Prediction Markets? The Accuracy and Efficiency of $2.4 Billion in the 2024 Presidential Election*

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Abstract

Political prediction markets have exploded in size and influence, moving billions of dollars and shaping how journalists, donors, and voters interpret electoral odds. If these prices truly capture rational expectations, they should efficiently aggregate information about political outcomes. But do they? We analyze more than 2,500 political prediction markets traded across the *Iowa Electronic Markets*, *Kalshi*, *PredictIt*, and *Polymarket* during the final five weeks of the 2024 U.S. presidential campaign involving more than than two billion dollars in transactions to assess whether prices accurately and efficiently aggregate political information. While 93% of *PredictIt* markets correctly predicted outcomes better than chance on the Election Night eve, accuracy fell to 78% on *Kalshi* and 67% on *Polymarket* among all active markets. Even the most accurate markets showed little evidence of efficiency: prices for identical contracts diverged across exchanges, daily price changes were weakly correlated or negatively autocorrelated, and arbitrage opportunities peaked in the final two weeks before Election Day. Together, these findings challenge the view that prediction markets necessarily efficiently and accurately aggregate information about political outcomes and suggest that traders often react not only to political developments but also to the dynamics of the markets themselves.

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In 2024, nearly $2.4 billion dollars waas wagered on the outcome of U.S. elections across political prediction markets such as the *Iowa Electronic Markets*, *Kalshi*, *PredictIt*, and *Polymarket* between September 1st and Election Day. Once confined to academic experiments, these markets now shape campaign narratives and elite expectations, with prices reported by media outlets as real-time indicators of who is likely to win. The growing prominence of political prediction markets raises an important question: if vast sums and high attention are believed to produce collective wisdom, do these markets actually accurately and efficiently aggregate political information?

Political prediction markets have been around since the 16th century (Rhode et al., 2013), but the size and scope of new markets – perhaps combined with the performance of pre-election polling in recent years (e.g., Jennings and Wlezien (2018), Kennedy et al. (2018)) and increasing concerns about how AI affects polling (Westwood, 2025) – has led to political prediction markets being increasingly used as a political barometer. Unlike polls which reflect the opinions of voters at the time of the survey (and pollsters' weighting decisions), prediction markets are intentionally forward-looking and backed by the financial stakes of the traders involved (Erikson and Wlezien, 2008). A political prediction market is defined by a contract that will pay $1 if the event occurs (e.g., candidate X wins, turnout exceeds Y, etc.). Under the logic of the Efficient Market Hypothesis, not only should the prices in these markets incorporate all available information, making them efficient and accurate predictors of future events (Arrow et al., 2008; Forsythe et al., 1992; Wolfers and Zitzewitz, 2004), but the fact that the contract pays $1 means that the price can be directly interpreted as the expected value that the event occurs. As Elon Musk recently claimed, "More accurate than polls, as actual money is on the line."[1]

This logic has helped drive both the popularity and influence of political prediction markets. In the 2024 U.S. presidential election, prices on exchanges such as *Polymarket* and *Kalshi* often diverged sharply from polling averages, producing headlines like "Markets

1. `https://x.com/elonmusk/status/1843132050242777187`

Favor Trump Despite Biden's Polling Lead" (Jones, 2024; Wilson, 2024). Coverage in major outlets from *The Wall Street Journal* and *Bloomberg* to *Politico* have treated these markets as credible reflections of public expectations, even as they revealed volatile price changes being driven by a handful of large traders (Hüfner and Wilson, 2024; Jones, 2024; Kharif, 2024; McHugh, 2025; Osipovich, 2024; Wilson, 2024). And when some of the prediction markets appeared to outperform polls by seemingly anticipating President Trump's victory (Cutting et al. (2024); Urquhart (2024), but see Crane and Vinson (2023)), confidence in the predictive power of markets further deepened. Reflecting this perception and demonstrating the increasing and changing coverage of prediction markets by the media, in the days leading up to the 2025 elections, *Politico* declared: "Pollsters Have a New Kind of Competitor. They Should Be Worried" (McHugh, 2025).

Although the financial incentives of traders and the efficient market hypothesis suggests a compelling theory for why political prediction markets may be an accurate and efficient aggregation of the "wisdom of the crowd" willing to put actual dollars at risk, there are equally compelling reasons to expect systematic inaccuracy and inefficiency. Markets are composed of humans, not omniscient rational forecasters, and trader behavior may reflect the same biases documented elsewhere in financial and political decision-making. Some participants may act on irrational beliefs or overreact to recent information, as classic models of investor psychology predict (Barberis, Shleifer and Vishny, 1998). Others may engage in expressive/identity-driven trading rooted in partisan or candidate psychological attachments rather than profit maximization (Hong and Kostovetsky, 2012). The prominence of social media, message boards, and blockchain transparency that allows traders to follow the trades of self-styled "alphas" further blurs the line between information aggregation and collective speculation (Desiderio et al., 2025; Guan, 2022). Still other traders may use prediction markets instrumentally rather than informationally by purchasing contracts as a political hedge to offset potential business or portfolio losses (Axén and Cortis, 2020; Christensen et al., 2022) or by acquiring enough positions to influence prices and shape media narratives focused on market movements rather than electoral realities (Thompson, 2012). There are as many reasons to expect inefficiency and distortion as there are to expect collective wisdom.

We test these competing expectations using data from nearly 2,500 political prediction markets traded on the *Kalshi*, *Polymarket*, *PredictIt*, and *Iowa Electronic Markets (IEM)* exchanges over the final five weeks of the 2024 presidential campaign. Contracts on these exchanges exist for a wide variety of political events, including: the outcome of the national presidential contest, outcomes in state-level races, predictions regarding the number of voters who will vote, contracts on what polling averages, pollsters and prediction markets will show on certain dates, and markets related to political events that are even more speculative (e.g., whether a candidate mentions a specific word in a specific speech). Assessing the performance of political predication markets across a variety of markets and the exchanges that host those markets allows us to systematically assess both the accuracy (i.e., how well market prices anticipated realized outcomes) and efficiency (i.e., whether prices adjusted in ways consistent with rational information updating) of political prediction markets.

Better understanding the accuracy and characteristics of political prediction markets is substantively important for several reasons. First, just as pre-election polling coverage can distort campaign narratives (Molly Jong-Fast, 2023; Toff et al., 2020) and influence both candidates (Mutz, 1995) and voters (Westwood, Messing and Lelkes, 2020), so too can the expanding focus on prediction markets. Donors seeking to back viable candidates (e..g, Meisels, Clinton and Huber (2024)) may use market prices to decide where to give, potentially amplifying momentum for perceived frontrunners and starving trailing campaigns of resources. Activists and party organizations may likewise adjust mobilization efforts based on market signals, reallocating staff, attention, or advertising toward races seen as "winnable." Insofar as journalists, candidates, elites or the public treat market prices as an authoritative, forward-looking expectation of the probability of a political event occurring, assessing their actual accuracy and efficiency becomes crucial. Otherwise, prediction markets risk constructing rather than reflecting political realities; prices that are presumed to reveal collective wisdom may actually amplify perceptions, momentum, and bias.

Second, the surge of money flowing through political prediction markets has created a new financial pathway linking money and politics. $2.4 billion in money was transacted on the *PredictIt*, *Polymarket*, and *Kalshi* exchanges between September 1st and Election Day, an amount that exceeded the $1.8 billion raised by Republican candidates and affiliated groups throughout the 2024 presidential campaign and nearly matched the $2.9 billion raised by Democrats (Schleifer and Sun, 2024). The sheer scale of financial activity underscores that political prediction markets are no longer marginal and largely academic curiosities. Understanding whether the prices of political prediction markets reflect genuine information or concentrated speculation becomes critical for assessing their role in democratic accountability and public belief formation.

We find that even the largest and most visible markets frequently behaved in ways inconsistent with rational, information-driven updating. Across the nearly 2,500 political markets traded on *PredictIt*, *Kalshi*, *Polymarket*, and the *Iowa Electronic Markets*, we find substantial variation in both accuracy and efficiency. While 93% of PredictIt markets overall correctly predicted outcomes better than chance, accuracy fell to 78% on *Kalshi* and 67% on *Polymarket*. Yet even accurate markets rarely behaved as if aggregating information efficiently. Prices for nearly identical contracts diverged sharply across exchanges, and price movements were only weakly correlated, if at all, both within and between markets and exchanges. A random-walk analysis reveals that most markets exhibit negative serial correlation in price changes—suggesting overreaction rather than rational updating—and opportunities for between-exchange arbitrage were most frequent in the final two weeks of the campaign, when information was most abundant. Moreover, there were almost no days in which the prices of similar contracts moved together in rationalizable ways, even when only considering the most salient and similar markets involving the outcome of the national presidential race. Instead, changes in the daily closing prices were largely unconnected – suggesting that prices were shaped more by the actions of traders in each individual market than changes in the overall political landscape. As expected, performance was weakest in more speculative markets, such as those predicting speech content or the margin of victory in the presidential popular vote. Overall, our results cast doubt on whether political prediction markets necessarily aggregate private information into accurate and efficient collective forecasts.

1 Reasons for Accuracy and Efficiency

Prediction markets differ from pre-election polls in both purpose and logic. While polls capture current voter sentiment and reflect the weighting choices of pollsters, prediction markets are explicitly forward-looking based on the actions of traders putting their money at risk. Because contracts pay $1 if the event occurs, the resulting equilibrium price can be directly interpreted as the market-implied probability of that outcome. In theory, the price of a contract on a prediction market should reflect expectations that traders have about future outcomes given currently available information and incentives (Rothschild, 2009; Wlezien and Erikson, 2002; Wolfers and Zitzewitz, 2004). Under the Efficient Market Hypothesis, competition between traders acting to maximize expected returns (rather than express preferences), will lead prices to reflect the collective probability of an outcome (Arrow et al., 2008; Fama, 1970; Snowberg, Wolfers and Zitzewitz, 2013). Participants who possess either private information or superior interpretations of public data will trade until prices stabilize at their expected value. By tying beliefs to monetary consequences, prediction markets are presumed to align incentives with accuracy rather than expressive preference, mitigating the partisan and social-desirability distortions that can arise in surveys (Bullock et al., 2015).

Under these conditions, political prediction markets should be both accurate and efficient (Berg and Rietz, 2014; Crane and Vinson, 2023; Pennock et al., 2012; Urquhart, 2024). When multiple exchanges trade similar, well-defined, political contracts in an information-rich environment, arbitrage pressures should eliminate price discrepancies and cause traders' dispersed information to be efficiently aggregated into a single, common price that reflects the public signal (Gruca and Berg, 2012; Rhode and Strumpf, 2004). But when contracts concern ambiguous or speculative outcomes (e.g., the contents of an upcoming speech, or whether a candidate wins by a specified margin), traders may not have much, if any, information and prices may reflect noise, speculation, or entertainment motives (Barberis, Shleifer and Vishny, 1998).

Deviations from efficiency may also arise if traders are motivated by goals other than maximizing expected value by buying a contract they expect to pay out $1 when the event occurs. Political prediction markets seem particularly ripe for distortions caused by traders motivated by expressive, speculative, or strategic reasons. Some traders, for example, may seek to influence perceptions. When prediction market prices are covered as news, financially motivated or ideologically aligned actors may buy contracts to shift prices in the hopes of shaping media narratives and public expectations (Thompson, 2012). The 2024 "French Whale" episode illustrates this dynamic: a single, well-financed trader on *Polymarket* substantially altered prices and dominated press coverage, demonstrating how market visibility can amplify individual influence (Hüfner and Wilson, 2024; Kharif, 2024; Osipovich, 2024).

Other traders may trade expressively rather than instrumentally. Much like partisan donors who contribute to losing campaigns out of loyalty, some traders may purchase contracts favoring their preferred candidates because of affective/identity-based motivations (Hong and Kostovetsky, 2012; Reade and Vaughan Williams, 2019). Such behavior can sustain biased prices if it is sufficiently widespread (as with partisan attachment (Bartels, 2002; Green, Palmquist and Schickler, 2002)) or if liquidity is thin.

Short-term speculation and momentum trading can also generate volatility divorced from fundamentals. Traders may buy and sell based on recent trends and social media cues rather than new information, producing self-reinforcing swings and temporary mispricings (Deck, Lin and Porter, 2013; Oliven and Rietz, 2004; Segol, 2012). The integration of blockchain-based trading, public leaderboards, and discussion forums further encourages herd behavior driven by visibility and hype rather than news (Desiderio et al., 2025; Guan, 2022).

Still other participants may use political prediction markets to hedge political risk. Investors exposed to partisan or policy risk may bet against their preferences to offset potential losses if undesired outcomes occur (Axén and Cortis, 2020; Christensen et al., 2022). If so, trades may reflect rational portfolio diversification while also undermining the interpretation of prices as collective beliefs about expected outcomes.

Finally, the structural features of markets and exchanges can compound these behavioral biases. Markets of political contracts related to political events are hosted on exchanges that vary in terms of who is able to participate, size and liquidity constraints, and the size of the transaction costs involved – all of which can affect market performance (Atanasov et al., 2017; Berg and Rietz, 2014; Crane and Vinson, 2023; Dana et al., 2019; Page and Clemen, 2013; Urquhart, 2024) Differences in the types and motivations of traders trading on the different exchanges may also affect market performance if, for example, the academics who conducted limited trading on *IEM* differ in their skill, information, or motivation than the non-US citizens trading using nearly unlimited cryptocurrency on *Polymarket*.

To assess the extent to which political prediction markets aggregate information accurately and efficiently we analyze several properties of contract prices across exchanges, market types, and time. Because the price of a $1 contract represents the market's implied probability that an event will occur, accuracy is evaluated by whether contracts priced above $0.50 correspond to outcomes that actually occur. Put simply, do events priced above even odds happen more often than those priced below them? We assess efficiency by characterizing how prices for similar contracts within and between trading exchanges covary over time. Because contracts pay out based on whether an event occurs, the prices on contracts related to a victory by candidate X should not only be similarly priced, but they should also go up and down in response to changes in the political environment in similar ways; we should not see contracts for the same even being priced differently. Relatedly, it should not be possible to construct an arbitrage profit by purchasing contracts on both candidate X and candidate Y winning for a combined cost of less than \$1, since one of the two outcomes must occur. While our market-level analyses cannot reveal the behavioral or institutional reasons for inaccuracy or inefficiency, by comparing the accuracy and efficiency across markets and exchanges with different designs and information environments we can identify when and where prediction markets approximate the accurate and efficient aggregation of political information. Even if we cannot fully diagnose the sources of market failure, our analysis of whether political prediction markets are accurate and efficient is a first-order question of tremendous substantive importance given the rapidly growing attention, visibility, and financial volume involved.

To assess the accuracy of political prediction markets we follow the extant literature and rely on the logarithmic (log-skill) score (we report similar results based on the Brier score in the appendix). The log-skill accuracy evaluates the predictive accuracy of a market using a normalized loss function that evaluates how closely the contract price aligns with the realized outcome relative to an uninformed 50-50 baseline:

$$\text{LogLoss} = -\frac{1}{N}\sum_{t=1}^{N}\left[y_i \log(p_i t) + (1-y_i)\log(1-p_i t)\right],$$

$$A^{\text{Log}} = 1 - \frac{\text{LogLoss}}{\text{LogLoss}_{0.5}}.$$

The loss function emphasizes the confidence of predictions by heavily penalizing extreme probabilities assigned to incorrect outcomes so as to distinguish markets that are merely well-calibrated from those that are confidently and correctly informed.

To be clear, one important complication for interpreting *any* measure of accuracy based on a comparison of the market price at a point in time and the realized outcome is that we never observe the counterfactual of what would happen had the contracted event resolved at the moment the price was set. As a result, it is impossible to know if markets are "inaccurate" because the price failed to accurately reflect the underlying state of the world at that time, or whether the underlying political reality shifted between the moment of pricing and the time of the eventual outcome. Any claim that a market was "wrong" inevitably, and unavoidably, conflates market performance and changing political realities.[2] Even so, it remains valuable to calculate the accuracy of these prices with respect to the eventual result – being mindful of what what is actually being measured by those measures – because market prices are so often treated as shorthand for the likelihood of a future outcome.

Accuracy measures predictive success, but not whether the market efficiently aggregates information. A market may appear accurate simply because one outcome was ex ante overwhelmingly likely or because random variation happened to align with its predictions. Efficiency, by contrast, considers whether market prices respond rationally, proportionally, and consistently to new information. A market can be accurate without ever being efficient, but a market that is efficient will tend to become more accurate as uncertainty resolves.

If markets efficiently aggregate information, contract prices should vary in predictable ways. Absent systematic differences in trader information or priors, identical contracts should trade at similar prices across exchanges; contracts that pay $1 if a candidate wins should be identically priced. Moreover, within and across exchanges, prices of related contracts should covary in predictable ways because the contracts are based on the occurrence of a common political event. As a result, the price of a contract paying if candidate X wins should move inversely with the price for candidate Y and positively with contracts specifying nonzero margins of victory for X. Aside from negligible residual risks, arbitrage opportunities should be rare and it should not be possible to purchase mutually exclusive contracts—for example, on both Harris and Trump winning the national presidential election—for less than the guaranteed $1 payout. Efficiency also implies serial independence in the change in daily closing prices: in the absence of new information, daily price changes should be a random walk because changes in today's price should not predict tomorrow's. Patterns of price changes over time that deviate from a random walk, such as positive autocorrelation suggesting mo-

2. Just like pollsters can always claim to provide an accurate characterization when the poll was taken, so too can one argue that the market was correctly priced when the price was set. It is technically impossible to disprove either assertion.

mentum or negative autocorrelation suggesting mean reversion indicates market inefficiency due to delayed reactions to new information or a correction of prior mispricing. Although a sequence of genuinely unexpected and politically reinforcing revelations could certainly generate temporary serial dependence in price changes, such patterns should be short-lived and quickly priced in by forward looking traders. Finally, when we do observe notable changes in market prices consistent with the revelation of new information, that information should affect the prices of all related contracts across every exchange. We should not see the prices of similar contracts moving in unconnected ways as that would suggest that traders are reacting to the actions of other traders in that market rather than changes in the informational environment that are relevant for multiple markets.

