.2362	0.0460	0.8302	0.1592	0.3629	0.1925	0.6608
6	0.9996	0.2365	0.0000	0.9986	0.0278	0.3582	0.0060	0.9382
7	1.0250	0.2491	0.0100	0.9202	0.1595	0.3877	0.1693	0.6807
8	0.9963	0.2394	0.0002	0.9877	0.1278	0.3684	0.1204	0.7287
9	0.9668	0.2269	0.0214	0.8838	0.0698	0.3350	0.0434	0.8349
10	0.9921	0.2274	0.0012	0.9724	0.0252	0.3245	0.0060	0.9381
11	1.0342	0.2512	0.0185	0.8918	0.1570	0.3724	0.1778	0.6733
12	0.9991	0.2323	0.0000	0.9969	0.1637	0.3263	0.2516	0.6160

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
13	0.9052	0.2045	0.2150	0.6429	0.0746	0.2406	0.0962	0.7564
14	0.9223	0.2003	0.1506	0.6980	0.1002	0.2188	0.2099	0.6468
15	0.9254	0.2063	0.1307	0.7177	0.0677	0.2179	0.0966	0.7560
16	0.9026	0.1947	0.2503	0.6169	0.0330	0.2031	0.0264	0.8709
17	0.9593	0.2067	0.0388	0.8438	0.0039	0.1971	0.0004	0.9842
18	1.0072	0.2178	0.0011	0.9735	0.0434	0.2080	0.0436	0.8346
19	1.0728	0.2287	0.1013	0.7503	0.1199	0.2416	0.2464	0.6197
20	1.1404	0.2661	0.2785	0.5977	0.2674	0.3359	0.6340	0.4259
21	1.1952	0.2790	0.4896	0.4841	0.2429	0.3112	0.6093	0.4350
22	1.2568	0.2680	0.9186	0.3378	0.2151	0.2919	0.5434	0.4610
23	1.2735	0.2911	0.8824	0.3476	0.3227	0.3617	0.7959	0.3723
24	1.2957	0.2979	0.9849	0.3210	0.3043	0.3656	0.6928	0.4052
25	1.2957	0.2974	0.9887	0.3201	0.3207	0.3605	0.7916	0.3736
26	1.2994	0.3008	0.9910	0.3195	0.3290	0.3604	0.8330	0.3614
27	1.3736	0.3176	1.3835	0.2395	0.3430	0.3752	0.8360	0.3606
28	1.4431	0.3493	1.6093	0.2046	0.3642	0.3874	0.8836	0.3472
29	1.4770	0.3367	2.0067	0.1566	0.3069	0.3412	0.8090	0.3684
30	1.4470	0.3244	1.8989	0.1682	0.3437	0.3319	1.0724	0.3004
31	1.4740	0.3260	2.1142	0.1459	0.3879	0.3253	1.4221	0.2331
32	1.4944	0.3231	2.3413	0.1260	0.3922	0.3034	1.6706	0.1962
33	1.5349	0.3467	2.3801	0.1229	0.4678	0.3370	1.9270	0.1651
34	1.5706	0.3597	2.5161	0.1127	0.4687	0.3596	1.6984	0.1925
35	1.5829	0.3731	2.4410	0.1182	0.4055	0.3569	1.2909	0.2559
36	1.5071	0.3638	1.9434	0.1633	0.3599	0.3414	1.1108	0.2919
37	1.4320	0.3557	1.4754	0.2245	0.2683	0.3354	0.6399	0.4237
38	1.4245	0.3604	1.3873	0.2389	0.2532	0.3389	0.5581	0.4550
39	1.4156	0.3657	1.2915	0.2558	0.2529	0.3468	0.5320	0.4658
40	1.4429	0.3905	1.2865	0.2567	0.2313	0.3580	0.4174	0.5182
41	1.4154	0.3958	1.1016	0.2939	0.2393	0.3739	0.4096	0.5222
42	1.4171	0.4112	1.0288	0.3104	0.2462	0.3961	0.3864	0.5342
43	1.3883	0.3990	0.9467	0.3306	0.2360	0.3700	0.4067	0.5236
44	1.3475	0.3967	0.7673	0.3811	0.2451	0.3950	0.3851	0.5349
45	1.3618	0.3994	0.8207	0.3650	0.2689	0.3941	0.4656	0.4950
46	1.3427	0.4026	0.7244	0.3947	0.2654	0.4011	0.4378	0.5082
47	1.3588	0.4044	0.7874	0.3749	0.2804	0.4173	0.4515	0.5016
48	1.3071	0.3945	0.6059	0.4363	0.2591	0.4309	0.3614	0.5477
49	1.2935	0.3803	0.5954	0.4403	0.2530	0.4097	0.3814	0.5369
50	1.1866	0.3400	0.3011	0.5832	0.2545	0.3852	0.4364	0.5088
51	1.1644	0.3496	0.2211	0.6382	0.2385	0.4254	0.3142	0.5751
52	1.2280	0.3619	0.3971	0.5286	0.2641	0.4415	0.3579	0.5497
53	1.1784	0.3548	0.2527	0.6152	0.1834	0.4350	0.1777	0.6734
54	1.1842	0.3658	0.2537	0.6145	0.2518	0.4881	0.2661	0.6060
55	1.1845	0.3728	0.2449	0.6207	0.2483	0.5071	0.2398	0.6243
56	1.1903	0.3550	0.2873	0.5919	0.2736	0.4768	0.3294	0.5660
57	1.2008	0.3539	0.3221	0.5704	0.2105	0.4565	0.2126	0.6448
58	1.1326	0.3465	0.1464	0.7020	0.1638	0.4511	0.1319	0.7165
59	1.1611	0.3553	0.2055	0.6503	0.2167	0.4511	0.2306	0.6311
60	1.1742	0.3556	0.2400	0.6242	0.2087	0.4582	0.2074	0.6488
61	1.1413	0.3451	0.1676	0.6823	0.1567	0.4519	0.1202	0.7288
62	1.1399	0.3382	0.1711	0.6791	0.1468	0.4341	0.1144	0.7352