2 Prediction Markets & the 2024 U.S. Elections

To assess the performance of political prediction markets during the 2024 U.S. presidential campaign, we analyze nearly 2,500 markets traded across four major exchanges—the *Iowa Electronic Markets (IEM)*, *PredictIt*, *Kalshi*, and *Polymarket*—which differ substantially in age, regulation, and market design. In recent years, the scale and scope of political prediction markets have expanded dramatically following a series of court and regulatory decisions loosening prior restrictions (Frankel, 2025; Salmon, 2024). As a result, political prediction markets have moved beyond their academic origin and most activity now occurs on commercial exchanges attracting millions of trades and billions of dollars.

The *IEM* exchange was founded in 1988 and it is operated by the University of Iowa primarily as an academic research tool with small stakes and restricted participation (e.g., traders limited to $500, single daily trades).[3] The *PredictIt* exchange was launched in 2014 by Victoria University of Wellington and it subsequently expanded to a broader retail audience, but with considerable limits in place. Only 5,000 traders were allowed per market and the

3. Between September 1st and the day before Election Day 2024, roughly $31 thousand was transacted.

total market cap was limited to $850. In addition, *PredictIt* changes a 10% fee on profits and also a 5% withdrawal fee. Despite these limits, nearly $ 5.9 million dollars was traded between September 1, 2024 and Election Day.

Exchange	**Access & Participation**	**Trading Limits & Design**	**# Markets**
Iowa Electronic Markets (IEM)	Academic / not-for-profit, U.S. only, small stakes	$5–$500 stakes per trader; simple winner-take-all (WTA) contracts	4
PredictIt	U.S. retail (subject to KYC), capped at $850 per contract	Position and trader caps (e.g., 5,000 traders); transaction fees on trades	29
Kalshi	Open to U.S. retail traders; institutional-grade exchange	Uses position accountability limits rather than hard caps; allows higher volume per trader	520
Polymarket	Crypto and foreign user base (U.S. access restricted since 2022)	Very large stakes possible; on-chain liquidity; high concentration of large traders	1,956

Table 1. Comparison of Major Political Prediction Market Exchanges in 2024.

Kalshi and *Polymarket* represent a newer generation of high-volume, technologically sophisticated exchanges that operate at a vastly different scale. *Kalshi*, established in 2020 and registered as a Designated Contract Market (DCM) under the Commodity Futures Trading Commission, offers institutional-grade infrastructure and far higher position allowances than earlier exchanges. The larger limits and number of markets resulted in $321 million dollars being transacted between September 1st and November 4th on the 520 political markets it hosted. Transaction costs are based on the price of a contract, but the maximum fee for a contract selling for $0.5 is 1.75%. *Polymarket* was also founded in 2020 and it has become the largest political prediction market exchange with nearly $2.1 billion dollars being transacted on nearly 2,000 political markets running on a blockchain architecture that allowed decentralized, crypto-denominated trading with near-unlimited stakes. *Polymarket* does not charge a fee for trading, but it does impose a very low transaction cost of around $0.007 per trade. U.S. users were also restricted after 2022, meaning that *Polymarket* political markets were populated by non-US traders in 2024 (or US traders using VPNs and other technologies to evade regulatory bans).[4]

Because these four exchanges differ in design, regulation, and trader restrictions, they may also differ in how efficiently information should be aggregated. *IEM* and *PredictIt* attract smaller, more academically oriented traders facing strict participation caps and higher fees in ways that limit liquidity and should reduce speculative volatility. In contrast, *Kalshi* and especially *Polymarket* feature fewer restrictions, more liquidity, and more money involved (including cryptocurrency). As a result, traders seeking to hedge against political risk, use momentum-trading strategies, or take risky bets in the hopes of securing very large payouts are far more likely to trade on *Polymarket* or *Kalshi*. Because market prices are known, pricing differences in similar contracts is difficult to rationalize in terms of the efficient market hypothesis and they likely indicate heterogeneous beliefs, skill or motivation.

The number and nature of contracts varies dramatically across the four exchanges.[5] Some markets are highly liquid, information-rich, and widely followed (e.g., contracts related to whether a candidate or party will win the 2024 U.S. presidential election). Others concern niche or low-information events that are more akin to speculation or entertainment (e.g., whether a candidate will win by a specific vote margin or utter a specific word in a specific speech). The number and variety of contracts across and within exchanges facilitates our investigation by allowing us to analyze the variation in prices of similar markets within and between exchanges: if markets truly aggregate all available information, then well-defined contracts dealing with information-rich outcomes such as election results should display higher accuracy and efficiency than contracts based on ambiguous or entertainment-driven

4. The fact that *Polymarket* relies on cryptocurrency means that US users could avoid having to use the regulated banking system to get money into and out of *Polymarket*.

5. Every market technically includes two contracts—“Yes” and “No”—but we focus on one side of each, given that the two are nearly perfectly correlated.

events. [6] As a result, focusing primarily on the most salient and information-dense markets is sufficient for evaluating whether political prediction markets accurately and efficiently aggregate information in ways consistent with the efficient market hypothesis.

To begin, we characterize the accuracy of every actively traded market on *Kalshi*, *PredictIt*, and *Polymarket* using the average contract price of the day prior to Election Day.[7] While some markets had resolution dates after Election Day, assessing markets as of the day prior to Election Day is an appropriate baseline as the prices on that day reflect more information for more unresolved contracts than any other day prior to Election Day itself (when nearly all markets converge once actual election results begin to be reported).

3 Assessing Market Accuracy

If political prediction markets correctly and accurately aggregate information, a necessary condition is that we should see a high level of accuracy; prices greater than $.5 should predict events that occur and prices less than $.5 should signal those that do not. Even if there is some variation in performance because of differences in the information environment across the various markets, we should not see many markets that are worse than a coin-flip unless

6. There are 188 markets on the national presidential race, 38 related to turnout, and 493 on state-level presidential outcomes (e.g., "Will the Democratic Party win Massachusetts?" or "Will Trump flip a Biden state?"). Another 313 markets covered non-presidential contests such as gubernatorial, Senate, or House races (e.g., "Will Republicans hold between 200 and 204 House seats?"). In addition, 208 markets focused on polling or prediction-based metrics (e.g., "Will Trump win 55% of voters without a college degree?"). The largest category—1,034 markets, mostly found on *Polymarket*—concern the content of political speeches (e.g., "Will Trump say 'McDonald's' during the Hannity town hall?"). Finally, 221 markets covered other politically relevant events.

7. We exclude the *IEM* exchange for this analysis because it has only two markets - a market for who will win and a market for the popular vote margin.

the political reality changes between when the closing price was set the day before Election Day and the outcome is resolved. While this may certainly be true for some markets, it seems unlikely to be true for most.

To descriptively and succinctly characterize the distribution of market performance on the three major trading exchanges using both accuracy measures, Figure 1 graphs the average log-skill accuracy for each market using the daily closing price of the 1,237 active markets on November 4, 2024 – the day before Election Day. Markets are those with a log skill greater than 0 – meaning that the making a prediction based on the closing price on the day before Election Day is more accurate than making a prediction based on the outcome of a flip of a fair coin. (Markets that closed prior to Election Day are analyzed in the Appendix; markets on *IEM* are excluded because there are only four contracts.)

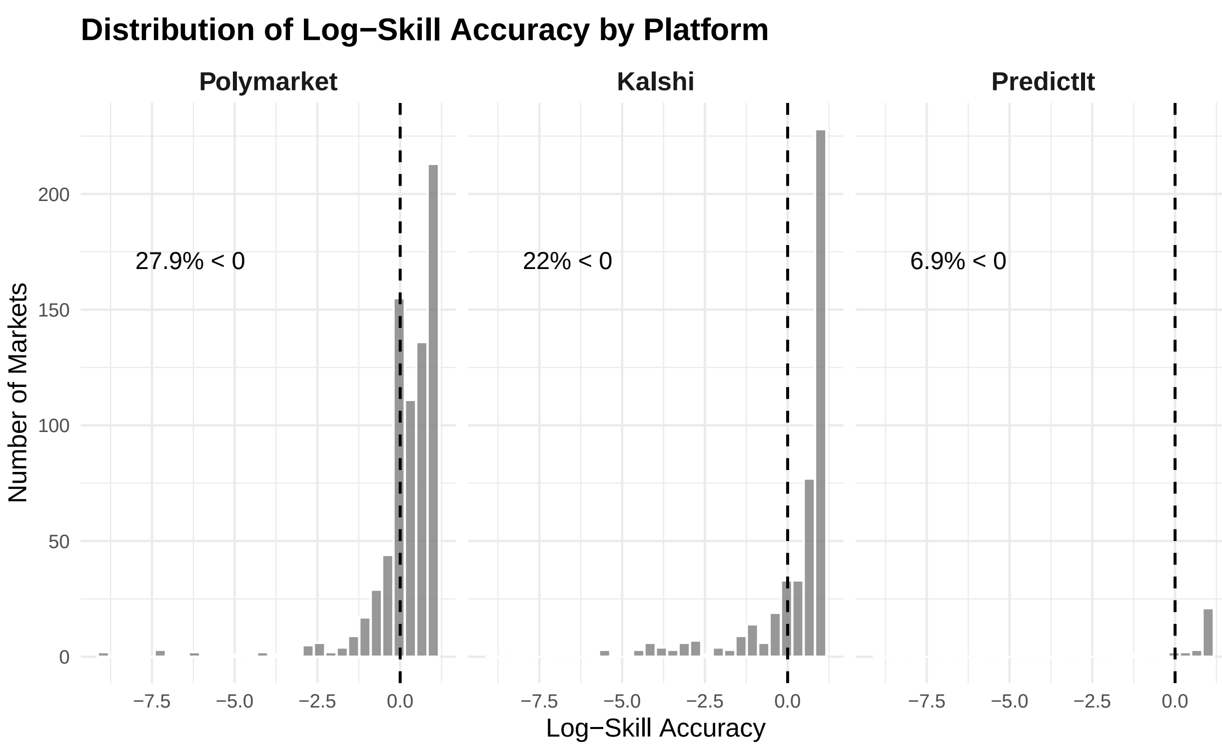


Figure 1. Market-Level Accuracy by Exchange as of November 4, 2024: The day before the 2024 U.S. General Election). Each plot graphs the distribution of log-accuracy scores on *Kalshi*, *Polymarket*, and *PredictIt* as of the day before the U.S. General Election on November 5, 2024. See Figure A1 for the analogous distribution of brier scores, Figure A2 for the relationship between the two measures, and Figure A5 for the accuracy using alternative forecasting windows.

The results reveal substantial variation across exchanges – *Predictit* has the highest percentage of accurate contracts and *Polymarket* the least. More specifically, prices in 93% of *PredictIt*'s markets correctly predicted the outcome better than a coin-flip, compared to 78% of *Kalshi* markets, and 67% of *Polymarket* markets using the log-skill measure. Of course, the overall average accuracy is difficult to interpret because differences may be due to the type of markets being traded on each exchange as well as perhaps the characteristics of traders and nature of trades being made. The costs and restrictions on *PredictIt*, for example, may make it less appealing for those seeking to make large purchases as a political hedge and/or discourage risk-acceptant traders seeking to use momentum-based trading strategies relative to the more liquid and unrestricted trading available on *Polymarket* and *Kalshi*. Moreover, there are many more low-volume and low-information markets on *Kalshi* and *Polymarket* for which may be inherently harder to predict (e.g., whether a candidate says a particular word in a speech or whether a candidate wins by a specific margin).[8] Suggestive of this possibility, although nearly $198 million dollars was transacted between September 1st and November 5th on markets that were less predictive than a coin flip, most of the money – more than $2.2 billion dollars – was transacted on markets whose prices were more accurate than a coin-flip.

To better, but not perfectly, characterize the extent to which market accuracy depends on trading volume and other features of the exchange and contract, we predict the accuracy of markets graphed in Figure 1 as a function of: the exchange the contract is being traded on (and therefore the type of traders who are trading the contract), the total volume of trading on that contract (is more volume associated with more accuracy?), and the type of contract being traded. To account for variation in market accuracy related to differences in either the

8. As a result, the summary measures of overall accuracy are obviously not a statement about the relative quality of the various exchanges. Nor are these differences obviously related to how much traders can profit from each exchange (or each contract). In fact, the more inaccurate and inefficient a market is, the more profit a well-informed trader can make.

baseline probability of the event (e.g., a market involving a rare event is more easily predicted than an event with even odds) or the amount of available and knowable information (e.g., a contract on who will win the presidential election versus a contract whether a particular candidate will say a specific word at a given event) we hand code the topical content of the 1,237 political contracts being analyzed. (See Appendix B for details on the coding rubric.) Because contracts that require specific conditions may be harder than those that do not - e.g., a contract for whether President Trump will win versus a market for whether President Trump will win with between 3% and 4% of the national popular vote, or by a specific margin in the Electoral College - we also code whether the contract requires specific conditions to successfully resolve (*Margin*).

We characterize the correlates of market accuracy on the day before Election Day using:[9]

$$\begin{aligned} \text{Accuracy}_i \; &= \beta_0 + \beta_1 \, \text{DaysBeforeElection}_i + \beta_2 \log(\text{TradingVolume})_i \\ &+ \beta_3 \, \text{PredictIt}_i + \beta_4 \, \text{Polymarket}_i + \gamma_i + \varepsilon_i. \end{aligned} \tag{1}$$

Figure 2 plots the resulting coefficients and 95% confidence intervals.

All else equal, and consistent with Figure 1, markets on *PredictIt* are more accurate on average and markets on *Polymarket* are the least accurate (*Kalshi* is the omitted base category).[10] Whether this is due to the type of traders (e.g., does the higher costs of PredictIt mean that more traders are focused on the long-run contract rather than short-run momen-

9. Note that some of the markets – e.g., those related to political speech – were already resolved and are subsequently excluded. Appendix C reports analyses examining the average daily accuracy starting October 1st. We also pool the daily data and augment the estimating equation with daily fixed effects to measure changing accuracy over time across all markets. See Section D for the average accuracy of presidential markets over time.

10. When looking at the average performance starting on September 1st and allowing for systemic daily shift captured by daily fixed effects *Polymarket* emerges as more accurate, on average, than *Kalshi.* This is because *Polymarket* has many more markets that resolve prior to Election Day related to rare-events which

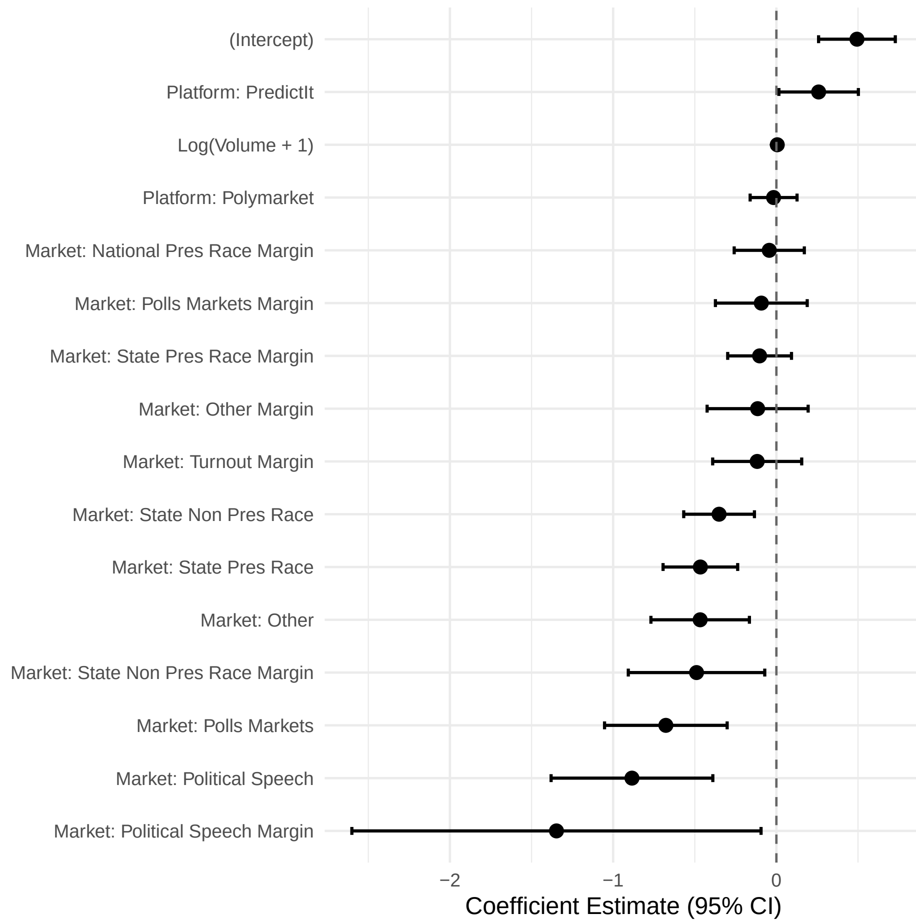


Figure 2. Correlates of Market Accuracy Using Log Loss Measure on November 4, 2024. Dependent variable is the Log Loss Accuracy score of the market on November 4, 2024, Hetereoskedastic consistent standard errors used to construct 95% confidence intervals. Regression coefficients reported in Table A1.

tum trading; do foreign traders using cryptocurrency interpret the political events in the US differently that US citizens trading on Kalshi?) or the residual effect of differences in the markets being offered that are not captured by the crude indicators we employ is uncertain, but the larger point is that there is variation that seems important to consider when trying to interpret how well the price might forecast the outcome. Consistent with the amount of attention and information available, contracts dealing with the national presidential outcome (the omitted category) are the most accurate, on average, with 82% of the 72 contracts being

produce a higher average accuracy due to prices for unlikely events being < \$.5.

more accurate than a coin-flip. The average accuracy of markets involving presidential (*State Presidential Race*) and non-presidential (*State Non Pres Race*) races are less accurate, with average accuracies of 72% and 71% respectively. Markets related to whether a politician says a specific word at a specific event have the worst overall average accuracy; prices on *Political Speech* markets correctly anticipate the outcome in only 62% of the contracts. The (logged) number of trades on a contract are unrelated to accuracy controlling for exchange contracts differences.[11]

It is clear, and perhaps expected, that generic conclusions about the overall performance of prediction markets are hard to sustain in light of these analyses. Although some markets and exchanges, appear to perform well, accuracy is not an inherent property of political prediction markets per se. Many markets in 2024 were inaccurate despite the amount of money involved and the amount of trading activity we observe is largely unrelated to overall accuracy. It is difficult to precisely characterize the amount of information associated with each market, but markets dealing with political outcomes receiving more information and public attention were generally more accurate.

Although it is impossible to determine whether the level of accuracy reflects the nature of the market or the variability of the political environment, it is clear that while political prediction markets are generally accurate – perhaps even surprisingly so given the number of low-volume and low-information markets – that they do not necessarily provide an accurate forecast of what is yet to come. Instead, it is important to consider the ways in which the characteristics of each market – and the nature of the political event being bought – may affect how well the price is likely to reflect the eventual outcome.

11. Including an interaction between the number of transactions and the exchange does not change conclusions - see Tables A5 and A6.

4 Assessing Market Efficiency

Accuracy is necessary, but not sufficient to claim that prediction markets aggregate information in ways that would justify treating contract prices as a statement about expected outcomes. To assess the extent to which the political prediction markets can be interpreted as efficiently incorporating new information and capture all existing information we conduct several analyses. The motivating idea is that if prices reflect a forward-looking expectation based on an aggregation of all available information – which includes the prices of similar contracts on other exchanges! – then the prices of all markets involving similar markets should covary in meaningful and expected ways.

First, similar contracts related to the same political event should be priced similarly. It should not be possible to find arbitrage opportunities whereby traders can buy both Harris and Trump contracts for less than $1 and guarantee a risk-free profit (minus transaction costs). Second, prices of related contracts involving the same political event should covary over time. An increase in the price of a Trump contract in one market/exchange, for example, should be associated with an increase in the price of Trump on similar contracts across all similar markets on all exchanges, and it should also be associated with a decrease in the price of a Harris contract. Third, if the price of a contract, contrary to public opinion polls, reflects a forward-looking expectation about what current information suggests is likely to happen in the future based on rational expectations, daily price changes should be uncorrelated over time because expected future consequences should be priced in (absent recurring, correlated, and unexpected revelations).

To evaluate the extent to which similar markets behave similarly we focus on the efficiency of the most similar contracts involving the most accurate – and salient – contracts related to the national presidential outcome. Because there are many markets related to various aspects of the national presidential outcome, we focus specifically on the Harris and Trump markets in each of the four exchanges dealing with who would win.[12] We analyze the behavior of

12. Prediction market contracts varied slightly across exchanges. On *Kalshi*, traders could purchase contracts

market prices over the last five weeks of the campaign starting October 1, 2024. Given the dramatic restructuring of the presidential contest caused by President Biden dropping out and Vice President Harris stepping in, focusing only on the latter part of the campaign not only gives traders participating on political prediction markets enough time to digest the consequences of the earlier turmoil, but it also focuses on the time in which there is the most cumulatively available information and attention. Put simply, the conditions we examine should be relatively favorable for finding evidence consistent with efficient markets.

Figure 3 plots the daily closing price for a contract paying $1 if Trump, Harris, generic Democrat, or a generic Republican wins the presidential election.[13]

Although there are some similarities in the contract prices during the last 5 weeks of the campaign – e.g., Trump generally led and Harris generally trailed over this period – the prices on these similar contracts are clearly different and not moving together. Over this

phrased as: "Will Kamala Harris or another Democrat win the Presidency?" and "Will Donald Trump or another Republican win the Presidency?" On *Polymarket*, analogous contracts included: "Will Kamala Harris win the 2024 US Presidential Election?", "Will Donald Trump win the 2024 US Presidential Election?", and "Which party wins 2024 US Presidential Election?" On *PredictIt*, contracts were phrased: "Who will win the 2024 US presidential election — Harris" and "Who will win the 2024 US presidential election — Trump." Finally, on the *Iowa Electronic Markets (IEM)*, the contracts were: "$1 if the Democratic Party nominee receives the majority of popular votes cast for the two major parties in the 2024 U.S. Presidential election, $0 otherwise" and "$1 if the Republican Party nominee receives the majority of popular votes cast for the two major parties in the 2024 U.S. Presidential election, $0 otherwise."

13. Both *Kalshi* and *Polymarket* use UTC timestamps, but *PredictIt* is based on Eastern Standard Time (and therefore 4-5 hours behind UTC). As a result, there are slight and unavoidable differences in how closing prices map onto the political time when comparing either *Kalshi* or *Polymarket* to *PredictIt*. Restricting the analysis to contracts on *Kalshi* or *Polymarket* to ensure a consistent temporal mapping does not change our substantive conclusions.

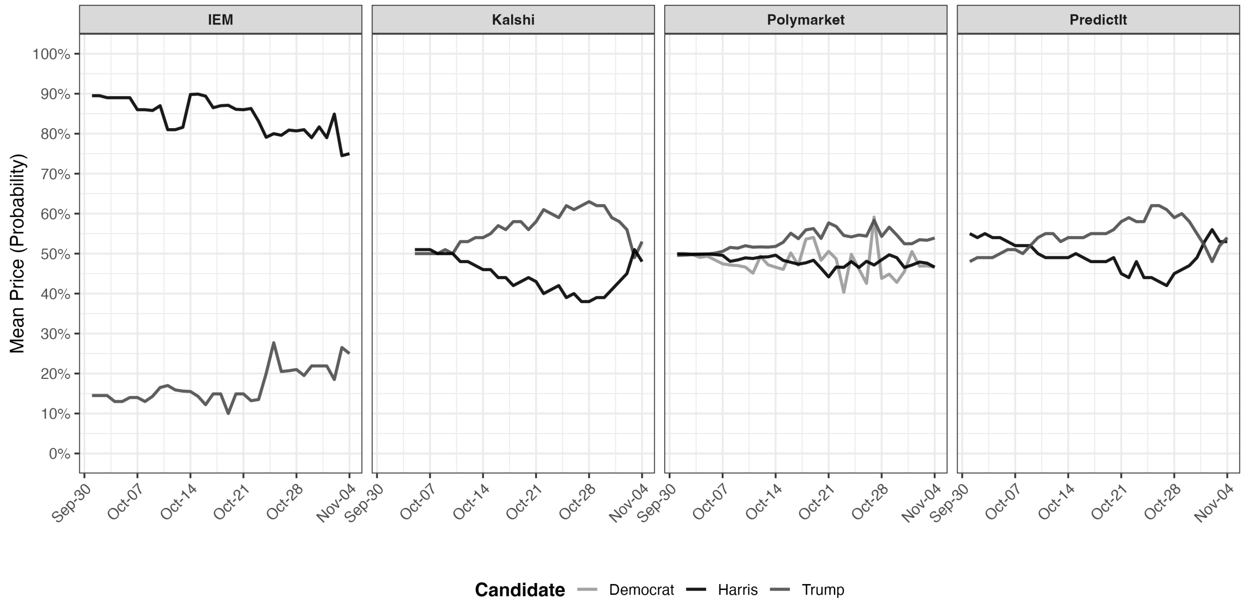


Figure 3. Daily Closing Prices for Presidential Outcome Market Price By Exchange, 10/1/24 - 11/4/24. Only the most-similar contracts related to the national presidential outcome on each exchange are included. The IEM market is related to the national popular vote.

period, Trump never loses the lead in *Polymarket*, and on *Kalshi* he leads every day except 10/05, 10/06, 10/07, and 11/03. On *PredictIt*, Harris begins October with the lead, loses it, and then regains the lead immediately prior to Election Day. Perhaps reflecting the fact that the *IEM* contract was a winner-take-all market based on the national popular vote, the pricing was completely different as it suggested that Harris was going to easily win through the entirety of the time period (in reality, President Trump won the national popular vote by 1.5%). These price differences are hard to reconcile with the idea that traders motived by the desire to win $1 are placing bets with the sole purpose of trying to buy the contract that they think will pay out. Not only are the prices (implied probabilities) different, but the pricing differences persist even as more information is revealed and the opportunity for new information decreases. As of the day before Election Day, the closing price differs between similar contracts on different exchanges.

Beyond the dissimilarity of levels evident in Figure 3, we can also compare the extent to which prices and changes in daily closing prices are correlated between markets over time.

If market prices reflect common information, including the prices of similar contracts on the other political prediction markets, the average prices and price changes should be highly correlated. Given the anomalous behavior of the *IEM* markets, in the analyses that follow we focus on markets being traded on *PredictIt*, *Kalshi*, and *Polymarket*.

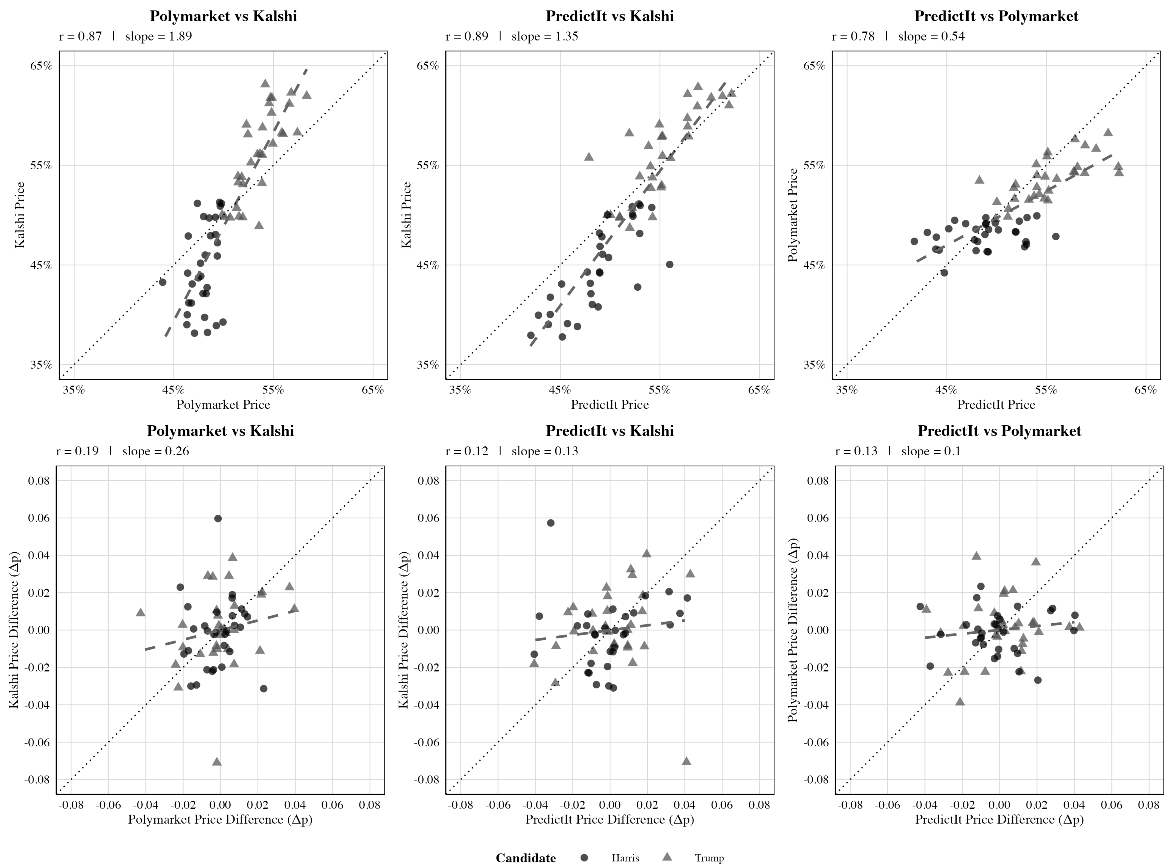


Figure 4. Cross-Market Daily Price (top) and Change (bottom) for 2024 U.S. Presidential Contracts: 10/1/24-11/4/24. Each panel compares the daily average "yes"-contract price for *Trump* and *Harris* across the *Kalshi*, *PredictIt*, and *Polymarket* exchanges. The 45-degree dotted line denotes parity between exchanges, while the dashed line is the least-squares fit for the observations. In appendix E, Figure A10 presents the relationship for the closing price change using 2 and 3 day windows, Figure A11 presents the relationship for 4 and 5 day windows, and Figure A12 presents the relationship for 6 and 7 day windows. Although the correlation in price changes increases as the temporal bandwidth increases, there is still substantial variability. The maximal correlation occurs for 7-day price changes and it is 0.42 for *Polymarket* and *Kalshi*, 0.78 for *PredictIt* and *Kalshi*, and 0.31 for *PredictIt* and *Polymarket*.

The top row of plots in Figure 4 shows that the closing prices are indeed correlated across exchanges – with correlations ranging from 0.78 to 0.89 – but that there are also curious differences. The slope in the relationship between *Polymarket* and *Kalshi* is 1.89 meaning that every increase in price in *Polymarket* is associated with a 1.89 increase in *Kalshi*. It is unclear why the fluctuations would be more dramatic in *Kalshi* than *Polymaket*. In contrast, *PredictIt* is far less variable than *Polymaket*; a one unit increase in *Polymarket* price is associated with only a 0.54 increase in price for the equivalent *PredictIt* contract. While the high correlations in prices are reassuring, meaning that when one market price is above its average price it is likely that the other markets are also likely to be greater than their means, the relationship is imperfect and hard to rationalize under the efficient market hypothesis given that the contracts all depend on the same political outcome. Moreover, the fact that *PredictIt* and *Kalshi* are more similar, and *Polymarket* is more dissimilar, suggests potential differences in how traders react to the same information.

The bottom row of plots in Figure 4 compares how the daily prices change compare across exchanges and raises additional questions about the efficiency of these most-similar markets. *PredictIt* and *Kalshi* have the highest correlation in daily price changes during the last five weeks of the campaign, but the bivariate correlation is only 0.36 and the relationship between the daily price changes is modest at best; a one unit change in the daily price change on *PredictIt* is associated with only a 0.09 increase in the daily price change of the *Kalshi* contract. The lack of correlated price changes we observe on contracts involving the same political event suggests that traders are not responding similarly to either actual political events or the prices of similar contracts on other exchanges. Instead, the price changes appear to vary idiosyncratically within a specific market – suggesting that internal market dynamics rather than the larger political dynamics affect market prices. As the analyses in Appendix E reveal, expanding the temporal window to allow for a lagging responsiveness increases the correlation in price changes across markets, but the relationship continues to exhibit considerable variability. Even looking at the 7-day difference in prices (Figure A12), the correlation in final closing prices is only 0.42 between *Polymarket* and *Kalshi*, 0.78 between *PredictIt*, and *Kalshi*, and 0.31 between *PredictIt* and *Polymarket*.

The inefficiency of the national presidential market is highlighted by considering the available arbitrage opportunities from buying both a contract for Harris winning and a contract for Trump winning using the cheapest daily closing price on *Kalshi*, *PredictIt*, and *Polymarket*. Insofar as either Harris or Trump was going to win – i.e., there was not some other candidate who could become president (which, although constitutionally possible seems infinitesimally likely) – then it should not be possible to buy contracts for both Trump and Harris winning for less than $1 total as this would guarantee a risk-free profit for the trader (minus transaction costs). If the markets are efficient and reflect all available information, including the information contained in the prices for similar contracts on the other exchanges, the total cost to buy the cheapest Harris and Trump contracts should sum to $1 every day.

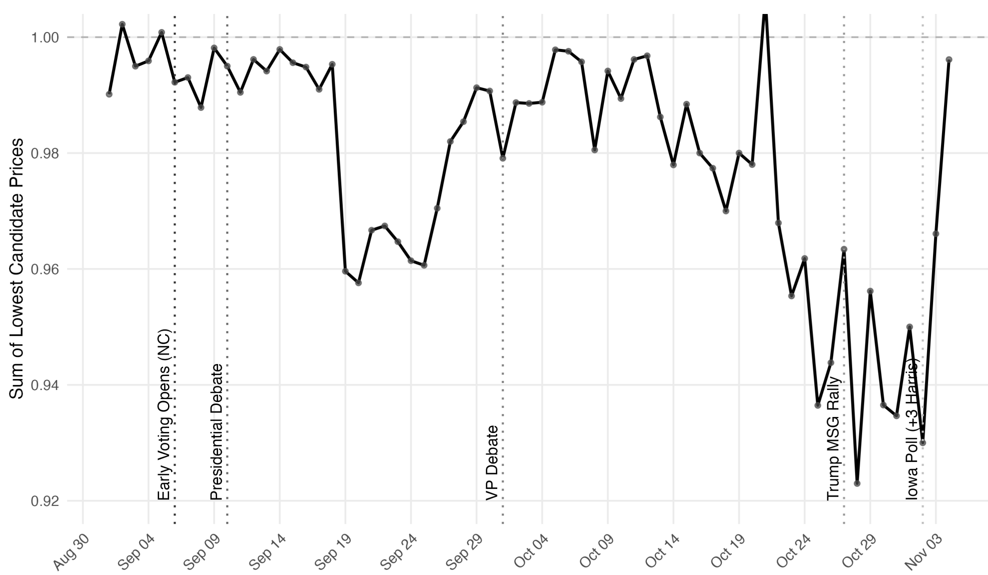


Figure 5. Cross-Market Daily Price (top) and Change (bottom) for 2024 U.S. Presidential Contracts: 9/1/24-11/4/24. Each panel compares the daily arbitrage opportunity from buying both *Trump* and *Harris* contracts at the cheapest daily closing price on *Kalshi*, *PredictIt*, and *Polymarket* assuming no transaction costs. See Figure A9 for substantively similar results accounting for the transaction costs.