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
63	1.1146	0.3228	0.1260	0.7226	0.1240	0.4023	0.0950	0.7579
64	1.1061	0.3261	0.1059	0.7448	0.1041	0.4127	0.0636	0.8009
65	1.0692	0.3130	0.0488	0.8251	0.1231	0.4012	0.0941	0.7590
66	1.0452	0.3048	0.0220	0.8820	0.1110	0.3909	0.0806	0.7765
67	1.0469	0.3029	0.0240	0.8770	0.0953	0.3849	0.0613	0.8044
68	1.0401	0.2997	0.0179	0.8937	0.0360	0.3637	0.0098	0.9211
69	0.9998	0.2792	0.0000	0.9994	0.0204	0.3282	0.0039	0.9504
70	0.9761	0.2730	0.0077	0.9303	0.0295	0.3100	0.0090	0.9242
71	0.9896	0.2852	0.0013	0.9708	0.0698	0.3413	0.0419	0.8379
72	0.9773	0.2717	0.0070	0.9333	0.0349	0.3124	0.0125	0.9110
73	0.9765	0.2720	0.0075	0.9310	0.0400	0.3067	0.0170	0.8962
74	0.9258	0.2838	0.0684	0.7936	0.1364	0.3502	0.1516	0.6970
75	0.9234	0.2800	0.0749	0.7844	0.1322	0.3486	0.1438	0.7045
76	0.9399	0.2804	0.0460	0.8302	0.1803	0.3573	0.2547	0.6138
77	0.9443	0.2881	0.0374	0.8467	0.1784	0.3612	0.2439	0.6214
78	0.9338	0.2870	0.0531	0.8177	0.1689	0.3640	0.2154	0.6425
79	0.9088	0.2822	0.1045	0.7465	0.1463	0.3496	0.1751	0.6757
80	0.8982	0.2756	0.1364	0.7119	0.1187	0.3353	0.1253	0.7234
81	0.9042	0.2750	0.1215	0.7275	0.1273	0.3413	0.1391	0.7092
82	0.8903	0.2704	0.1646	0.6849	0.1086	0.3318	0.1072	0.7433
83	0.9184	0.2752	0.0880	0.7668	0.1201	0.3298	0.1325	0.7158
84	0.9340	0.2791	0.0559	0.8131	0.1829	0.3488	0.2749	0.6000
85	0.9217	0.2793	0.0786	0.7792	0.2431	0.3679	0.4364	0.5089
86	0.9367	0.2772	0.0521	0.8194	0.2325	0.3791	0.3762	0.5396
87	0.9448	0.2770	0.0397	0.8420	0.2250	0.3814	0.3480	0.5553
88	0.9348	0.2744	0.0565	0.8121	0.2557	0.3899	0.4302	0.5119
89	0.9564	0.2794	0.0244	0.8759	0.2783	0.3944	0.4978	0.4805
90	0.9197	0.2690	0.0892	0.7652	0.2732	0.3910	0.4881	0.4848
91	0.9792	0.2851	0.0053	0.9417	0.2533	0.4017	0.3976	0.5283
92	0.9480	0.2782	0.0349	0.8518	0.2150	0.4041	0.2831	0.5947
93	1.0055	0.2959	0.0003	0.9851	0.2720	0.4301	0.3999	0.5271
94	0.9637	0.2807	0.0167	0.8971	0.2342	0.4089	0.3281	0.5668
95	0.9614	0.2798	0.0190	0.8902	0.2585	0.4032	0.4109	0.5215
96	0.9055	0.2662	0.1260	0.7226	0.2486	0.3947	0.3966	0.5289
97	0.9024	0.2646	0.1361	0.7121	0.2937	0.4053	0.5254	0.4686
98	0.8762	0.2558	0.2341	0.6285	0.2603	0.3803	0.4686	0.4936
99	0.8812	0.2630	0.2041	0.6515	0.3147	0.4102	0.5887	0.4429
100	0.8917	0.2657	0.1662	0.6836	0.3238	0.4144	0.6106	0.4346

Table A.4. Impact of the number of days the market ran. Estimates of the β and γ coefficients in McFadden (1974) choice models with logged IEM forecasts and the interaction with the normalized number of days the market ran as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\gamma = 0$.

Days Before Election	β **Est.**	**Std. Error**	$\chi^2(1)$	$p > \chi^2$	γ **Est.**	**Std. Error**	$\chi^2(1)$	$p > \chi^2$
1	1.0624	0.2174	0.0823	0.7743	0.0331	0.1141	0.0844	0.7714
2	1.0770	0.2242	0.1180	0.7312	0.0818	0.1152	0.5042	0.4777
3	1.0436	0.2419	0.0325	0.8569	0.0462	0.1292	0.1281	0.7204
4	1.1038	0.2535	0.1678	0.6821	0.0649	0.1342	0.2339	0.6286
5	1.0925	0.2531	0.1337	0.7146	0.1084	0.1423	0.5806	0.4461
6	1.1262	0.2729	0.2139	0.6437	0.1394	0.1447	0.9281	0.3354
7	1.0713	0.2617	0.0741	0.7854	0.1077	0.1355	0.6323	0.4265
8	1.0419	0.2529	0.0275	0.8684	0.0958	0.1324	0.5243	0.4690
9	1.0312	0.2589	0.0145	0.9040	0.0929	0.1296	0.5142	0.4733
10	1.0475	0.2577	0.0339	0.8538	0.0734	0.1323	0.3082	0.5788
11	1.0275	0.2540	0.0118	0.9137	0.0563	0.1324	0.1809	0.6706
12	0.9611	0.2314	0.0282	0.8666	0.0215	0.1251	0.0297	0.8633
13	0.8579	0.2025	0.4925	0.4828	-0.0401	0.1205	0.1109	0.7391
14	0.8536	0.1969	0.5528	0.4572	-0.0712	0.1227	0.3363	0.5620
15	0.8647	0.2074	0.4253	0.5143	-0.0780	0.1285	0.3687	0.5437
16	0.8622	0.2059	0.4481	0.5032	-0.0510	0.1191	0.1837	0.6682
17	0.9293	0.2211	0.1021	0.7493	-0.0482	0.1323	0.1326	0.7158
18	0.9648	0.2257	0.0243	0.8761	-0.0507	0.1397	0.1316	0.7168
19	1.0223	0.2297	0.0094	0.9227	-0.0227	0.1367	0.0276	0.8682
20	1.0504	0.2433	0.0430	0.8357	-0.0038	0.1347	0.0008	0.9776
21	1.1101	0.2617	0.1769	0.6741	-0.0153	0.1531	0.0100	0.9202
22	1.2200	0.2752	0.6387	0.4242	0.0394	0.1548	0.0647	0.7993
23	1.2541	0.2921	0.7567	0.3844	0.1023	0.1552	0.4343	0.5099
24	1.2757	0.2954	0.8710	0.3507	0.0960	0.1587	0.3663	0.5450
25	1.2588	0.2896	0.7983	0.3716	0.0839	0.1568	0.2861	0.5927
26	1.2532	0.2942	0.7404	0.3895	0.0726	0.1652	0.1930	0.6604
27	1.2991	0.3028	0.9754	0.3233	0.0435	0.1720	0.0639	0.8004
28	1.3258	0.3239	1.0114	0.3146	-0.0125	0.2019	0.0039	0.9505
29	1.3563	0.3175	1.2594	0.2618	-0.0632	0.1894	0.1114	0.7386
30	1.3299	0.3217	1.0517	0.3051	-0.0236	0.1804	0.0171	0.8960
31	1.3596	0.3367	1.1406	0.2855	0.0017	0.1777	0.0001	0.9925
32	1.3832	0.3438	1.2428	0.2649	0.0031	0.1815	0.0003	0.9862
33	1.3880	0.3713	1.0920	0.2960	-0.0065	0.1943	0.0011	0.9733
34	1.3884	0.3624	1.1486	0.2838	-0.0594	0.2009	0.0875	0.7674
35	1.3866	0.3600	1.1530	0.2829	-0.1439	0.2286	0.3965	0.5289
36	1.3373	0.3609	0.8732	0.3501	-0.1070	0.2203	0.2361	0.6270
37	1.3383	0.3682	0.8441	0.3582	-0.0194	0.2144	0.0082	0.9279
38	1.3437	0.3740	0.8445	0.3581	-0.0075	0.2173	0.0012	0.9724
39	1.3313	0.3809	0.7562	0.3845	-0.0110	0.2199	0.0025	0.9600
40	1.3605	0.4115	0.7676	0.3810	-0.0172	0.2312	0.0055	0.9406
41	1.3492	0.4252	0.6746	0.4114	0.0085	0.2334	0.0013	0.9709
42	1.3683	0.4479	0.6763	0.4109	0.0325	0.2382	0.0186	0.8916
43	1.3380	0.4383	0.5947	0.4406	0.0251	0.2356	0.0113	0.9152
44	1.2948	0.4349	0.4595	0.4979	0.0279	0.2277	0.0150	0.9026
45	1.2722	0.4227	0.4149	0.5195	-0.0035	0.2258	0.0002	0.9876

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
46	1.2706	0.4277	0.4004	0.5269	0.0156	0.2259	0.0048	0.9448
47	1.2853	0.4274	0.4457	0.5044	0.0201	0.2300	0.0076	0.9305
48	1.2306	0.4021	0.3288	0.5663	0.0120	0.2175	0.0030	0.9561
49	1.1827	0.3827	0.2280	0.6330	-0.0298	0.2159	0.0191	0.8901
50	1.0642	0.3391	0.0359	0.8498	-0.0402	0.1891	0.0452	0.8316
51	1.0416	0.3385	0.0151	0.9021	-0.0453	0.1874	0.0584	0.8090
52	1.0808	0.3519	0.0527	0.8184	-0.0632	0.1979	0.1019	0.7496
53	1.0824	0.3350	0.0605	0.8056	-0.0371	0.1894	0.0383	0.8449
54	1.1021	0.3363	0.0922	0.7615	0.0096	0.1805	0.0028	0.9575
55	1.0920	0.3394	0.0735	0.7864	-0.0042	0.1810	0.0005	0.9814
56	1.0866	0.3326	0.0679	0.7944	-0.0107	0.1782	0.0036	0.9520
57	1.1449	0.3507	0.1708	0.6794	0.0183	0.1838	0.0099	0.9208
58	1.0904	0.3429	0.0695	0.7921	0.0158	0.1759	0.0080	0.9285
59	1.0925	0.3494	0.0701	0.7912	0.0049	0.1817	0.0007	0.9784
60	1.1162	0.3463	0.1125	0.7373	0.0139	0.1821	0.0058	0.9392
61	1.1091	0.3379	0.1043	0.7467	0.0236	0.1795	0.0173	0.8953
62	1.1297	0.3452	0.1412	0.7071	0.0433	0.1786	0.0588	0.8084
63	1.1129	0.3408	0.1098	0.7404	0.0431	0.1748	0.0608	0.8053
64	1.1321	0.3563	0.1375	0.7108	0.0632	0.1768	0.1279	0.7206
65	1.0823	0.3447	0.0571	0.8112	0.0547	0.1733	0.0996	0.7523
66	1.0582	0.3376	0.0297	0.8632	0.0498	0.1688	0.0870	0.7681
67	1.0696	0.3404	0.0418	0.8379	0.0541	0.1684	0.1030	0.7482
68	1.0623	0.3424	0.0331	0.8557	0.0342	0.1773	0.0373	0.8469
69	1.0274	0.3347	0.0067	0.9347	0.0345	0.1675	0.0425	0.8367
70	1.0152	0.3398	0.0020	0.9642	0.0482	0.1645	0.0859	0.7694
71	1.0154	0.3365	0.0021	0.9635	0.0479	0.1638	0.0853	0.7702
72	1.0013	0.3258	0.0000	0.9969	0.0361	0.1609	0.0504	0.8223
73	0.9770	0.3198	0.0052	0.9427	0.0136	0.1618	0.0071	0.9331
74	1.0101	0.3284	0.0009	0.9754	0.1638	0.1886	0.7546	0.3850
75	1.0037	0.3272	0.0001	0.9909	0.1563	0.1872	0.6973	0.4037
76	1.0083	0.3103	0.0007	0.9786	0.1753	0.1901	0.8506	0.3564
77	1.0153	0.3302	0.0021	0.9631	0.1735	0.1971	0.7750	0.3787
78	0.9778	0.3339	0.0044	0.9470	0.1364	0.1963	0.4830	0.4871
79	0.9652	0.3362	0.0107	0.9176	0.1471	0.2005	0.5381	0.4632
80	0.9816	0.3409	0.0029	0.9570	0.1713	0.1995	0.7377	0.3904
81	0.9895	0.3365	0.0010	0.9751	0.1794	0.1997	0.8069	0.3690
82	0.9854	0.3387	0.0019	0.9656	0.1805	0.1998	0.8166	0.3662
83	1.0095	0.3418	0.0008	0.9779	0.1835	0.2038	0.8110	0.3678
84	1.0037	0.3369	0.0001	0.9912	0.1754	0.1983	0.7825	0.3764
85	0.9859	0.3352	0.0018	0.9663	0.1842	0.1955	0.8870	0.3463
86	0.9523	0.3179	0.0226	0.8806	0.1163	0.1855	0.3932	0.5306
87	0.9531	0.3109	0.0228	0.8801	0.1063	0.1852	0.3295	0.5660
88	0.9777	0.3189	0.0049	0.9442	0.1607	0.1857	0.7488	0.3868
89	0.9916	0.3233	0.0007	0.9793	0.1576	0.1840	0.7332	0.3918
90	0.9433	0.2978	0.0362	0.8490	0.1446	0.1777	0.6621	0.4158
91	1.0002	0.3204	0.0000	0.9995	0.1420	0.1916	0.5495	0.4585
92	0.9845	0.3176	0.0024	0.9610	0.1439	0.1870	0.5920	0.4416
93	0.9908	0.3158	0.0009	0.9767	0.1016	0.1895	0.2875	0.5918
94	0.9683	0.3076	0.0106	0.9178	0.1146	0.1844	0.3862	0.5343
95	0.9788	0.3124	0.0046	0.9460	0.1430	0.1874	0.5821	0.4455