Figure 5 graphs the daily cost of buying the cheapest contract for both Harris and Trump based on the closing price on the *Kalshi*, *PredictIt*, and *Polymarket* exchanges and shows that arbitrage opportunities exist on 62 out of the 65 days. Moreover, the opportunity for arbitrage actually grows in the last two weeks before converging to zero on Election Day once the actual vote begins to be reported. The fact that the opportunity for arbitrage increases rather than decreases in the end is contrary to what should be observed by traders seeking to maximize their profit by buying contracts that they think are most likely to payout. Rather than seeing the most convergence in prices immediately prior to the election when almost all of the information has been revealed and there is the least amount of time remaining for an unexpected revelation, we instead see that the differences in the closing prices between most-similar contracts are larger than any other point since the official nomination of Vice President Harris by the Democrats.

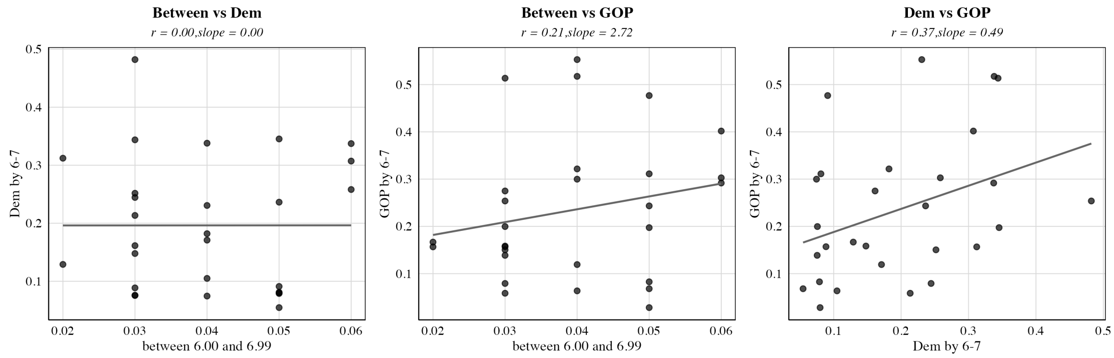
4.1 Benchmarking Efficiency

To benchmark the efficiency of the national presidential markets, we compare them to contracts that are related but harder to accurately price. Specifically, we focus on contracts involving whether a presidential candidate wins the national race by a specific popular vote margin. Information about who is likely to win is relatively abundant, but accurately predicting by how much is nearly impossible given the number of unknowable contingencies (e.g., differential turnout, late shifts in persuasion, local variation in support, polling error). Even so, if traders in these markets who are rationally processing limited information (which includes the prices of related markets on prediction markets), we should still observe relatively high correlations among the most similar contracts because the prices on similar contracts should reflect the same sparse but salient signals. But if these contracts attract more speculative or recreational traders who are chasing momentum or wagering on long odds, then prices on markets pertaining to the same outcome may diverge substantially across markets and exchanges.

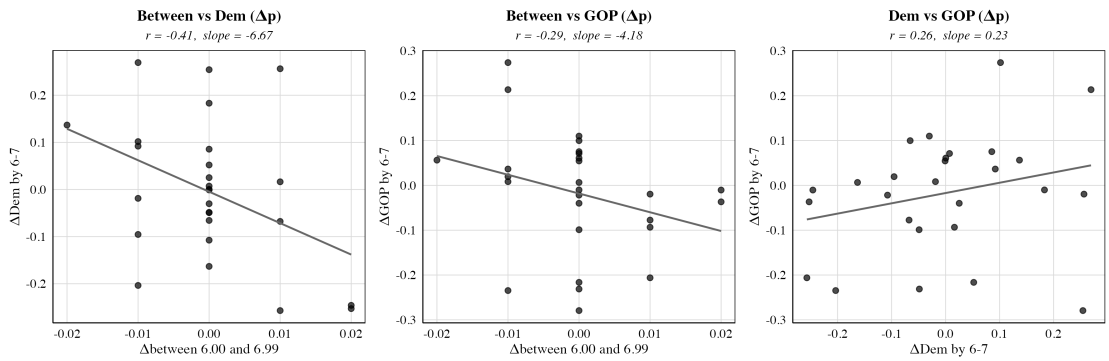
To illustrate the general relationship we find, Figure 6 presents a comparisons of the temporal correlation of prices and daily price changes for a market predicting that the Democrat/Harris and/or Republican/Trump candidate will win by between 6.0 % and 7%.[14]

14. The left panel of Figure 6 is *Kalshi* (“between 6.00 and 6.99") vs. *Polymarket* (“Dem by 6-7"). The

(Appendix F reports similar results for the other existing margin contracts.)



(a) Price levels for 6–7% margin group



(b) Daily price changes (Δp) for 6–7% margin group

Figure 6. Comparison of price level correlations and daily price change correlations among contracts in the 6–7% winning margin group. Each scatterplot shows pairwise relationships between *Overall Between vs Dem*, *Overall Between vs GOP*, and *Dem vs GOP* contracts. Each point represents a single trading day during the pre-election window (October 1 – November 4, 2024), and fitted regression lines summarize the daily co-movement of prices. Correlation coefficients (r) and slope estimates (β) are annotated in each panel. Results for other winning-margin groups (0–1% through 7%+) are provided in Appendix F.

The relationships summarized in Figure 6 provide little evidence of informational efficiency. The top-left plots compare the price for a contract that Harris wins by the specified margin and price for a contract that either candidate wins by the same margin. The bottom-left plots the change in closing prices for the same two contracts. As Harris is one of the two

middle panel is also *Kalshi* and the Republican margin contract "Rep by 6-7" on *Polymarket*. The right panel is a comparison of two markets that are both on *Polymarket* ("Dem by 6-7", "Rep by 6-7").

candidates running, there should be a positive correlation between both the price and the price change for these two contracts, but it is immediately clear that there is no relationship between prices (top) and there is a unexpectedly negative correlation among price changes. We see a similar lack of expected relationship when looking at the relationship with Trump in terms of prices (top middle) and price changes (bottom middle). The sole positive relationship emerges in prices, but the correlation is so modest (0.29) as to underscore the weak alignment of related markets. Even more striking is the fact that the correlation between the “Democrat by 6–7%" and “Republican by 6–7%" contracts is positive for both comparisons. The logical inconsistency of both outcomes simultaneously becoming more or less likely suggests that traders on these markets were almost certainly engaging in speculative or idiosyncratic trading disconnected from the underlying fundamentals. No information being aggregated in a rational and forward-looking manner would ever suggest that the probability that a Democrat wins by between 6% and 7% is positively correlated with the probability that a Republican wins by the exact same margin in the same race, but this is what the correlated prices on this market suggests.

Beyond suggesting that there is very little information in the prices of these markets, these markets can also be used to benchmark the performance of the national presidential market considered earlier in Figure 4. The correlation of prices and price changes for markets involving the presidential outcome are never negative, but the highest correlation we observe in daily price changes (0.19) is actually less than the correlation we observe in margin markets predicting mutually exclusive outcomes (0.29). The fact that the correlation in daily price changes for two logically incompatible contracts exceeds that for nearly identical contracts on different exchanges raises important questions about whether changing prices in political prediction markets are revealing genuine political information or whether they are merely reflecting the speculative behavior of participants reacting to one another.

4.2 Are Political Markets Random Walks?

The classic test of market efficiency examines the extent to which daily price changes follow a martingale process whereby the change in prices on day t is unrelated to the change in prices on day $t-1$ (Fama, 1970). Theoretically, price changes should be uncorrelated over time because the closing price on day t should reflect all available information as well as the effect of that information on forward-looking expectations. If so, future price changes should only reflect new, unexpected information because the expected effects of "political momentum" should already be priced in. Positive correlated price changes should not occur absent a sequence of unexpected information reinforces prior information. This seems plausible given the nature of the information environment. Negative correlated price changes are harder to rationalize because they suggest that an increase in prices on day t is more likely to result in a decrease in prices the following day. Although it could reflect off-setting news cycles whereby a positive focus on one day causes a negative focus the following day in ways that traders are seemingly unable to expect, it is also consistent with a price correction caused by traders reacting to a price increase that was larger than can be rationalized in retrospect.

To evaluate this hypothesis, for each market i, we estimate:

$$\Delta P_{it} = \rho_i \, \Delta P_{i,t-1} + \varepsilon_{it}$$

where $\Delta P_{it} = P_{it} - P_{i,t-1}$ is the daily change in the market-implied probability of the event occurring and ρ_i is the within-contract correlation of price changes. To fix the temporal window, we estimate the equation using daily price changes starting on September 1st.

If prices fully reflect available information and traders are correctly forecasting the impact of future events, changes should be serially uncorrelated ($\rho = 0$). However, $\rho = 0$ is also consistent with the possibility that there is no new information that would update traders' beliefs. Finding $\rho > 0$ suggests that positive price changes in the past are correlated with positive price changes in the future (and likewise for negative changes) as might be consistent with long periods of unexpected and confirmatory information that creates political momentum for a candidate. Finding $\rho < 0$ is more difficult to reconcile with efficient information processing, as this indicates that an increase in price tends to be followed by a decrease – a pattern consistent with short-term overreaction or profit-taking by momentum traders who sell after recent gains. A negative ρ can also arise if many traders discount or reinterpret incoming information, causing those who believe "nothing has changed" to unwind the adjustments made by others. In this case, prices oscillate around a stable underlying belief rather than track new information.

We separately estimate ρ_i for each market and then summarize the percentage for each market type that are: indistinguishable from zero and consistent with a random walk, significantly positive, and significantly negative.

Market Type	**# Markets**	**Mean ρ**	**Insignificant (%)**	**Negative (%)**	**Positive (%)**
Turnout	36	−0.233	94.4	5.6	0.0
Political Speech	105	−0.644	89.5	8.6	1.9
Polls & Prediction Markets	152	−0.299	75.5	24.5	0.0
Other	173	−0.344	57.7	41.0	0.0
State Presidential Race	450	−0.335	55.9	44.1	0.0
State Non-Presidential Race	235	−0.334	46.4	53.6	0.0
National Presidential Race	182	−0.324	41.7	58.3	0.0

Table 2. Average Price Autocorrelation by Market Type. Entries show the mean first-order autocorrelation coefficient (ρ) from random-walk regressions of daily price returns by market type. Percentages indicate the share of markets with statistically insignificant, significantly negative, or significantly positive autocorrelation. $\rho < 0$ indicates mean reversion (i.e., price reversals rather than persistence).

Table 2 reveals considerable heterogeneity in the correlation of price changes over time based on the nature of the political contract. For the 182 markets dealing with national presidential outcome, only 41.7% have uncorrelated price changes. In fact, most of the 182 markets (58.3%) have negative, statistically distinguishable, daily price changes. For markets dealing with turnout, political speech, and the outcomes of polls and prediction markets there is much less correlation between daily prices.

These findings reveal a notable disconnect between predictive accuracy and informational efficiency. National presidential markets were the most accurate in predicting outcomes, yet the most inefficient in how they incorporated information as they frequently exhibit short-term reversals rather than a smooth convergence toward the eventual outcome. Two possibilities can account for this pattern. One is belief stability: if many traders interpret political developments as inconsequential, they may routinely unwind the price movements generated by those who react to new information, producing a back-and-forth pattern around a stable expectation. The other is overreaction: high attention, liquidity, and speculative trading can cause new information to be incorporated too aggressively, leading to subsequent corrections or profit-taking that generate the same oscillatory dynamics.[15] Among less salient markets (e.g., markets focused on turnout, political speech, or electoral margins), the patterns appear more "efficient," but this likely reflects limited participation and sparse information, which naturally dampen volatility, rather than more rational information processing. Regardless of how we interpret the meaning of the negative serial correlation we find, the broader pattern suggests that prediction markets can arrive at correct final forecasts even while processing information inefficiently, with prices drifting toward the truth through alternating waves of enthusiasm and correction rather than a steady, monotonic convergence.

4.3 Correlated Responses Across Similar Markets

Turning to the relationship of prices, we should observe that the prices of correlated markets react similarly over time. Focusing on the national presidential contracts provides the most compelling examination of this property not only because they are the most widely traded, but also because they are the most accurate. If these markets efficiently aggregate information, the fact that all contract prices are public means that an increase in the price

15. That said, the fact that markets containing much less information – and which therefore also involve traders with stable beliefs due to the lack of any new information – are more likely to be estimated to have no relationship raises interesting questions about why stable beliefs would produce a negative serial correlation in winner-take-all presidential markets but no correlation others.

of a Trump contract in one market/exchange should be associated with an increase in the price of Trump on similar contracts, but it should also be associated with a decrease in the price of a Harris contract. Moreover, the days on which we observe a change in prices should not reflect "animal spirits," but they should instead correspond to politically relevant events.

To systematically assess whether daily price changes vary across similar markets in ways that would be consistent with the incorporation of new information, we conduct an event analysis using a lagged price regression that models the relationship between daily closing prices. To do so, we again focus on the most-similar contracts pertaining to either a Trump or Harris victory (see Table A7 for language of the 12 contracts) and we estimate the following specification for separately pooled Trump and Harris contracts to allow relationship to vary by candidate:

$$P_{it} = \alpha + \rho P_{i,t-1} + \iota_t + \gamma_i + \varepsilon_{it}, \tag{2}$$

where P_{it} is the closing price (implied probability) for contract i on day t and $P_{i,t-1}$ is the lagged price and γ_i are contract fixed effects. We separately estimate this specification for every day starting September 1st and vary the indicator ι_t each time to measure whether the prices for the candidate contracts changed significantly on day t.

If $\iota_t \neq 0$, this indicates that the prices of related contracts moved, on average, above and beyond the expected price on day t given the price at time $t-1$. This is consistent with information being revealed on that day being processed similarly by the related presidential candidate markets. Because we are separately estimating each specification for Harris and Trump contracts, we should observe a negative correlation for statistically distinguishable ι shifts – if the average Harris price increases on day t the average Trump price on day t should decrease (ideally by a similar amount).

If $\iota_t = 0$, there are two possibilities: either the event contained no new information, the effects were already anticipated by the market price, and the market prices were largely unchanged as a result, or else offsetting changes on similar markets produced no average price change. The former is consistent with the efficient aggregation of information, but the latter is not. Prices of similar contracts involving the same political outcome should not move in opposite directions on the same day. We can discern which pattern explains finding $\iota_t = 0$ by determining whether the observed average price changes on similar contracts on day t are all near zero or whether there are large and offsetting price changes.

Figure 7 plots the estimated coefficients for ι for separately estimated Harris and Trump contracts related to winning the presidential contest and shows the limited efficiency with which the prices on the most publicized and traded political prediction markets incorporate information. Across the sixty-day period preceding the 2024 election, significant price movements were rare and often occurred on days with no discernible political events. Major campaign moments such as debates, early voting, and key polling releases produced no measurable price changes. This pattern suggests that most information was either already commonly anticipated and priced-in, or that traders did not update their expectations in a coordinated, rational manner when new information emerged.

Even more striking, large shifts in one candidate's contract were seldom mirrored by offsetting movements in the opposing candidate's market, as efficiency would predict. Of the twelve days in which Trump contracts moved significantly, Harris contracts responded in the opposite direction only twice—and neither corresponded to any meaningful campaign event. Likewise, only two of Harris's five significant shifts coincided with comparable movement in Trump prices. Together, these results indicate that markets frequently failed to incorporate information symmetrically or contemporaneously across related contracts.

Consistent with this conclusion is the pattern of price changes occurring on days for which a statistically distinguishable shift does not occur. As the results of Section G reveal, the lack of change implied by $\iota = 0$ is more obviously related to the presence of irrational and offsetting price changes in similar markets than the absence of a price change. Put differently, finding $\iota_t = 0$ is more a consequence of prices on contracts dealing with with the same political event both increasing and decreasing by offsetting amounts in ways that

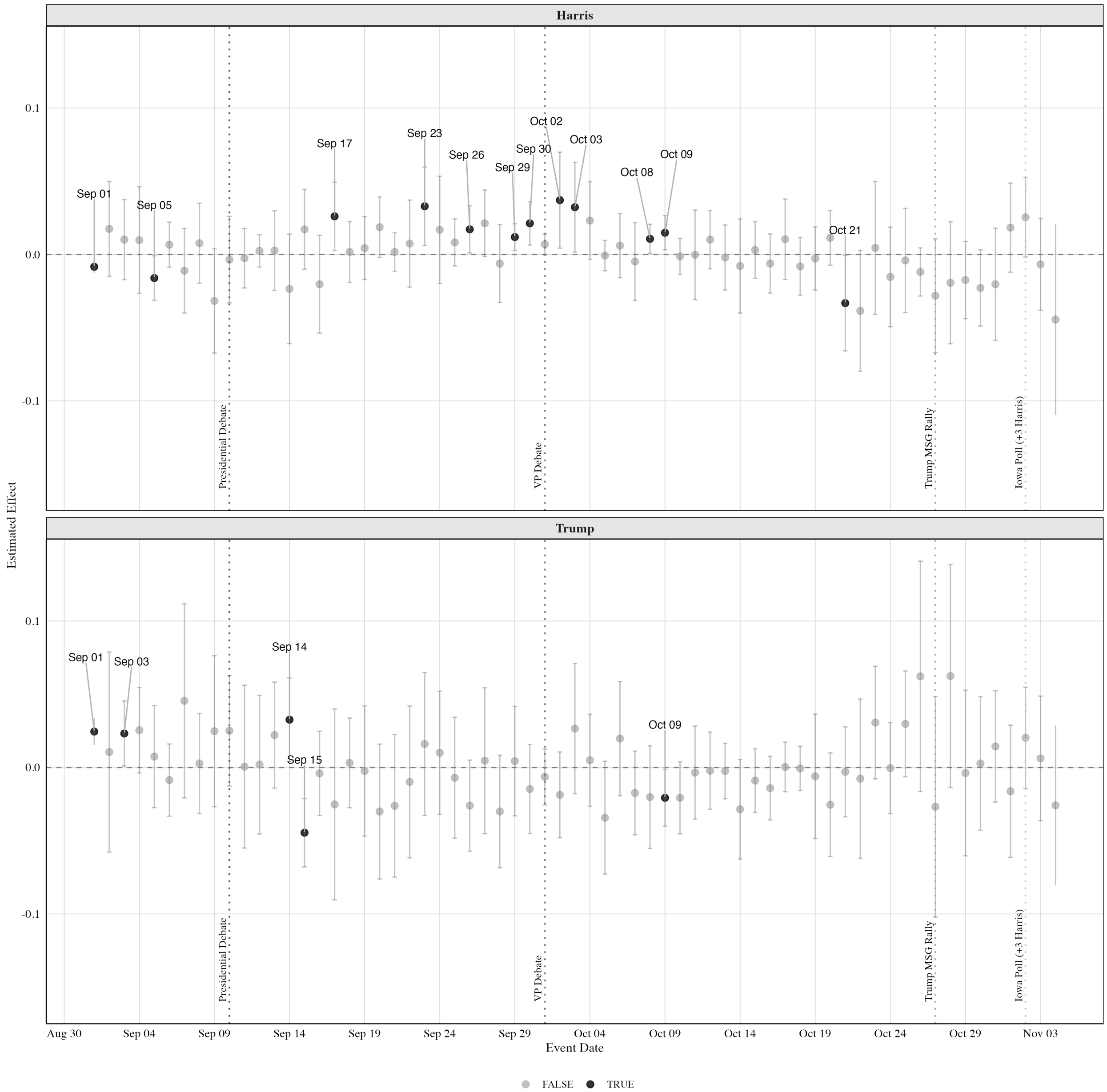


Figure 7. Regression Coefficients For Daily Price Change (ι), 9/1 - 11/4. Each point plots the estimated event coefficient (ι) from daily regressions of market prices on their one-day lag and an event indicator equal to 1 on that specific event day. Vertical dashed lines mark major campaign events, including the first presidential debate (Sep 10), the vice-presidential debate (Oct 1), Trump's MSG rally (Oct 27), and the Iowa poll release showing a +3 point lead for Harris (Nov 2). Filled points denote statistically significant effects at the 5% level ($p < 0.05$). Error bars represent 95% confidence intervals. Separate panels display results for Harris contracts (top) and Trump contracts (bottom).

produce no change in average prices rather than a lack of price changes.