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
96	0.9523	0.3117	0.0234	0.8784	0.1732	0.1821	0.9043	0.3416
97	0.9485	0.2997	0.0296	0.8635	0.1921	0.1772	1.1761	0.2781
98	0.9508	0.3032	0.0263	0.8711	0.2106	0.1785	1.3928	0.2379
99	0.9559	0.3049	0.0209	0.8851	0.2288	0.1752	1.7063	0.1915
100	0.9531	0.3037	0.0238	0.8774	0.2199	0.1753	1.5736	0.2097

Table A.5. Impact of the number of contracts in the market. Estimates of the β and γ coefficients in McFadden (1974) choice models with logged IEM forecasts and the interaction with the normalized number of contracts in the market as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\gamma = 0$.

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
1	1.0385	0.1855	0.0431	0.8355	-0.0295	0.1958	0.0227	0.8803
2	1.0100	0.1785	0.0031	0.9554	-0.0330	0.1905	0.0300	0.8626
3	1.0190	0.1944	0.0096	0.9221	0.0389	0.2349	0.0274	0.8685
4	1.0580	0.2024	0.0821	0.7745	0.0043	0.2422	0.0003	0.9859
5	1.0059	0.2013	0.0009	0.9767	0.0363	0.2469	0.0217	0.8830
6	1.0091	0.2085	0.0019	0.9651	0.0797	0.2556	0.0972	0.7552
7	0.9872	0.2012	0.0041	0.9491	0.0708	0.2573	0.0758	0.7830
8	0.9612	0.1908	0.0414	0.8388	0.0412	0.2307	0.0319	0.8582
9	0.9485	0.1895	0.0737	0.7860	0.0199	0.2267	0.0077	0.9301
10	0.9902	0.1981	0.0024	0.9607	0.0277	0.2330	0.0141	0.9054
11	0.9822	0.1994	0.0079	0.9290	0.0055	0.2360	0.0005	0.9815
12	0.9398	0.1877	0.1030	0.7483	-0.0385	0.2122	0.0329	0.8560
13	0.8736	0.1761	0.5148	0.4731	-0.0894	0.1984	0.2029	0.6524
14	0.8827	0.1756	0.4461	0.5042	-0.0940	0.2013	0.2183	0.6404
15	0.8959	0.1848	0.3175	0.5731	-0.0905	0.2088	0.1881	0.6645
16	0.8884	0.1788	0.3897	0.5325	-0.0287	0.2084	0.0189	0.8905
17	0.9493	0.1902	0.0711	0.7898	-0.0579	0.2388	0.0588	0.8084
18	0.9857	0.1965	0.0053	0.9422	-0.0561	0.2434	0.0532	0.8176
19	1.0322	0.1956	0.0271	0.8692	-0.0247	0.2518	0.0096	0.9220
20	1.0644	0.2080	0.0958	0.7569	0.0517	0.2659	0.0378	0.8458
21	1.1257	0.2243	0.3142	0.5751	0.0297	0.2872	0.0107	0.9177
22	1.2115	0.2299	0.8463	0.3576	0.0717	0.3078	0.0543	0.8158
23	1.2034	0.2367	0.7383	0.3902	0.1186	0.3152	0.1417	0.7066
24	1.2263	0.2417	0.8765	0.3492	0.0962	0.3218	0.0894	0.7650
25	1.2223	0.2384	0.8691	0.3512	0.0999	0.3274	0.0932	0.7602
26	1.2276	0.2428	0.8790	0.3485	0.1094	0.3348	0.1068	0.7438
27	1.3000	0.2523	1.4140	0.2344	0.1160	0.3485	0.1108	0.7393
28	1.3596	0.2752	1.7077	0.1913	0.1034	0.4032	0.0658	0.7976
29	1.4063	0.2740	2.1995	0.1381	0.0715	0.4056	0.0311	0.8601
30	1.3630	0.2703	1.8026	0.1794	0.0686	0.3980	0.0297	0.8632
31	1.4012	0.2752	2.1254	0.1449	0.1446	0.4056	0.1272	0.7214
32	1.4306	0.2838	2.3025	0.1292	0.1633	0.4136	0.1559	0.6930
33	1.4474	0.2979	2.2558	0.1331	0.1861	0.4479	0.1727	0.6778

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
34	1.4642	0.2939	2.4952	0.1142	0.1439	0.4499	0.1024	0.7490
35	1.4972	0.3072	2.6199	0.1055	0.1309	0.4574	0.0819	0.7747
36	1.4282	0.3051	1.9698	0.1605	0.0995	0.4370	0.0518	0.8199
37	1.3936	0.3099	1.6127	0.2041	0.1438	0.4162	0.1195	0.7296
38	1.3897	0.3133	1.5470	0.2136	0.1459	0.4231	0.1190	0.7301
39	1.3811	0.3205	1.4139	0.2344	0.1486	0.4287	0.1201	0.7289
40	1.4233	0.3518	1.4480	0.2288	0.1624	0.4751	0.1169	0.7325
41	1.3940	0.3623	1.1832	0.2767	0.1607	0.4903	0.1074	0.7432
42	1.3991	0.3795	1.1061	0.2929	0.1767	0.5140	0.1182	0.7310
43	1.3787	0.3723	1.0350	0.3090	0.1851	0.5057	0.1340	0.7143
44	1.3255	0.3597	0.8186	0.3656	0.1688	0.4995	0.1141	0.7355
45	1.3328	0.3516	0.8958	0.3439	0.1766	0.5078	0.1209	0.7281
46	1.3178	0.3645	0.7604	0.3832	0.1826	0.5161	0.1251	0.7235
47	1.3138	0.3590	0.7640	0.3821	0.1453	0.5085	0.0817	0.7750
48	1.2627	0.3390	0.6004	0.4384	0.1340	0.4876	0.0755	0.7835
49	1.2370	0.3338	0.5041	0.4777	0.0869	0.4882	0.0317	0.8587
50	1.1093	0.2761	0.1568	0.6921	0.0352	0.3873	0.0083	0.9275
51	1.0840	0.2687	0.0978	0.7545	0.0124	0.3744	0.0011	0.9736
52	1.1290	0.2752	0.2198	0.6392	-0.0190	0.3638	0.0027	0.9583
53	1.0980	0.2665	0.1352	0.7131	-0.0673	0.3232	0.0434	0.8350
54	1.0845	0.2602	0.1056	0.7452	-0.0405	0.3184	0.0162	0.8988
55	1.0824	0.2639	0.0974	0.7549	-0.0630	0.3084	0.0417	0.8381
56	1.0824	0.2606	0.1001	0.7518	-0.0725	0.2872	0.0637	0.8007
57	1.1108	0.2705	0.1679	0.6820	-0.1447	0.2533	0.3264	0.5678
58	1.0642	0.2609	0.0605	0.8057	-0.0766	0.2843	0.0725	0.7877
59	1.0740	0.2674	0.0766	0.7819	-0.0824	0.2988	0.0761	0.7826
60	1.0935	0.2683	0.1214	0.7275	-0.0714	0.3033	0.0555	0.8138
61	1.0753	0.2632	0.0818	0.7748	-0.1108	0.2672	0.1718	0.6785
62	1.0774	0.2656	0.0849	0.7708	-0.1248	0.2580	0.2340	0.6285
63	1.0594	0.2594	0.0525	0.8188	-0.1323	0.2463	0.2884	0.5912
64	1.0606	0.2666	0.0516	0.8202	-0.1232	0.2552	0.2331	0.6292
65	1.0194	0.2542	0.0058	0.9393	-0.1050	0.2485	0.1785	0.6727
66	0.9994	0.2455	0.0000	0.9980	-0.0953	0.2454	0.1510	0.6976
67	1.0076	0.2527	0.0009	0.9759	-0.1383	0.2397	0.3330	0.5639
68	1.0179	0.2522	0.0051	0.9433	-0.0929	0.2587	0.1290	0.7195
69	0.9834	0.2403	0.0048	0.9448	-0.0936	0.2466	0.1441	0.7043
70	0.9572	0.2384	0.0322	0.8575	-0.0879	0.2413	0.1328	0.7155
71	0.9573	0.2396	0.0318	0.8584	-0.1144	0.2318	0.2438	0.6215
72	0.9550	0.2358	0.0364	0.8486	-0.1195	0.2316	0.2664	0.6057
73	0.9488	0.2301	0.0494	0.8240	-0.1229	0.2269	0.2931	0.5882
74	0.8865	0.2538	0.2000	0.6547	-0.0697	0.2295	0.0924	0.7612
75	0.8853	0.2511	0.2088	0.6477	-0.0564	0.2350	0.0576	0.8103
76	0.8884	0.2414	0.2139	0.6437	-0.0607	0.2239	0.0735	0.7864
77	0.8956	0.2527	0.1706	0.6796	-0.0464	0.2450	0.0359	0.8497
78	0.8885	0.2576	0.1873	0.6652	-0.0278	0.2531	0.0121	0.9126
79	0.8718	0.2594	0.2444	0.6210	-0.0273	0.2502	0.0119	0.9132
80	0.8687	0.2601	0.2546	0.6138	-0.0437	0.2380	0.0336	0.8545
81	0.8731	0.2610	0.2364	0.6268	-0.0640	0.2259	0.0802	0.7770
82	0.8650	0.2583	0.2732	0.6012	-0.0508	0.2303	0.0486	0.8256
83	0.8893	0.2604	0.1806	0.6709	-0.0400	0.2350	0.0289	0.8649

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	γ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
84	0.8884	0.2569	0.1886	0.6641	-0.0327	0.2355	0.0193	0.8895
85	0.8595	0.2506	0.3142	0.5751	-0.0424	0.2223	0.0364	0.8486
86	0.8749	0.2455	0.2598	0.6103	-0.0493	0.2256	0.0477	0.8272
87	0.8856	0.2475	0.2138	0.6438	-0.0530	0.2285	0.0537	0.8167
88	0.8655	0.2381	0.3190	0.5722	-0.0398	0.2152	0.0342	0.8532
89	0.8819	0.2402	0.2418	0.6229	-0.0249	0.2236	0.0124	0.9115
90	0.8460	0.2269	0.4604	0.4974	-0.0236	0.2144	0.0121	0.9122
91	0.9108	0.2507	0.1265	0.7220	-0.0719	0.2186	0.1083	0.7421
92	0.8904	0.2440	0.2017	0.6533	-0.0564	0.2202	0.0656	0.7979
93	0.9299	0.2545	0.0759	0.7829	-0.0684	0.2291	0.0892	0.7652
94	0.9007	0.2455	0.1635	0.6859	-0.0554	0.2268	0.0596	0.8071
95	0.8936	0.2461	0.1869	0.6655	-0.0641	0.2165	0.0877	0.7671
96	0.8426	0.2360	0.4450	0.5047	-0.0601	0.2009	0.0896	0.7647
97	0.8262	0.2284	0.5789	0.4467	-0.0530	0.1952	0.0737	0.7860
98	0.8127	0.2240	0.6989	0.4031	-0.0552	0.1819	0.0920	0.7617
99	0.7999	0.2200	0.8275	0.3630	-0.0298	0.1868	0.0254	0.8734
100	0.8079	0.2236	0.7377	0.3904	-0.0247	0.1913	0.0167	0.8973

Table A.6. Absolute bias for or against Democratic contracts. Estimates of the β and τ coefficients in McFadden (1974) choice models with logged IEM forecasts and a dummy variable indicating Democratic contracts as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\tau = 0$.

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	τ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
1	1.0385	0.1879	0.0421	0.8375	0.1038	0.4891	0.0450	0.8320
2	1.0106	0.1825	0.0034	0.9535	0.0698	0.4815	0.0210	0.8848
3	1.0094	0.1951	0.0023	0.9616	0.0359	0.4714	0.0058	0.9392
4	1.0532	0.2007	0.0704	0.7908	0.0560	0.4838	0.0134	0.9078
5	0.9942	0.2007	0.0008	0.9768	0.0624	0.4585	0.0185	0.8918
6	0.9867	0.2084	0.0040	0.9493	0.0780	0.4553	0.0293	0.8640
7	0.9643	0.1939	0.0338	0.8541	0.0638	0.4373	0.0213	0.8840
8	0.9452	0.1868	0.0860	0.7693	0.1368	0.4410	0.0963	0.7563
9	0.9378	0.1859	0.1121	0.7377	0.1391	0.4440	0.0982	0.7540
10	0.9775	0.1926	0.0137	0.9069	0.1542	0.4482	0.1184	0.7308
11	0.9750	0.1978	0.0160	0.8993	0.1099	0.4397	0.0625	0.8026
12	0.9396	0.1890	0.1021	0.7493	0.0756	0.4301	0.0309	0.8604
13	0.8775	0.1753	0.4878	0.4849	0.1017	0.4188	0.0589	0.8082
14	0.8878	0.1760	0.4063	0.5239	0.0747	0.4138	0.0326	0.8567
15	0.9029	0.1866	0.2709	0.6027	0.0520	0.4147	0.0157	0.9003
16	0.8894	0.1795	0.3794	0.5379	0.0685	0.4217	0.0263	0.8711
17	0.9561	0.1906	0.0532	0.8176	0.0325	0.4398	0.0055	0.9411
18	0.9949	0.1960	0.0007	0.9793	0.0004	0.4456	0.0000	0.9993
19	1.0413	0.1979	0.0436	0.8345	-0.0487	0.4562	0.0114	0.9149
20	1.0567	0.2144	0.0699	0.7915	-0.0412	0.4479	0.0084	0.9268
21	1.1278	0.2289	0.3114	0.5768	-0.0756	0.4613	0.0269	0.8697