All told, price changes on the most salient and information-rich market being traded in political prediction markets appear to be driven more by idiosyncratic trading behavior, speculation, or liquidity shocks than by the systematic arrival of politically relevant information. Prices of similar contracts do not react similarly when new information became public and markets often moved independently in the absence of any news at all. The patterns we find suggest that even highly visible, liquid political prediction markets did not behave as efficient aggregators of political information.

5 Conclusion and Implications

More money was transacted on political prediction markets in 2024 than ever before, and prices on national and state presidential markets frequently implied that Donald Trump was more likely to win. At the same time, the performance of pre-election polling continues to struggle with issues caused by increasing non-response as well as technological changes such as AI that threaten the accuracy and meaning of the "snapshots in time" that polling can arguably provide. Even so, the desire for forward-looking assessment of what people expect will happen is of tremendous interest to journalists, politicians, businesses and members of the public trying to assess the current and future political, social and economic environment. Prediction markets appear to offer a solution given the logic of the efficient markets hypothesis, the vast amount of money involved, and the accuracy of several high-profile markets in recent elections. Yet it would be a mistake to interpret the apparent accuracy of a few high-profile markets, or the scale of financial activity involved, as evidence that political prediction markets are either inherently accurate or efficient aggregators of information.

Our analysis of nearly 2,500 political markets involving nearly $2.3 billion in volume reveals that the accuracy and efficiency diverged sharply across markets, exchanges, and contract types. While some contracts correctly forecasted outcomes, many others did not, and even the most accurate exchanges exhibited little evidence of information efficiency.

Prices for nearly identical contracts often diverged across exchanges, price changes were only weakly correlated, and arbitrage opportunities existed on nearly one in ten days when information was most abundant during the final 90 days of the campaign. Although overall price levels tended to move together across time (correlations around 0.9 in the final five weeks), daily price changes were almost uncorrelated, implying that markets were not reacting similarly to the same information. In some cases, prices on contracts for mutually exclusive outcomes such as Harris and Trump winning by the same margin varied in tandem in ways that violate even the most basic expectations of rational updating. Event-based analyses reveal the same pattern: large swings in market prices often occurred on days with no identifiable political events, and shifts in one candidate's contract were rarely offset by corresponding declines in the other's.

These results matter because prediction market prices are not merely reflections of belief, they can also shape belief. When journalists, donors, campaigns, and voters treat market prices as authoritative forecasts, they may influence how the public understands what is probable or possible. Market movements can drive horse-race media coverage, donor activity, and even voter participation, while also shaping political and financial decisions tied to expectations about political outcomes. If the prices for political prediction markets deviate from efficient, information-based expectations, the consequences extend beyond traders to the broader democratic and economic systems that interpret them.

Our findings suggest that there are reasons for caution when interpreting the prices of political prediction markets as an accurate and informationally efficient expectation of the probability of an event. Despite unprecedented trading volume and technological sophistication, 2024's political prediction markets often behaved in ways inconsistent with rational information aggregation. The reasons for the inaccuracy and inefficiency we document are many and impossible to identify definitively with market-level data, but they likely stem from a blend of behavioral bias and strategic behavior. Some traders may act on irrational beliefs and cognitive over-reaction (Barberis, Shleifer and Vishny, 1998), or engage in expressive trading driven by the psychological attachments of partisanship (Hong and Kostovetsky, 2012). Others may chase momentum enabled by the interaction of social media, built-in message boards, and other features of the trading exchange highlight the trades of self-branded "alpha" investors (Desiderio et al., 2025; Guan, 2022). Still others may use prediction markets to hedge against political risk by betting on the outcome they most fear rather than the one they expect (Axén and Cortis, 2020; Christensen et al., 2022). Finally, some traders may attempt to manipulate prices to shape media coverage or public perceptions of electoral strength (Thompson, 2012). Put simply, there are at least as many reasons to think that political prediction markets will be inaccurate and inefficient as there are to think that they will. Our investigation shows that, at least in 2024, even though many political prediction markets ended with the correct prediction at the end and they converge once the actual vote count is reported on Election Night, there were many distortions from what we would expect from the efficient market hypothesis. As a result, we should be wary of thinking that these markets are infallible, or that contract prices reflect an unbiased expectation reflecting the forward-looking estimate based on the crowd-sourced aggregation of all available information even despite the amount of money they attract. Polling-based extrapolation poses serious challenges, but political prediction markets do not necessarily provide the imagined panacea.

References

Arrow, Kenneth J, Robert Forsythe, Michael Gorham, Robert Hahn, Robin Hanson, John O Ledyard, Saul Levmore, Robert Litan, Paul Milgrom, Forrest D Nelson, George R Neumann, Marco Ottaviani, Thomas C Schelling, Robert J Shiller, Vernon L Smith, Erik Snowberg, Cass R Sunstein, Paul C Tetlock, Philip E Tetlock, Hal R Varian, Justin Wolfers and Eric Zitzewitz. 2008. "The Promise of Prediction Markets." *Science* 320(5878):877.

Atanasov, Pavel, Phillip Rescober, Eric Stone, Samuel A. Swift, Emile Servan-Schreiber, Philip Tetlock, Lyle Ungar and Barbara Mellers. 2017. "Distilling the Wisdom of Crowds: Prediction Markets vs. Prediction Polls." *Management Science* 63(3):691–706.

Axén, Gustav and Dominic Cortis. 2020. "Hedging on Betting Markets." *Risks* 8(3):1–14.

Barberis, Nicholas, Andrei Shleifer and Robert Vishny. 1998. "A Model of Investor Sentiment." *Journal of Financial Economics* 49(3):307–343.

Bartels, Larry M. 2002. "Beyond the Running Tally: Partisan Bias in Political Perceptions." *Political Behavior* 24(2):117–150.

Berg, Joyce E. and Thomas A. Rietz. 2014. "Market Design, Manipulation, and Accuracy in Political Prediction Markets: Lessons from the Iowa Electronic Markets." *PS: Political Science & Politics* 47(2):293–296.

Bullock, John G., Alan S. Gerber, Seth J. Hill and Gregory A. Huber. 2015. "Partisan Bias in Factual Beliefs about Politics." *Quarterly Journal of Political Science* 10(4):519–578.

Christensen, Dane M., Hengda Jin, Suhas A. Sridharan and Laura A. Wellman. 2022. "Hedging on the Hill: Does Political Hedging Reduce Firm Risk?" *Management science* 68(6):4356–4379.

Crane, Harry and Darrion Vinson. 2023. "Models vs. Markets: Forecasting the 2020 U.S. Election." *Journal of Prediction Markets* 17(2):35–62.

Cutting, Laurie E., Sarah S. Hughes-Berheim, Paul M. Johnson, Hiba Baroud and Brett Goldstein. 2024. Bets vs. Polls: Comparing Prediction Market Forecasts and Poll-Based Averages. Technical report Vanderbilt University. Research Report, retrieved from `https://sos-vo.org/system/files/research.vanderbilt.edu/betsvspoll.pdf`.

Dana, Jason, Pavel Atanasov, Philip Tetlock and Barbara Mellers. 2019. "Are Markets More Accurate Than Polls? The Surprising Informational Value of "Just Asking"." *Judgment and Decision Making* 14(2):135–147.

Deck, Cary, Shengle Lin and David Porter. 2013. "Affecting Policy by Manipulating Prediction Markets: Experimental Evidence." *Journal of Economic Behavior & Organization* 85:48–62.

Desiderio, Antonio, Luca Maria Aiello, Giulio Cimini and Laura Alessandretti. 2025. "The Dynamics of the Reddit Collective Action Leading to the GameStop Short Squeeze." *NPJ Complexity (Online)* 2(1):5. `https://doi.org/10.1038/s44260-025-00029-z`.

Erikson, Robert S. and Christopher Wlezien. 2008. "Are Political Markets Really Superior to Polls as Election Predictors?" *Public Opinion Quarterly* 72(2):190–215.

Fama, Eugene F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *The Journal of Finance* 25(2):383–417.

Forsythe, Robert, Forrest Nelson, George R. Neumann and Jack Wright. 1992. "Anatomy of an Experimental Political Stock Market." *The American Economic Review* 82(5):1142–1161.

Frankel, Alison. 2025. "CFTC Moves to Drop Appeal in Kalshi's Event Contracts Case." *Reuters* . Published May 5, 2025. `https://www.reuters.com/markets/commodities/cftc-moves-drop-appeal-kalshis-event-contracts-case-2025-05-05/`.

Green, Donald P., Bradley Palmquist and Eric Schickler. 2002. *Partisan Hearts and Minds: Political Parties and the Social Identities of Voters*. New Haven, CT: Yale University Press.

Gruca, Thomas S and Joyce E. Berg. 2012. "Public Information Bias and Prediction Market Accuracy." *Journal of Prediction Markets* 1(3):219–231.

Guan, Sue S. 2022. "Meme Investors and Retail Risk." *Boston College Law Review* 63(7):2051–2109.

Hong, Harrison and Leonard Kostovetsky. 2012. "Red and Blue Investing: Values and Finance." *Journal of Financial Economics* 103(1):1–19.

Hüfner, Tassilo and Tom Wilson. 2024. "French Watchdog Probes Polymarket, Where Trader Won Big on Trump Bet." *Reuters* . Published November 7, 2024. `https://www.reuters.com/business/finance/french-watchdog-probes-polymarket-where-trader-won-big-trump-bet-2024-11-07/`.

Jennings, Will and Christopher Wlezien. 2018. "Election polling errors across time and space." *Nature Human Behaviour* 2:276–283.

Jones, Callum. 2024. "Opinion Polls Have Harris and Trump Locked in a Tight Race. 'Gambling Polls' Say Otherwise." *The Guardian* . Published October 31, 2024. `https://www.theguardian.com/us-news/2024/oct/31/election-betting-presidential-odds-polling`.

Kennedy, Courtney, Mark Blumenthal, Scott Clement, Joshua D. Clinton, Claire Durand, Charles Franklin, Kyley McGeeney, Lee Miringoff, Kristen Olson and Douglas Rivers. 2018. "An Evaluation of the 2016 Election Polls in the United States." *Public Opinion Quarterly* 82(1):1–33.

Kharif, Olga. 2024. "Polymarket Says Trump Whale Identified as French Trader." *Bloomberg* . Published October 24, 2024. `https://www.bloomberg.com/news/articles/2024-10-24/polymarket-says-trump-whale-identified-as-french-trader`.

McHugh, Calder. 2025. "Pollsters Have a New Kind of Competitor. They Should Be Worried." *Politico Magazine* . October 24. https://www.politico.com/news/magazine/2025/10/24/political-betting-markets-political-predictions-accuracy-00620431.

Meisels, Mellissa, Joshua D. Clinton and Gregory A. Huber. 2024. "Giving to the Extreme? Experimental Evidence on Donor Response to Candidate and District Characteristics." *British Journal of Political Science* 54(3):851–873.

Molly Jong-Fast. 2023. "Let's Stop Treating Polls as Actual News Events." *Vanity Fair* . Published November 15, 2023. https://www.vanityfair.com/news/2023/11/2024-election-polls-donald-trump-joe-biden.

Mutz, Diana C. 1995. "Effects of Horse-Race Coverage on Campaign Coffers: Strategic Contributing in Presidential Primaries." *The Journal of Politics* 57(4):1015–1042.

Oliven, Kenneth and Thomas A Rietz. 2004. "Suckers Are Born but Markets Are Made: Individual Rationality, Arbitrage, and Market Efficiency on an Electronic Futures Market." *Management Science* 50(3):336–351.

Osipovich, Alexander. 2024. "A Mystery $30 Million Wave of Pro-Trump Bets Has Moved a Popular Prediction Market." *The Wall Street Journal* . Published October 18, 2024. https://www.wsj.com/finance/betting-election-pro-trump-ad74aa71.

Page, Lionel and Robert T. Clemen. 2013. "Do Prediction Markets Produce Well-Calibrated Probability Forecasts?" *The Economic Journal* 123(568):491–513.

Pennock, David M, Sandip Debnath, Eric Glover and C. Lee Giles. 2012. "Modelling Information Incorporation in Markets, with Application to Detecting and Explaining Events.". **URL:** *https://arxiv.org/abs/1301.0594*

Reade, J. James and Leighton Vaughan Williams. 2019. "Polls to Probabilities: Comparing Prediction Markets and Opinion Polls." *International Journal of Forecasting* 35(1):336–350.

Rhode, Paul W. and Koleman S. Strumpf. 2004. "Historical Presidential Betting Markets." *The Journal of Economic Perspectives* 18(2):127–141.

Rhode, Paul W, Koleman Strumpf, Leighton Vaughan-Williams and Donald S Siegel. 2013. "The Long History of Political Betting Markets: An International Perspective.".

Rothschild, David. 2009. "Forecasting Elections: Comparing Prediction Markets, Polls, and Their Biases." *Public Opinion Quarterly* 73(5):895–916.

Salmon, Felix. 2024. "Election Betting is Cleared, for Now, by U.S. Appeals Court." *Axios* . Published October 2, 2024. https://www.axios.com/2024/10/02/election-betting-prediction-markets-kalshi-polymarket.

Schleifer, Theodore and Albert Sun. 2024. "Trump–Harris Campaigns Raise Record Funds in Final Month of 2024 Race." *The New York Times* . Published December 6, 2024. https://www.nytimes.com/2024/12/06/us/politics/trump-harris-campaign-fundraising.html.

Segol, Matthieu. 2012. "Aggregation of information and beliefs on prediction markets with non-bayesian traders." *IDEAS Working Paper Series from RePEc* .

Snowberg, Erik, Justin Wolfers and Eric Zitzewitz. 2013. Prediction Markets for Economic Forecasting. In *Handbook of Economic Forecasting*, ed. Graham Elliott and Allan Timmermann. Vol. 2 Elsevier chapter 11, pp. 657–687.

Thompson, Derek. 2012. "Should Presidential Campaigns Spend More Money Manipulating Intrade?" *The Atlantic* . Accessed October 23, 2025. https://www.theatlantic.com/business/archive/2012/10/should-presidential-campaigns-spend-more-money-manipulating-intrade/264000/.

Toff, Benjamin, Elizabeth Suhay, Alexander H Trechsel and Bernard Grofman. 2020. Horse-Race and Game-Framed Journalism's Effects on Turnout, Vote Choice, and Attitudes toward Politics. In *The Oxford Handbook of Electoral Persuasion*. Oxford Handbooks Oxford University Press.

Urquhart, Andrew. 2024. "Do Decentralized Markets Beat Centralized Forecasters? Evidence from the 2024 Presidential Elections." *Aledari* 46(171).

Westwood, Sean J. 2025. "The Potential Existential Threat of Large Language Models to Online Survey Research." *Proceedings of the National Academy of Sciences* 122.
URL: *https://doi.org/10.1073/pnas.2518075122*

Westwood, Sean Jeremy, Solomon Messing and Yphtach Lelkes. 2020. "Projecting Confidence: How the Probabilistic Horse Race Confuses and Demobilizes the Public." *The Journal of Politics* 82(4):1530–1544.

Wilson, Tom. 2024. "Cryptoverse: U.S. Election Speculators Play the Prediction Markets." *Reuters* . Published November 4, 2024. https://www.reuters.com/markets/currencies/cryptoverse-us-election-punters-play-prediction-markets-2024-11-04/.

Wlezien, Christopher and Robert S. Erikson. 2002. "The Timeline of Presidential Election Campaigns." *The Journal of Politics* 64(4):969–993.

Wolfers, Justin and Eric Zitzewitz. 2004. "Prediction Markets." *The Journal of Economic Perspectives* 18(2):107–126.

Supplemental Appendix Contents

A Updates

- Version 2 (Dec 6th): Clarified language regarding the meaning of "accuracy"; noted the ambiguity of finding a negative serial correlation in random-walk analyses; fixed miscellaneous typos.
- Version 3 (Dec 9th): Included Figure A9 (Arbitrage with transaction costs), expanded the analysis of correlated price changes in presidential winner-take-all markets from day-to-day to also include analyses of the change in closing prices using 2,3,4,5,6, and 7 day windows. See Figures A10, A11 and A12 in Section E. Slight tweaks to the abstract, fixed the appendix TOC and other pesky miscellaneous typos.

B Coding Market Types

All markets are coded in terms of their general content. They are all also coded in terms of whether the contract includes a specific threshold/condition to distinguish those contracts from simple "yes" or "no" contracts to distinguish between easier and harder contracts. This allows for the possibility that predicting who will win is easier than predicting whether someone will win by a specific margin, or by winning a set of states.

National Pres Race: These are contracts that involve the outcome of the popular vote or Electoral college vote in the U.S. Presidential Election. They may involve third party and non-major candidates (e.g., "Will Kanye West win the 2024 US Presidential Election?"). These do not include contracts related to polling, the composition of the electorate, whether a candidate wins a certain subgroup according to the Exit Poll. The contract is strictly about the outcome. These contracts can also include a Margin component: e.g., "Trump wins 287-251 - AZ, GA, NV, NC, PA" and those contracts are flagged accordingly.

State Pres Race: These are contracts involving whether a candidate wins a specific, named state. e.g., "Will a Democrat win Nevada Presidential Election?" These contracts may also be coded as margin: e.g., "Will Harris win California by 25+ points?" Contracts that are not specific to a named state are coded as referring to state presidential vote if they do not explicitly reference the national outcome. Examples include: "Trump wins a solid blue state?" "Trump wins every swing state?" "Will Donald Trump win 5 swing states?"

State Non Pres Race: These contracts include races for control of the House, specific House races, and the outcome of Senatorial and Gubernatorial contests. They can also include a margin component E.g., "Will Republicans have 230 or more seats in House after election?" Contracts for who will be Speaker are not included – they are coded as "Other"

Turnout: These are contracts related to the number of voters voting, but not the outcome. Examples include: "Will Kamala Harris get 80-82m votes in the 2024 U.S. Presidential Election?"; "Will Kamala get more votes than Biden?"; "Will Trump get more votes than 2020?" All of these contracts involved a margin/threshold requirement.

Political Speech: These are contracts related to a candidate saying a specific term during a specified event or by a certain type. Examples include: "Will Trump say "Mexico" 4 or more times during Pittsburgh rally on Nov 4?" and "Will Trump say "hispanic" 3 or more times during Univision town hall?"

Presidential Nominations: There were a few markets dealing with presidential primaries. They were outside of the time period we examined so they were not relevent – they were also uninteresting given the lack of meaningful primary contests in 2024.

Polls Markets: These are markets that are based on the outcome of polls and/or prediction markets. Examples of these contracts include: "Trump gets more black voters than in 2020?"; "Kamala Harris 538 odds >55% on Friday?"; "Will 538's polling average be above 1.0 for Democrats on election day?"; "Will Kamala flip Trump on Polymarket in August?"; "Will Kamala lead in RCP by 1-1.4 on Oct 4?"

Other This is a grab-bag containing other markets related to political events, or events that are politically adjacent but classified as dealing with Elections by the various exchanges. Examples include: "Biden diagnosed with "medical condition" before DNC?"; "Donald & Melania Trump divorce before election?"; "Kamala or Trump convention speech gets more viewers?"; "Kamala wins and immediately bans X?"

All markers are also evaluated according to whether the contract establishes a specific threshold or comparison that must be surpassed for the contract to pay out.

Margin:

We code a contract as involving a margin if it specifies some specific condition/threshold that must occur beyond winning or occurring. Winning by a certain percentage, or winning a specific set of states, or exceeding some threshold would all counts as *Margin*. A contract "Will Kamala do better than Biden with unmarried women?" is not a Margin contract as it is only about a relative threshold but Examples include: "Will Jill Stein get >1% of the popular vote?" and "Will Trump win West Virginia by the largest margin?" because it depends on the margins in other states. It can also refer to surpassing a certain amount of events – e.g., "Will Kamala Harris say "Donald" or "Trump" 5 or more times during DNC speech?" or an event occurring by a certain time: (e.g., "Will Kamala Harris go on the Joe Rogan Experience before Nov 5, 2024?").

C Market Accuracy

The Brier score quantifies the accuracy of probabilistic forecasts using the the mean squared error between the contract price and (0,1) outcome:

$$\text{Brier} = \frac{1}{N}\sum_{t=1}^{N}[1 - (p_{it} - y_i)^2]$$

where p_{it} is the contract price (i.e., market-implied probability of success) at time t and $y_i \in \{0, 1\}$ indicates the realized outcome. Because the Brier score is based on squared differences, it rewards predictions that assign higher probabilities to events that happen and lower probabilities to those that do not, while penalizing forecasts that are confident but wrong. As a result, the prediction that minimizes expected squared loss under uncertainty is a constant probability of 0.5, which yields an expected Brier accuracy of 0.5 when outcomes are equally likely. This value serves as the natural benchmark for assessing whether a market is performing better or worse than an uninformed forecast.

The two accuracy measures differ sharply when forecasts are confidently wrong. Predicting a 95% chance of victory for a candidate who loses results in a Brier accuracy of 0.10 but a log-skill accuracy of –3.3 that indicates that the performance was more than three times worse than an uninformed 50–50 forecast. Unlike the bounded Brier score, which is relatively forgiving of overconfident errors, log-skill accuracy penalizes misplaced certainty because by normalizing relative to the loss from a random (50–50) forecast.

Figure A1 replicates the results of Figure 1 using Brier Accuracy scores instead. A similar result obtains in that there is heterogeneity in market performance. Because the Brier score is a measure of mean-squared error, we compare the accuracy relative to the accuracy of simply guessing 0.5 as that is the prediction that minimizes mean squared loss in the absence of any information.

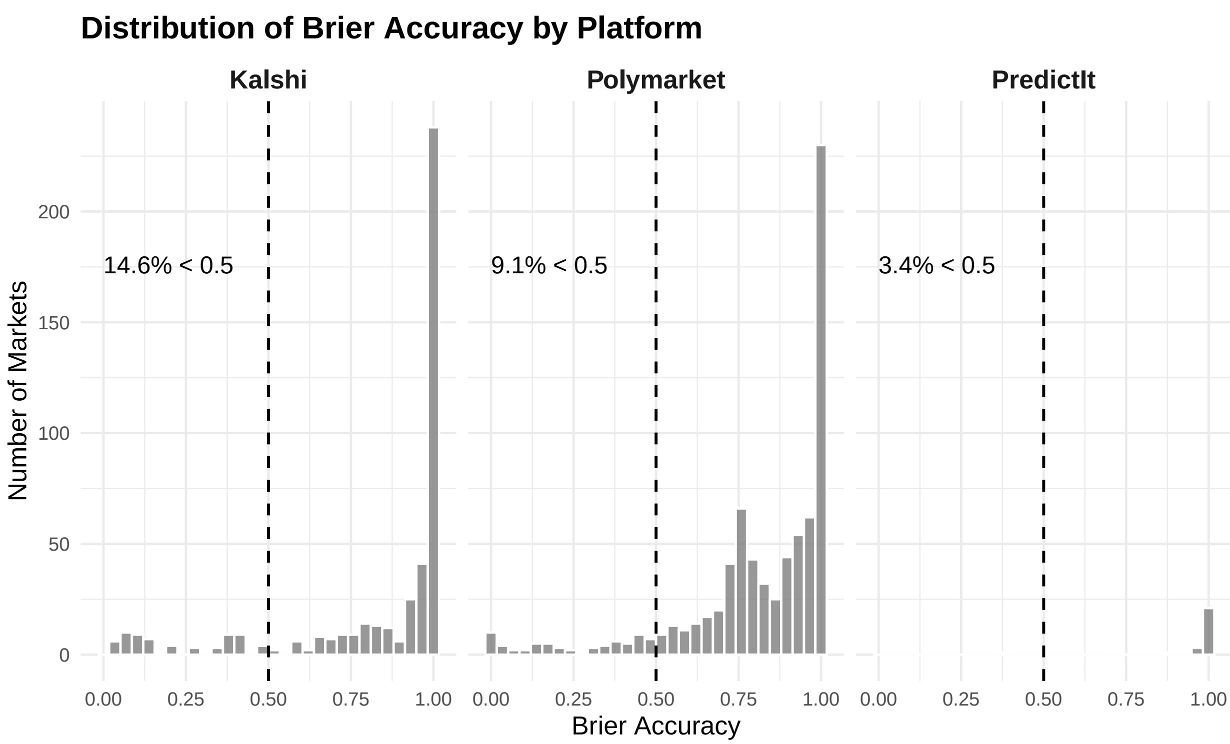


Figure A1. Market-Level Accuracy and Brier Accuracy Skill by Exchange as of November 4, 2024: The day before the 2024 U.S. General Election). This is the distribution of Brier scores for each active market in *Kalshi*, *Polymarket*, and *PredictIt* as of the day before Election Day. Although the measure is a distance measure from the truth, to provide a benchmark we use the percentage of markets whose score is strictly less than .5.

Figure A2 shows the descriptive relationship between logskill scores and Brier accuracy scores.

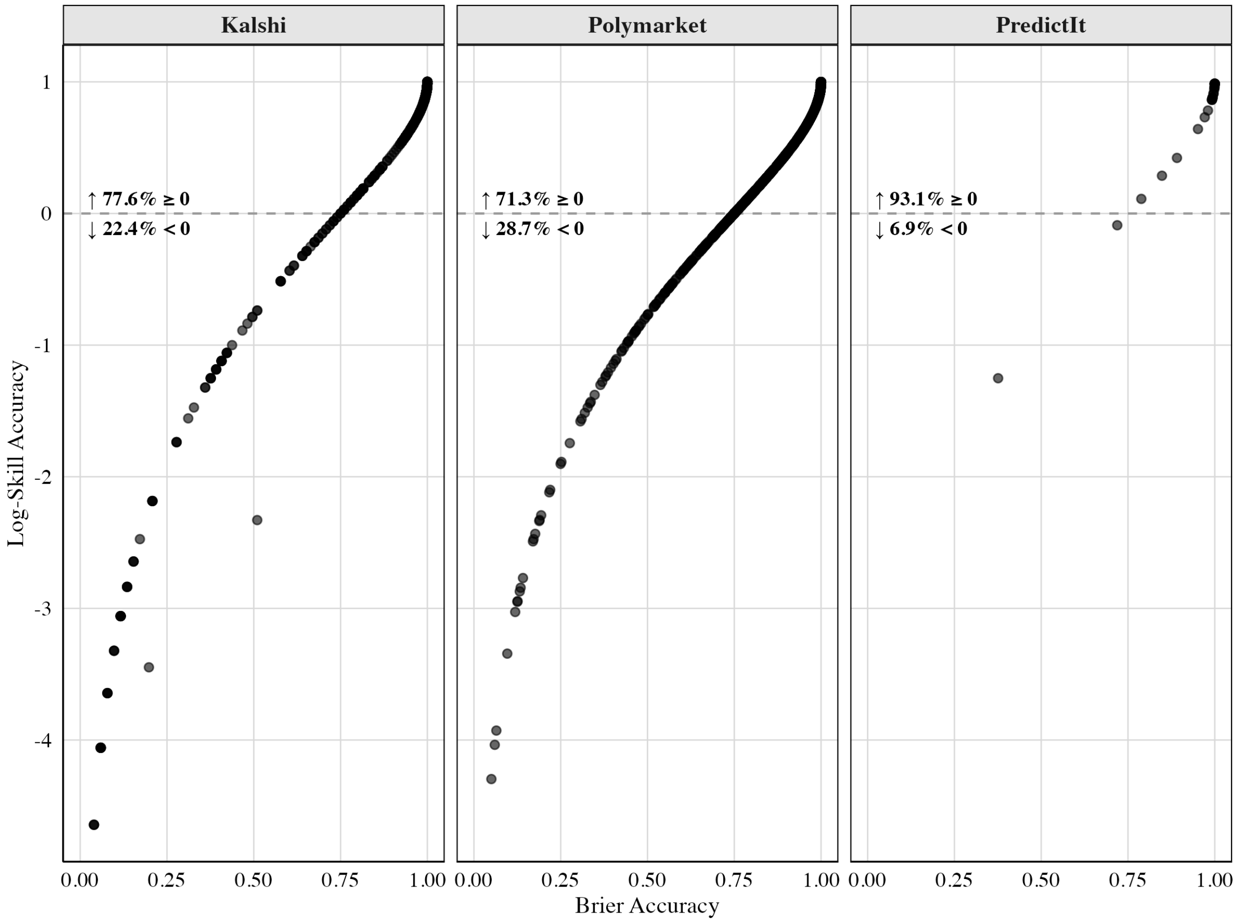


Figure A2. Market-Level Accuracy and Skill by Exchange as of November 4, 2024: The day before the 2024 U.S. General Election). Each point represents a separate market from one of three exchanges: *Kalshi*, *Polymarket*, and *PredictIt*. The x-axis gives the market's mean Brier accuracy, while the y-axis shows its mean log-skill accuracy. The data snapshot was taken on the day before the U.S. General Election on November 5, 2024. Similar accuracy levels using alternative forecasting windows are presented in Figure A5.

Table A1. OLS Regression of Log Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election). Coefficients plotted in Figure 2. Hetereoskedastic Consistent standard errors reported.

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.494	0.120	0.259	0.729	0.000
Market: National Pres Race Margin	-0.044	0.110	-0.259	0.171	0.690
Market: State Pres Race	-0.466	0.117	-0.694	-0.237	0.000
Market: State Pres Race Margin	-0.103	0.100	-0.298	0.093	0.302
Market: State Non Pres Race	-0.351	0.111	-0.568	-0.135	0.002
Market: State Non Pres Race Margin	-0.489	0.213	-0.907	-0.071	0.022
Market: Polls Markets	-0.677	0.192	-1.053	-0.302	0.000
Market: Polls Markets Margin	-0.092	0.143	-0.374	0.189	0.520
Market: Turnout Margin	-0.118	0.139	-0.390	0.155	0.398
Market: Political Speech	-0.885	0.253	-1.380	-0.390	0.000
Market: Political Speech Margin	-1.347	0.640	-2.601	-0.094	0.035
Market: Other	-0.467	0.154	-0.769	-0.165	0.002
Market: Other Margin	-0.115	0.158	-0.424	0.195	0.467
Exchange: Polymarket	-0.017	0.073	-0.161	0.126	0.815
Exchange: PredictIt	0.259	0.124	0.015	0.502	0.037
Log(Volume + 1)	0.005	0.015	-0.024	0.035	0.721

Table A2. OLS Regression of Brier Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election). Coefficients plotted in Figure **??**. Hetereoskedastic Consistent standard errors reported.

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.494	0.120	0.259	0.729	0.000
Market: National Pres Race Margin	-0.044	0.110	-0.259	0.171	0.690
Market: State Pres Race	-0.466	0.117	-0.694	-0.237	0.000
Market: State Pres Race Margin	-0.103	0.100	-0.298	0.093	0.302
Market: State Non Pres Race	-0.351	0.111	-0.568	-0.135	0.002
Market: State Non Pres Race Margin	-0.489	0.213	-0.907	-0.071	0.022
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Market: Political Speech	-0.885	0.253	-1.380	-0.390	0.000
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Market: Other	-0.467	0.154	-0.769	-0.165	0.002
Market: Other Margin	-0.115	0.158	-0.424	0.195	0.467
Exchange: Polymarket	-0.017	0.073	-0.161	0.126	0.815
Exchange: PredictIt	0.259	0.124	0.015	0.502	0.037
Log(Volume + 1)	0.005	0.015	-0.024	0.035	0.721

Figures A3 and A4 report the average daily accuracy of each exchange over time using the closing price of all active on that exchange for each day starting on September 1, 2024. Put differently, for each day, we compute the Brier score for every market on the exchange using the closing price for every active market and the final resolution of the market. Of primary interest is whether the average accuracy improves as Election Day approaches given the number of markets whose resolution is based on the information revealed on Election Day, the increase in information over time, and the decreasing opportunity for unexpected events due to the decreasing number of days remaining until Election Day.

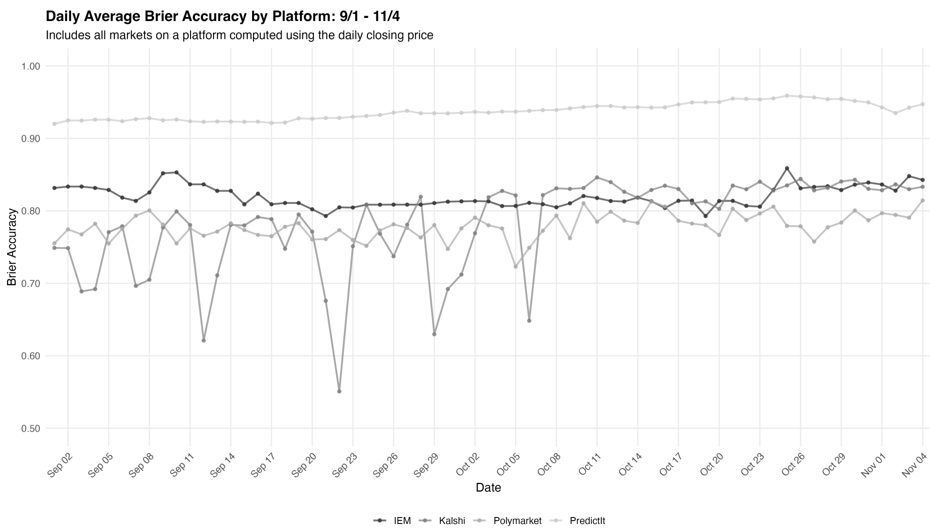


Figure A3. Average Daily Accuracy by Exchange Using Brier Measure. Each daily calculation includes all active contracts.