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	τ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
22	1.2060	0.2320	0.7883	0.3746	-0.1022	0.4707	0.0471	0.8282
23	1.1776	0.2288	0.6030	0.4374	-0.0758	0.4654	0.0265	0.8706
24	1.2070	0.2371	0.7619	0.3827	-0.0725	0.4736	0.0234	0.8784
25	1.2007	0.2332	0.7405	0.3895	-0.0736	0.4706	0.0244	0.8757
26	1.2054	0.2421	0.7198	0.3962	-0.0774	0.4687	0.0272	0.8689
27	1.2825	0.2575	1.2034	0.2726	-0.1173	0.4765	0.0606	0.8055
28	1.3543	0.2871	1.5224	0.2172	-0.1528	0.4684	0.1065	0.7442
29	1.4064	0.2895	1.9704	0.1604	-0.1396	0.4766	0.0859	0.7695
30	1.3506	0.2761	1.6129	0.2041	-0.0515	0.4673	0.0121	0.9123
31	1.3628	0.2808	1.6694	0.1963	-0.0414	0.4687	0.0078	0.9296
32	1.3824	0.2869	1.7767	0.1826	-0.0145	0.4757	0.0009	0.9758
33	1.3904	0.2990	1.7053	0.1916	0.0279	0.4583	0.0037	0.9515
34	1.4259	0.3048	1.9521	0.1624	0.0126	0.4607	0.0008	0.9781
35	1.4560	0.3168	2.0727	0.1500	0.1221	0.4660	0.0687	0.7933
36	1.3926	0.3085	1.6200	0.2031	0.1413	0.4610	0.0940	0.7592
37	1.3437	0.3019	1.2964	0.2549	0.1879	0.4605	0.1664	0.6833
38	1.3417	0.3074	1.2350	0.2664	0.1739	0.4561	0.1453	0.7031
39	1.3341	0.3104	1.1582	0.2818	0.1766	0.4463	0.1565	0.6924
40	1.3682	0.3332	1.2210	0.2692	0.1558	0.4444	0.1229	0.7259
41	1.3364	0.3330	1.0203	0.3124	0.1411	0.4442	0.1009	0.7508
42	1.3343	0.3421	0.9546	0.3285	0.1574	0.4404	0.1276	0.7209
43	1.3104	0.3392	0.8374	0.3602	0.1464	0.4385	0.1115	0.7384
44	1.2635	0.3265	0.6513	0.4197	0.1572	0.4302	0.1336	0.7148
45	1.2693	0.3280	0.6742	0.4116	0.1781	0.4263	0.1745	0.6762
46	1.2505	0.3298	0.5770	0.4475	0.1543	0.4251	0.1317	0.7166
47	1.2620	0.3308	0.6270	0.4284	0.1188	0.4249	0.0782	0.7798
48	1.2173	0.3114	0.4869	0.4853	0.1398	0.4194	0.1110	0.7390
49	1.2050	0.3052	0.4513	0.5017	0.1660	0.4140	0.1608	0.6884
50	1.0994	0.2725	0.1330	0.7154	0.2194	0.4015	0.2985	0.5849
51	1.0806	0.2718	0.0879	0.7668	0.2271	0.3959	0.3291	0.5662
52	1.1337	0.2799	0.2282	0.6328	0.2412	0.3964	0.3702	0.5429
53	1.1167	0.2762	0.1785	0.6727	0.2649	0.3979	0.4432	0.5056
54	1.1008	0.2713	0.1380	0.7102	0.2661	0.4012	0.4398	0.5072
55	1.1033	0.2750	0.1410	0.7073	0.2753	0.3998	0.4742	0.4911
56	1.0990	0.2712	0.1333	0.7151	0.2508	0.3986	0.3959	0.5292
57	1.1358	0.2776	0.2393	0.6247	0.2820	0.3987	0.5001	0.4795
58	1.0849	0.2710	0.0981	0.7541	0.2868	0.3975	0.5205	0.4706
59	1.0947	0.2806	0.1139	0.7357	0.2651	0.3990	0.4413	0.5065
60	1.1107	0.2791	0.1573	0.6916	0.2584	0.4001	0.4170	0.5184
61	1.0962	0.2708	0.1262	0.7224	0.2635	0.4007	0.4324	0.5108
62	1.0991	0.2717	0.1330	0.7154	0.2705	0.4002	0.4569	0.4991
63	1.0792	0.2656	0.0890	0.7655	0.2438	0.3984	0.3745	0.5406
64	1.0784	0.2709	0.0838	0.7722	0.2482	0.3978	0.3895	0.5326
65	1.0310	0.2593	0.0143	0.9048	0.1999	0.3952	0.2559	0.6130
66	1.0107	0.2525	0.0018	0.9662	0.2035	0.3926	0.2686	0.6043
67	1.0174	0.2539	0.0047	0.9454	0.2099	0.3924	0.2860	0.5928
68	1.0274	0.2592	0.0112	0.9158	0.2075	0.3943	0.2770	0.5987
69	0.9919	0.2487	0.0011	0.9740	0.1751	0.3926	0.1988	0.6557
70	0.9659	0.2478	0.0189	0.8906	0.1624	0.3878	0.1753	0.6754
71	0.9662	0.2471	0.0187	0.8912	0.1459	0.3888	0.1408	0.7075