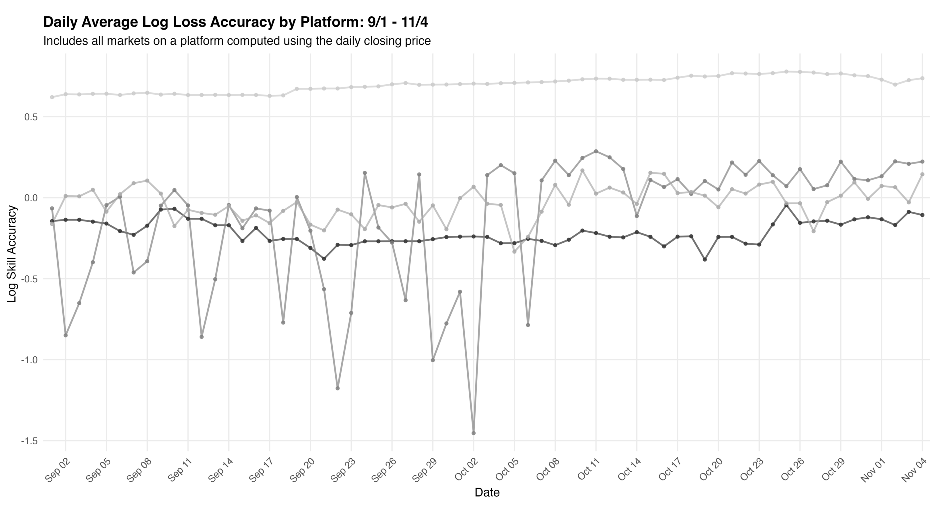


Figure A4. Average Daily Accuracy by Exchange Using Brier Measure. Each daily calculation includes all active contracts.

We can also compare how the accuracy measures compare to one another over time by considering the implied accuracy at various times. Figure 1 conducts the analysis for the day prior to Election Day, but we can also consider the relationship: 1 week prior to Election Day, 2 weeks prior to Election Day, as well as 30 and 60 days prior. Figure A5 presents these comparisons.

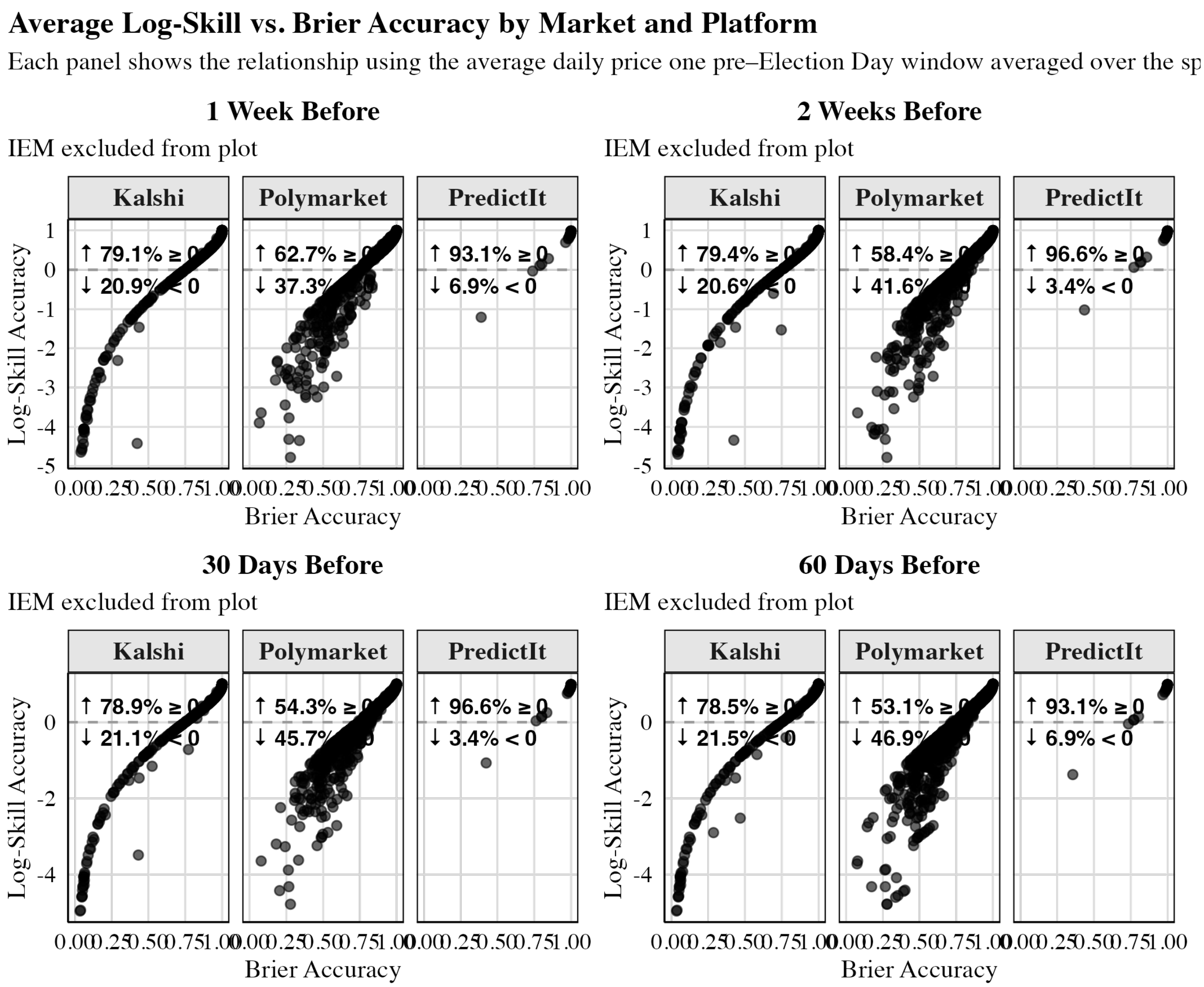


Figure A5. Average Daily Accuracy by Exchange At Selected Days Until Election Day 2024. This extends Figure 1 to consider the average accuracy of the exchanges over time by comparing how the average market accuracy for each exchange varies depending on whether we look: 1 week prior to Election Day, 2 weeks prior to Election Day, 30 days and 60 days. These graphs summarize the relationships plotted in Figures A3 and A4.

We estimate the model in the text using daily fixed effects for each accuracy measure. The results using the Brier score and log Accuracy are reported below. An observation in this regression is a market's accuracy based on the closing price on a day.

Table A3. OLS Regression of Log Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election)

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.103	0.073	-0.039	0.245	0.156
Market: National Pres Race Margin	-0.042	0.021	-0.083	-0.001	0.042
Market: State Pres Race	-0.454	0.022	-0.498	-0.410	0.000
Market: State Pres Race Margin	-0.116	0.027	-0.168	-0.063	0.000
Market: State Non Pres Race	-0.468	0.024	-0.515	-0.420	0.000
Market: State Non Pres Race Margin	-0.399	0.043	-0.484	-0.315	0.000
Market: Polls Markets	-0.414	0.033	-0.479	-0.348	0.000
Market: Polls Markets Margin	-0.092	0.056	-0.201	0.017	0.099
Market: Turnout Margin	-0.100	0.048	-0.193	-0.006	0.037
Market: Political Speech	-0.662	0.037	-0.733	-0.590	0.000
Market: Political Speech Margin	-0.708	0.066	-0.839	-0.578	0.000
Market: Other	-0.742	0.035	-0.812	-0.673	0.000
Market: Other Margin	-0.320	0.105	-0.525	-0.115	0.002
Exchange: Polymarket	0.165	0.036	0.095	0.235	0.000
Exchange: PredictIt	0.319	0.026	0.268	0.371	0.000
Log(Volume + 1)	0.046	0.005	0.037	0.056	0.000
as.factor(day)1	-0.021	0.095	-0.208	0.166	0.823
as.factor(day)2	-0.003	0.077	-0.153	0.147	0.969
as.factor(day)3	-0.019	0.074	-0.164	0.127	0.804
as.factor(day)4	-0.254	0.083	-0.416	-0.092	0.002
as.factor(day)5	-0.213	0.087	-0.383	-0.043	0.014
as.factor(day)6	-0.065	0.078	-0.218	0.087	0.401
as.factor(day)7	0.091	0.065	-0.038	0.219	0.166
as.factor(day)8	-0.023	0.070	-0.160	0.114	0.744
as.factor(day)9	0.146	0.064	0.021	0.271	0.022
as.factor(day)10	0.061	0.069	-0.074	0.195	0.377
as.factor(day)11	0.065	0.072	-0.075	0.206	0.363
as.factor(day)12	0.032	0.071	-0.108	0.171	0.656
as.factor(day)13	-0.078	0.088	-0.251	0.096	0.379
as.factor(day)14	0.120	0.070	-0.018	0.257	0.088
as.factor(day)15	0.087	0.070	-0.051	0.225	0.216
as.factor(day)16	0.022	0.070	-0.115	0.159	0.753
as.factor(day)17	-0.011	0.069	-0.147	0.124	0.868
as.factor(day)18	0.001	0.067	-0.129	0.132	0.982
as.factor(day)19	-0.061	0.068	-0.195	0.073	0.373
as.factor(day)20	0.050	0.069	-0.085	0.185	0.471
as.factor(day)21	0.003	0.069	-0.132	0.138	0.963
as.factor(day)22	0.082	0.064	-0.044	0.208	0.201
as.factor(day)23	0.077	0.067	-0.055	0.208	0.253
as.factor(day)24	-0.039	0.073	-0.181	0.104	0.592
as.factor(day)25	0.011	0.070	-0.126	0.148	0.875
as.factor(day)26	-0.171	0.079	-0.325	-0.017	0.030
as.factor(day)27	-0.035	0.072	-0.175	0.106	0.627
as.factor(day)28	0.055	0.065	-0.072	0.181	0.397
as.factor(day)29	0.070	0.070	-0.066	0.206	0.315
as.factor(day)30	-0.003	0.069	-0.139	0.132	0.962
as.factor(day)31	0.052	0.067	-0.080	0.183	0.441
as.factor(day)32	0.053	0.063	-0.071	0.177	0.401
as.factor(day)33	-0.012	0.067	-0.143	0.118	0.851
as.factor(day)34	0.144	0.063	0.021	0.267	0.022

Table A4. OLS Regression of Log Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election)

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.862	0.012	0.838	0.887	0.000
Market: National Pres Race Margin	0.003	0.005	-0.006	0.013	0.524
Market: State Pres Race	-0.092	0.005	-0.101	-0.083	0.000
Market: State Pres Race Margin	-0.038	0.006	-0.049	-0.026	0.000
Market: State Non Pres Race	-0.106	0.005	-0.115	-0.096	0.000
Market: State Non Pres Race Margin	-0.097	0.010	-0.116	-0.078	0.000
Market: Polls Markets	-0.121	0.009	-0.138	-0.103	0.000
Market: Polls Markets Margin	-0.015	0.007	-0.029	-0.001	0.032
Market: Turnout Margin	-0.034	0.012	-0.058	-0.010	0.005
Market: Political Speech	-0.156	0.006	-0.169	-0.144	0.000
Market: Political Speech Margin	-0.163	0.009	-0.181	-0.145	0.000
Market: Other	-0.150	0.006	-0.163	-0.138	0.000
Market: Other Margin	-0.056	0.017	-0.089	-0.023	0.001
Exchange: Polymarket	-0.010	0.005	-0.019	0.000	0.039
Exchange: PredictIt	0.059	0.006	0.048	0.070	0.000
Log(Volume + 1)	0.003	0.001	0.001	0.004	0.000
as.factor(day)1	0.013	0.014	-0.015	0.040	0.370
as.factor(day)2	0.008	0.014	-0.020	0.035	0.598
as.factor(day)3	0.002	0.014	-0.026	0.029	0.898
as.factor(day)4	-0.040	0.014	-0.068	-0.012	0.005
as.factor(day)5	-0.022	0.015	-0.051	0.006	0.129
as.factor(day)6	-0.001	0.014	-0.030	0.027	0.922
as.factor(day)7	0.016	0.013	-0.010	0.042	0.237
as.factor(day)8	-0.007	0.013	-0.032	0.019	0.599
as.factor(day)9	0.029	0.013	0.003	0.055	0.027
as.factor(day)10	0.014	0.014	-0.012	0.041	0.298
as.factor(day)11	0.019	0.014	-0.008	0.046	0.165
as.factor(day)12	0.009	0.014	-0.018	0.037	0.519
as.factor(day)13	0.005	0.014	-0.023	0.033	0.726
as.factor(day)14	0.031	0.013	0.005	0.057	0.020
as.factor(day)15	0.029	0.013	0.004	0.054	0.024
as.factor(day)16	0.012	0.013	-0.013	0.037	0.347
as.factor(day)17	0.003	0.013	-0.022	0.028	0.820
as.factor(day)18	0.004	0.013	-0.022	0.029	0.766
as.factor(day)19	-0.009	0.013	-0.035	0.017	0.483
as.factor(day)20	0.023	0.013	-0.003	0.049	0.088
as.factor(day)21	0.011	0.013	-0.015	0.037	0.419
as.factor(day)22	0.024	0.013	-0.001	0.049	0.057
as.factor(day)23	0.029	0.013	0.003	0.054	0.026
as.factor(day)24	0.010	0.013	-0.015	0.036	0.432
as.factor(day)25	0.016	0.013	-0.009	0.041	0.200
as.factor(day)26	-0.009	0.013	-0.035	0.017	0.513
as.factor(day)27	0.007	0.013	-0.019	0.032	0.611
as.factor(day)28	0.019	0.013	-0.006	0.044	0.129
as.factor(day)29	0.030	0.013	0.005	0.055	0.020
as.factor(day)30	0.016	0.013	-0.010	0.041	0.226
as.factor(day)31	0.023	0.013	-0.002	0.048	0.072
as.factor(day)32	0.019	0.012	-0.005	0.043	0.123
as.factor(day)33	0.015	0.012	-0.009	0.039	0.229
as.factor(day)34	0.033	0.012	0.009	0.056	0.007

We also allowing the effect of trading volume on accuracy to vary by exchange.

Table A5. OLS Regression of Log Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election)

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.489	0.135	0.225	0.754	0.000
Market: National Pres Race Margin	0.035	0.118	-0.196	0.266	0.766
Market: State Pres Race	-0.371	0.124	-0.614	-0.129	0.003
Market: State Pres Race Margin	0.023	0.117	-0.207	0.252	0.845
Market: State Non Pres Race	-0.227	0.125	-0.472	0.019	0.071
Market: State Non Pres Race Margin	-0.333	0.221	-0.767	0.100	0.132
Market: Polls Markets	-0.561	0.206	-0.964	-0.158	0.006
Market: Polls Markets Margin	-0.035	0.154	-0.336	0.266	0.818
Market: Turnout Margin	0.042	0.158	-0.268	0.353	0.789
Market: Political Speech	-0.810	0.240	-1.281	-0.339	0.001
Market: Political Speech Margin	-1.261	0.618	-2.473	-0.049	0.042
Market: Other	-0.361	0.154	-0.664	-0.058	0.020
Market: Other Margin	-0.002	0.165	-0.326	0.321	0.988
Exchange: Polymarket	-0.329	0.167	-0.656	-0.002	0.049
Exchange: PredictIt	0.561	0.149	0.268	0.853	0.000
Log(Volume + 1)	-0.015	0.018	-0.049	0.020	0.409
Exchange: Polymarket:Log(Volume + 1)	0.087	0.040	0.008	0.165	0.031
Exchange: PredictIt:Log(Volume + 1)	-0.018	0.022	-0.062	0.025	0.410

Table A6. OLS Regression of Brier Accuracy on Market Type, Exchange, and Volume (Day Before 2024 Election)

Term	Estimate	Std. Error	95% CI (Lower)	95% CI (Upper)	p-value
(Intercept)	0.887	0.032	0.824	0.949	0.000
Market: National Pres Race Margin	0.016	0.031	-0.044	0.075	0.611
Market: State Pres Race	-0.071	0.029	-0.128	-0.015	0.014
Market: State Pres Race Margin	-0.002	0.029	-0.060	0.055	0.939
Market: State Non Pres Race	-0.054	0.030	-0.112	0.004	0.069
Market: State Non Pres Race Margin	-0.076	0.052	-0.178	0.025	0.139
Market: Polls Markets	-0.163	0.054	-0.269	-0.058	0.002
Market: Polls Markets Margin	-0.008	0.039	-0.084	0.068	0.840
Market: Turnout Margin	0.002	0.039	-0.075	0.078	0.965
Market: Political Speech	-0.159	0.040	-0.238	-0.079	0.000
Market: Political Speech Margin	-0.217	0.067	-0.348	-0.086	0.001
Market: Other	-0.066	0.032	-0.130	-0.003	0.041
Market: Other Margin	-0.007	0.042	-0.090	0.076	0.867
Exchange: Polymarket	-0.045	0.029	-0.102	0.012	0.119
Exchange: PredictIt	0.129	0.036	0.058	0.199	0.000
Log(Volume + 1)	-0.003	0.004	-0.010	0.005	0.472
Exchange: Polymarket:Log(Volume + 1)	0.010	0.007	-0.003	0.023	0.136
Exchange: PredictIt:Log(Volume + 1)	-0.005	0.005	-0.015	0.005	0.350

D Average Accuracy of National Presidential Markets Over Time

Whereas Figure 1 reports the distribution of accuracy across the exchanges as of the day prior to Election Day, we can also compute the average overall accuracy of all contracts being actively traded as of every day prior to Election Day. Although the markets being traded may slightly vary, comparing the average overall accuracy based on the average price in each market as of each day reveals the extent to which overall accuracy changes over time as Election Day approaches. As Figure A6 reveals, the overall accuracy is relatively stable, although the overall avrerage accuracy of markets on *PredictIt* and *Kalshi* appear to increase closer to Election Day. (The average accuracy of markets on *Polymarket* appear to increase in the last week of the campaign.)