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	τ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
72	0.9649	0.2451	0.0205	0.8861	0.1478	0.3905	0.1432	0.7051
73	0.9617	0.2436	0.0247	0.8751	0.1462	0.3867	0.1430	0.7053
74	0.8949	0.2591	0.1644	0.6852	0.1661	0.3821	0.1889	0.6638
75	0.8932	0.2569	0.1729	0.6775	0.1653	0.3830	0.1863	0.6660
76	0.8995	0.2463	0.1665	0.6832	0.2420	0.3873	0.3906	0.5320
77	0.9051	0.2577	0.1356	0.7127	0.2390	0.3876	0.3803	0.5374
78	0.8973	0.2650	0.1501	0.6985	0.2333	0.3847	0.3677	0.5442
79	0.8784	0.2658	0.2094	0.6472	0.2203	0.3833	0.3303	0.5655
80	0.8761	0.2637	0.2207	0.6385	0.2217	0.3824	0.3362	0.5620
81	0.8783	0.2607	0.2178	0.6408	0.2124	0.3828	0.3079	0.5790
82	0.8698	0.2576	0.2555	0.6132	0.2184	0.3832	0.3247	0.5688
83	0.8947	0.2612	0.1625	0.6868	0.2205	0.3881	0.3228	0.5699
84	0.8943	0.2570	0.1692	0.6808	0.2248	0.3874	0.3365	0.5618
85	0.8657	0.2497	0.2892	0.5907	0.2324	0.3862	0.3619	0.5474
86	0.8783	0.2472	0.2422	0.6226	0.1962	0.3840	0.2611	0.6094
87	0.8889	0.2463	0.2036	0.6519	0.2003	0.3831	0.2733	0.6011
88	0.8707	0.2373	0.2970	0.5858	0.2092	0.3848	0.2955	0.5867
89	0.8862	0.2418	0.2214	0.6380	0.2048	0.3860	0.2815	0.5957
90	0.8503	0.2277	0.4319	0.5110	0.2008	0.3832	0.2744	0.6004
91	0.9148	0.2483	0.1176	0.7316	0.2012	0.3877	0.2693	0.6038
92	0.8940	0.2416	0.1924	0.6610	0.1982	0.3862	0.2635	0.6077
93	0.9320	0.2528	0.0724	0.7879	0.1828	0.3871	0.2230	0.6368
94	0.9026	0.2451	0.1579	0.6911	0.1755	0.3884	0.2042	0.6513
95	0.8955	0.2434	0.1844	0.6676	0.1891	0.3887	0.2367	0.6266
96	0.8431	0.2304	0.4636	0.4960	0.1846	0.3843	0.2309	0.6309
97	0.8293	0.2201	0.6017	0.4379	0.2123	0.3848	0.3044	0.5812
98	0.8162	0.2140	0.7374	0.3905	0.2243	0.3837	0.3418	0.5588
99	0.8064	0.2111	0.8411	0.3591	0.2288	0.3857	0.3519	0.5531
100	0.8142	0.2143	0.7515	0.3860	0.2276	0.3845	0.3504	0.5539

Table A.7. Absolute bias for or against Incumbent contracts. Estimates of the β and τ coefficients in McFadden (1974) choice models with logged IEM forecasts and a dummy variable indicating Incumbent party associated contracts as the independent variables for 1 to 100 days before the associated elections. The null hypotheses in the χ^2 tests are that $\beta = 1$ and $\tau = 0$.

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	τ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
1	1.0719	0.2301	0.0977	0.7546	0.7333	0.4589	2.5543	0.1100
2	1.0525	0.2229	0.0555	0.8138	0.7521	0.4521	2.7678	0.0962
3	1.0467	0.2326	0.0404	0.8407	0.7186	0.4555	2.4886	0.1147
4	1.0983	0.2491	0.1559	0.6929	0.7238	0.4597	2.4792	0.1154
5	1.0373	0.2437	0.0234	0.8784	0.7592	0.4462	2.8951	0.0888
6	1.0249	0.2524	0.0097	0.9214	0.7306	0.4359	2.8090	0.0937
7	1.0114	0.2459	0.0022	0.9629	0.7724	0.4477	2.9768	0.0845
8	0.9899	0.2371	0.0018	0.9660	0.7096	0.4318	2.7005	0.1003
9	0.9736	0.2322	0.0130	0.9094	0.6987	0.4353	2.5765	0.1085

Days Before Election	β Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$	τ Est.	Std. Error	$\chi^2(1)$	$p > \chi^2$
10	1.0102	0.2380	0.0018	0.9659	0.6751	0.4353	2.4054	0.1209
11	1.0083	0.2463	0.0011	0.9730	0.6788	0.4310	2.4800	0.1153
12	0.9687	0.2323	0.0181	0.8930	0.6768	0.4260	2.5241	0.1121
13	0.8921	0.2086	0.2677	0.6049	0.6244	0.4162	2.2510	0.1335
14	0.9068	0.2123	0.1926	0.6608	0.6519	0.4281	2.3189	0.1278
15	0.9199	0.2237	0.1283	0.7202	0.6451	0.4281	2.2710	0.1318
16	0.9149	0.2227	0.1462	0.7022	0.6860	0.4376	2.4568	0.1170
17	0.9812	0.2356	0.0064	0.9365	0.6753	0.4388	2.3684	0.1238
18	1.0184	0.2412	0.0058	0.9391	0.6666	0.4460	2.2341	0.1350
19	1.0607	0.2450	0.0613	0.8044	0.6666	0.4553	2.1440	0.1431
20	1.0735	0.2641	0.0776	0.7806	0.6537	0.4485	2.1248	0.1449
21	1.1483	0.2838	0.2731	0.6013	0.6947	0.4630	2.2510	0.1335
22	1.2285	0.2963	0.5950	0.4405	0.6735	0.4668	2.0816	0.1491
23	1.1887	0.2773	0.4633	0.4961	0.6620	0.4468	2.1953	0.1384
24	1.2155	0.2819	0.5843	0.4446	0.6154	0.4451	1.9115	0.1668
25	1.2096	0.2796	0.5623	0.4533	0.6311	0.4486	1.9791	0.1595
26	1.2063	0.2820	0.5351	0.4645	0.5710	0.4410	1.6758	0.1955
27	1.2715	0.2925	0.8616	0.3533	0.5469	0.4447	1.5122	0.2188
28	1.3291	0.3186	1.0669	0.3017	0.5371	0.4481	1.4369	0.2306
29	1.3725	0.3083	1.4601	0.2269	0.4781	0.4388	1.1873	0.2759
30	1.3225	0.2902	1.2352	0.2664	0.4625	0.4296	1.1590	0.2817
31	1.3330	0.2900	1.3189	0.2508	0.4304	0.4273	1.0145	0.3138
32	1.3509	0.2896	1.4675	0.2257	0.3881	0.4209	0.8504	0.3564
33	1.3620	0.3060	1.3993	0.2368	0.3949	0.4141	0.9098	0.3402
34	1.3958	0.3048	1.6858	0.1942	0.3341	0.4066	0.6753	0.4112
35	1.4391	0.3084	2.0273	0.1545	0.2133	0.4096	0.2712	0.6026
36	1.3799	0.3018	1.5848	0.2081	0.1982	0.4147	0.2284	0.6327
37	1.3268	0.2959	1.2201	0.2693	0.2181	0.4048	0.2902	0.5901
38	1.3217	0.3012	1.1414	0.2854	0.2270	0.4004	0.3213	0.5708
39	1.3109	0.3050	1.0395	0.3079	0.2363	0.3941	0.3596	0.5487
40	1.3422	0.3256	1.1042	0.2933	0.2455	0.3892	0.3977	0.5283
41	1.3109	0.3249	0.9156	0.3386	0.2553	0.3862	0.4370	0.5086
42	1.3058	0.3328	0.8443	0.3582	0.2604	0.3801	0.4692	0.4934
43	1.2841	0.3350	0.7189	0.3965	0.2848	0.3858	0.5450	0.4604
44	1.2368	0.3295	0.5166	0.4723	0.3365	0.3911	0.7403	0.3896
45	1.2407	0.3333	0.5216	0.4701	0.3710	0.3911	0.8995	0.3429
46	1.2225	0.3365	0.4373	0.5084	0.3938	0.3889	1.0257	0.3112
47	1.2359	0.3393	0.4834	0.4869	0.4122	0.3913	1.1096	0.2922
48	1.1939	0.3274	0.3505	0.5538	0.4513	0.3981	1.2848	0.2570
49	1.1859	0.3266	0.3241	0.5692	0.4894	0.4006	1.4921	0.2219
50	1.0809	0.2978	0.0738	0.7859	0.5383	0.4020	1.7928	0.1806
51	1.0671	0.2984	0.0506	0.8220	0.5536	0.3992	1.9229	0.1655
52	1.1220	0.3093	0.1555	0.6933	0.5522	0.4002	1.9034	0.1677
53	1.1015	0.3040	0.1114	0.7385	0.5652	0.4028	1.9687	0.1606
54	1.0906	0.3036	0.0891	0.7653	0.5456	0.4069	1.7980	0.1800
55	1.0950	0.3082	0.0951	0.7578	0.5566	0.4074	1.8668	0.1718
56	1.1012	0.3090	0.1073	0.7433	0.5747	0.4118	1.9474	0.1629
57	1.1474	0.3205	0.2116	0.6455	0.6093	0.4169	2.1355	0.1439
58	1.0908	0.3124	0.0845	0.7712	0.5980	0.4158	2.0681	0.1504
59	1.1046	0.3213	0.1059	0.7449	0.5951	0.4184	2.0230	0.1549

Days Before Election	β **Est.**	**Std. Error**	$\chi^2(1)$	$p > \chi^2$	τ **Est.**	**Std. Error**	$\chi^2(1)$	$p > \chi^2$
60	1.1224	0.3206	0.1457	0.7027	0.6215	0.4215	2.1744	0.1403
61	1.1121	0.3140	0.1275	0.7210	0.6379	0.4220	2.2848	0.1306
62	1.1140	0.3160	0.1300	0.7184	0.6355	0.4190	2.3000	0.1294
63	1.0891	0.3057	0.0849	0.7708	0.5994	0.4127	2.1098	0.1464
64	1.0806	0.3087	0.0682	0.7939	0.5868	0.4084	2.0651	0.1507
65	1.0407	0.2981	0.0186	0.8915	0.6022	0.4126	2.1304	0.1444
66	1.0137	0.2865	0.0023	0.9619	0.5881	0.4090	2.0678	0.1504
67	1.0218	0.2900	0.0056	0.9401	0.6011	0.4096	2.1540	0.1422
68	1.0299	0.2956	0.0102	0.9195	0.6032	0.4039	2.2305	0.1353
69	1.0005	0.2864	0.0000	0.9986	0.6040	0.4049	2.2253	0.1358
70	0.9757	0.2872	0.0071	0.9327	0.6012	0.4054	2.1996	0.1380
71	0.9743	0.2827	0.0083	0.9276	0.6070	0.4062	2.2334	0.1351
72	0.9701	0.2782	0.0116	0.9143	0.5949	0.4092	2.1143	0.1459
73	0.9635	0.2721	0.0179	0.8934	0.6011	0.4107	2.1417	0.1433
74	0.9083	0.2917	0.0989	0.7531	0.5572	0.4112	1.8362	0.1754
75	0.9054	0.2869	0.1087	0.7416	0.5550	0.4111	1.8223	0.1770
76	0.9019	0.2674	0.1344	0.7139	0.4835	0.4218	1.3142	0.2516
77	0.9145	0.2835	0.0910	0.7630	0.4954	0.4198	1.3930	0.2379
78	0.9059	0.2867	0.1078	0.7426	0.4996	0.4189	1.4224	0.2330
79	0.8895	0.2889	0.1462	0.7022	0.4947	0.4197	1.3894	0.2385
80	0.8905	0.2889	0.1437	0.7046	0.5044	0.4190	1.4488	0.2287
81	0.8906	0.2825	0.1500	0.6985	0.4955	0.4163	1.4165	0.2340
82	0.8777	0.2792	0.1919	0.6614	0.4843	0.4181	1.3418	0.2467
83	0.9080	0.2847	0.1044	0.7467	0.4921	0.4188	1.3807	0.2400
84	0.9033	0.2790	0.1201	0.7289	0.4816	0.4183	1.3259	0.2495
85	0.8723	0.2708	0.2224	0.6372	0.4786	0.4168	1.3183	0.2509
86	0.8887	0.2628	0.1794	0.6719	0.4957	0.4173	1.4107	0.2349
87	0.8971	0.2606	0.1558	0.6930	0.4953	0.4173	1.4086	0.2353
88	0.8747	0.2512	0.2489	0.6179	0.4991	0.4145	1.4498	0.2286
89	0.8896	0.2556	0.1864	0.6660	0.4934	0.4143	1.4184	0.2337
90	0.8511	0.2402	0.3844	0.5352	0.4869	0.4153	1.3743	0.2411
91	0.9275	0.2651	0.0749	0.7844	0.5132	0.4155	1.5257	0.2168
92	0.9034	0.2577	0.1405	0.7078	0.5037	0.4149	1.4739	0.2247
93	0.9478	0.2688	0.0378	0.8459	0.5141	0.4186	1.5086	0.2193
94	0.9217	0.2643	0.0877	0.7671	0.5198	0.4185	1.5425	0.2142
95	0.9087	0.2610	0.1224	0.7265	0.5009	0.4172	1.4414	0.2299
96	0.8557	0.2496	0.3342	0.5632	0.4994	0.4136	1.4577	0.2273
97	0.8334	0.2368	0.4952	0.4816	0.4876	0.4133	1.3916	0.2381
98	0.8157	0.2316	0.6337	0.4260	0.4762	0.4109	1.3430	0.2465
99	0.8047	0.2293	0.7251	0.3945	0.4765	0.4141	1.3239	0.2499
100	0.8113	0.2312	0.6664	0.4143	0.4741	0.4155	1.3022	0.2538