Table A7. List of Markets Included in Efficiency of the National Presidential Market

1. Who will win the 2024 U.S. presidential election — Trump
2. Who will win the 2024 U.S. presidential election — Harris
3. Who will win the 2024 U.S. presidential election — Biden
4. Will Donald Trump or another Republican win the Presidency?
5. Will Kamala Harris or another Democrat win the Presidency?
6. Will Kamala Harris win the 2024 U.S. Presidential Election?
7. Will Donald Trump win the 2024 U.S. Presidential Election?
8. Which party wins the 2024 U.S. Presidential Election?
9. $1 if the Democratic Party nominee receives the majority of popular votes cast for the two major parties in the 2024 U.S. presidential election, $0 otherwise.
10. $1 if the Republican Party nominee receives the majority of popular votes cast for the two major parties in the 2024 U.S. presidential election, $0 otherwise.

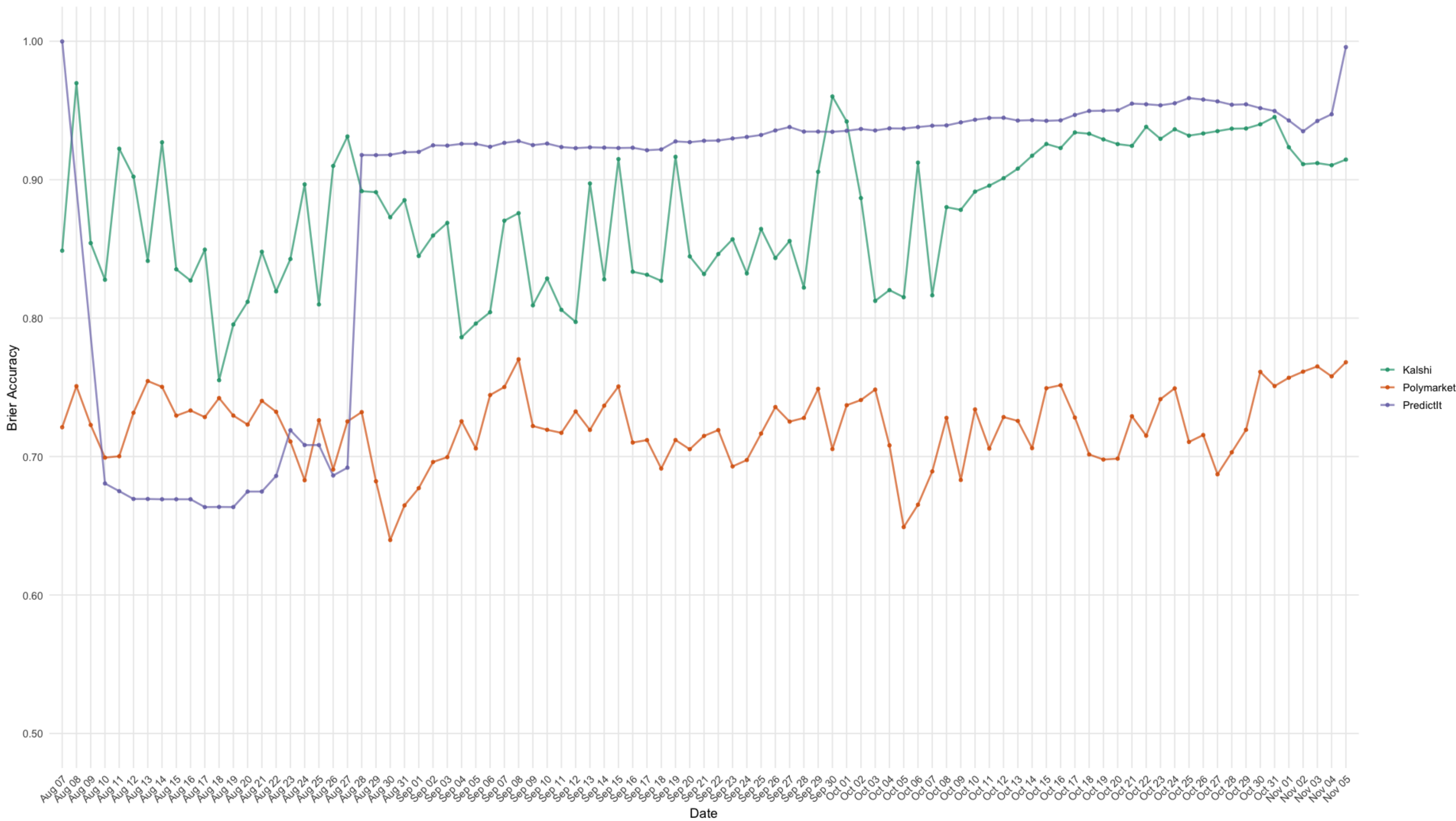


Figure A6. ***Average Daily Prediction Accuracy by Exchange (90 days before the 2024 U.S. General Election).*** *Each point represents the average market-level accuracy for all active contracts on that day. The figure shows the daily mean Brier accuracy for each exchange starting 90 days before the 2024 U.S. General Election.*

If we restrict our analysis to the most accurate markets – those involving the outcome of the national presidential race – it is not the case that accuracy increases as Election Day approaches. In fact, as Figure A7 reveals, the accuracy of presidential prediction markets is highest more than week before Election Day and the accuracy actually decreases as Election Day approaches.

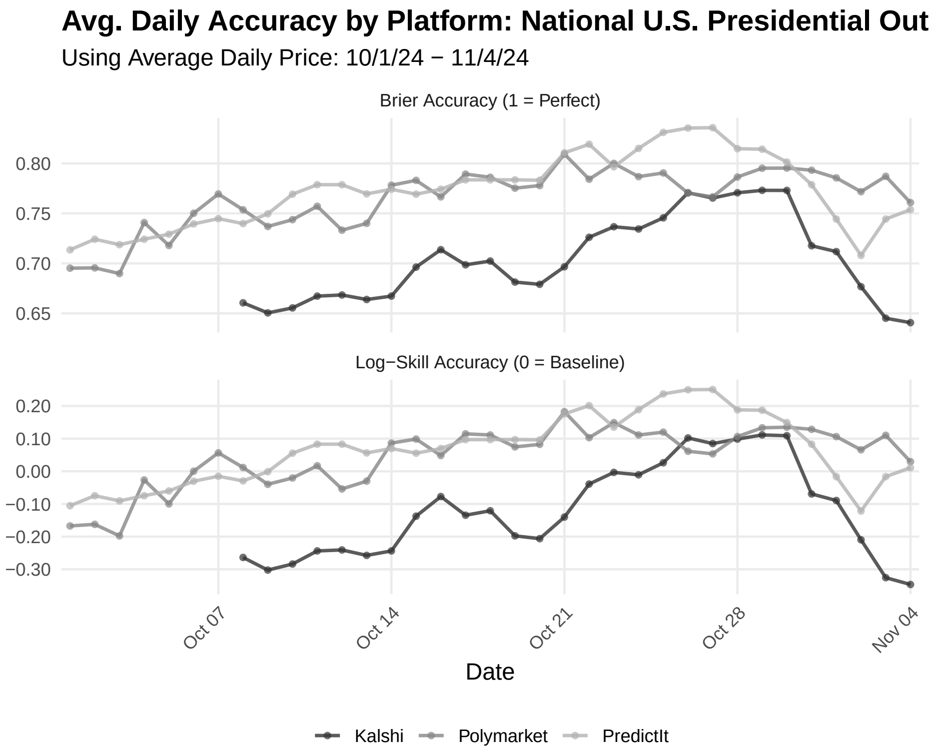


Figure A7. Daily Accuracy of Presidential Outcome Markets. Computed using the daily closing price for every day between October 1 and November 4.

It is impossible to know whether this reflects the impact of the rapidly changing information environment (e.g., early voting reports) or not, but it is clear that market accuracy *relative to the eventual outcome* in the most information-rich markets (and which presumably involve traders with the strongest priors given the amount of information revealed to date), is not necessarily converging over time.[16] To be clear, just like public opinion polls reflection opinion at a snapshot in time, it is certainly possible that assessing accuracy based on the final outcome is misleading if the outcome would have differed had the election been held on the day of the contract.

16. Of course, the markets all eventually converged prior to the resolution of the contract.

We can also compare the correlation of daily closing prices for contracts related to the national presidential race starting on October 1st. Figure A8 reports the bivariate correlations from the 10 markets across all four exchanges that are most-similar and related to the outcome of the national presidential race.

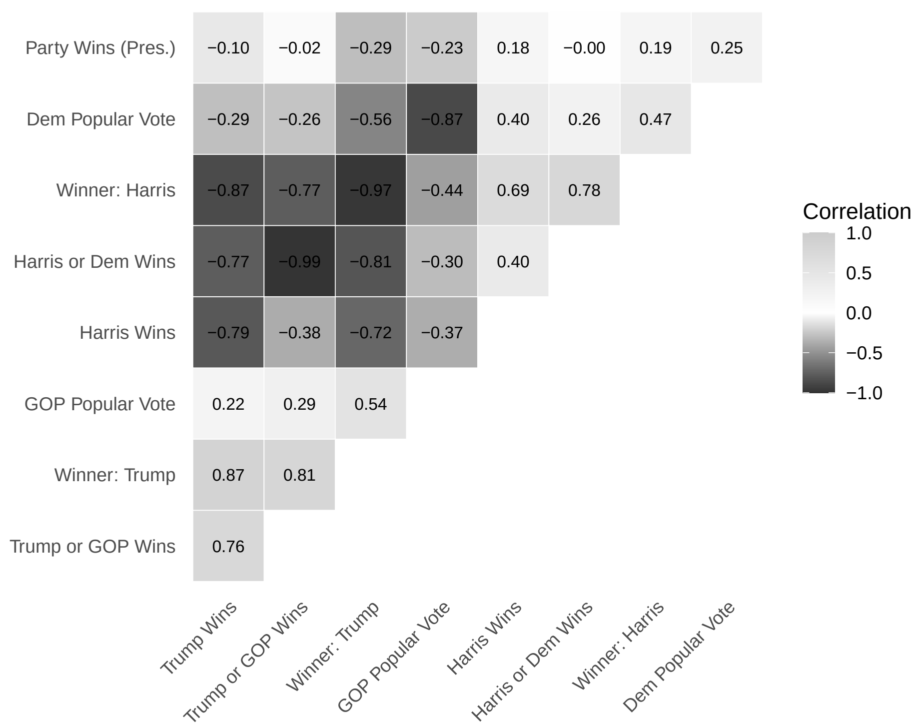


Figure A8. Correlogram of Presidential Market Closing Prices Since October: October 1 - November 4.

Figure 5 reported the costs of buying shares of both Harris and Trump winning at the cheapest possible daily closing price from *Kalshi*, *Polymarket*, and *PredictIt* in the absence of transaction costs. To ensure that conclusions are not sensitive to the costs of buying and selling we replicate the analysis focusing only on markets in *Kalshi* and *Polymarket* and accounting for the costs involved in transacting in each market. In so doing, we only include the financial costs of buying and selling, not the costs of getting access and funding to each market. As Figure A9 reveals, the pattern is very similar, although the magnitudes are obviously smaller. There are opportunities on most days and the largest opportunities occur at the end of the campaign when the most attention is being paid and the most information is available (relative to prior periods). Although accounting for the transaction costs affects the quantities involved, it does not alter the larger substantive conclusions about the nature of the market.

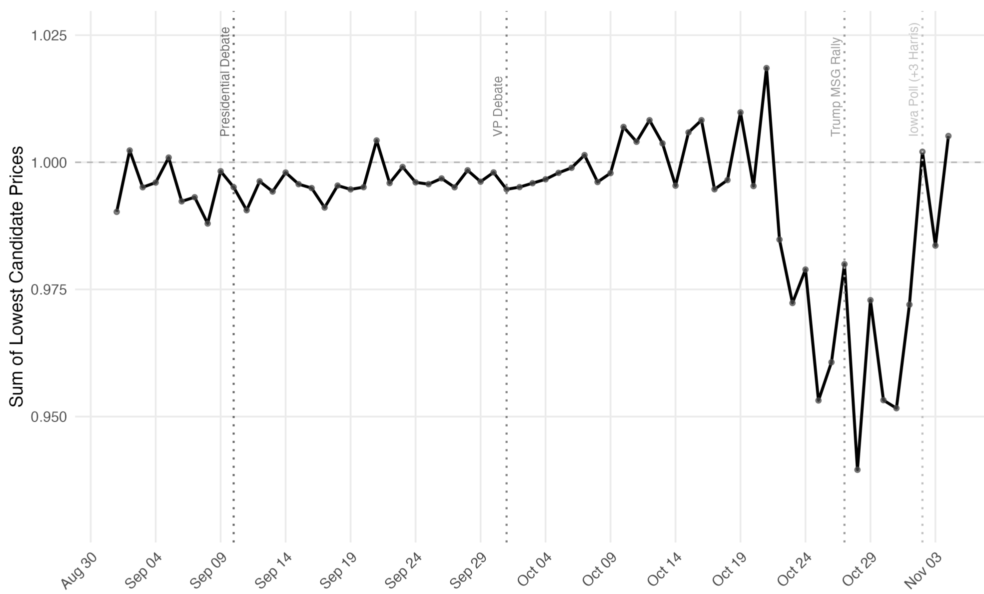


Figure A9. Cross-Market Daily Price (top) and Change (bottom) for 2024 U.S. Presidential Contracts: 9/1/24-11/4/24. Each panel compares the daily arbitrage opportunity from buying both *Trump* and *Harris* contracts at the cheapest daily closing price on *Kalshi* and *Polymarket* with transaction costs. See Figure 5 for results that ignore transaction costs.

E Correlation of Pricing Changes in Presidential Winner-Take-All markets for Various Temporal Windows

Figure 4 reports the correlation in the change in daily closing prices between exchanges, but we may worry that focusing on day-to-day changes prevents traders from being able to react to changes in the various markets over time. To account for this possibility, we examine the relationship in changes in the daily closing price for several additional temporal bandwidths - 2 days, 3 days, 4 days, 5 days, 6 days, and 7 days. That is we calculate the change in daily closing prices for differences of varying length to see how well the correlation improves – the larger the bandwidth the higher the correlation should be as the more time traders have to assess their position in light of what is going on in the other markets. While the correlation increases, it is obvious that considerable variation remains and that there is often only a relatively weak correlation in the prices of a similar contract across exchanges. In fact, the maximal correlation occurs for 7-day price changes and it is 0.42 for *Polymarket* and *Kalshi*, 0.78 for *PredictIt* and *Kalshi*, and 0.31 for *PredictIt* and *Polymarket*.

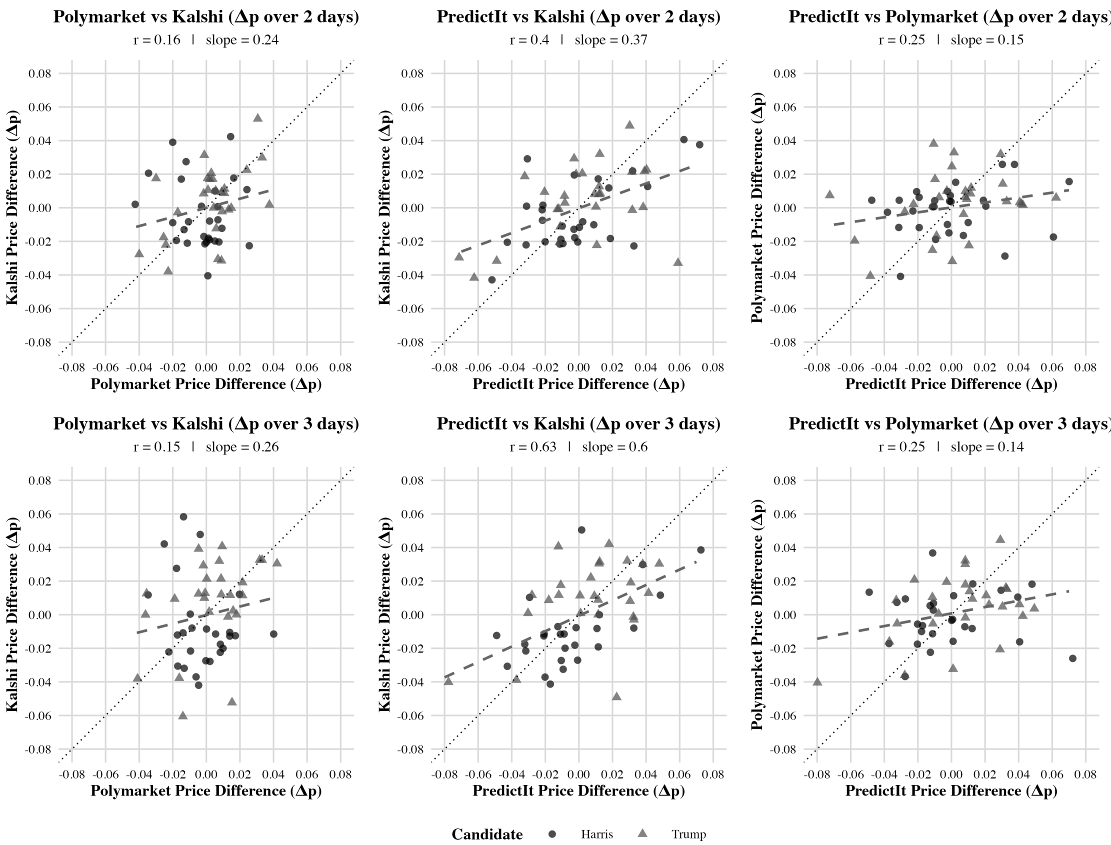


Figure A10. 2 & 3 Day Cross-Market Closing Price Changes for 2024 U.S. Presidential Contracts: 10/1/24-11/4/24. Each panel compares the daily average "yes"-contract price for *Trump* and *Harris* across the *Kalshi*, *PredictIt*, and *Polymarket* exchanges. The 45-degree dotted line denotes parity between exchanges, while the dashed line is the least-squares fit for the observations.

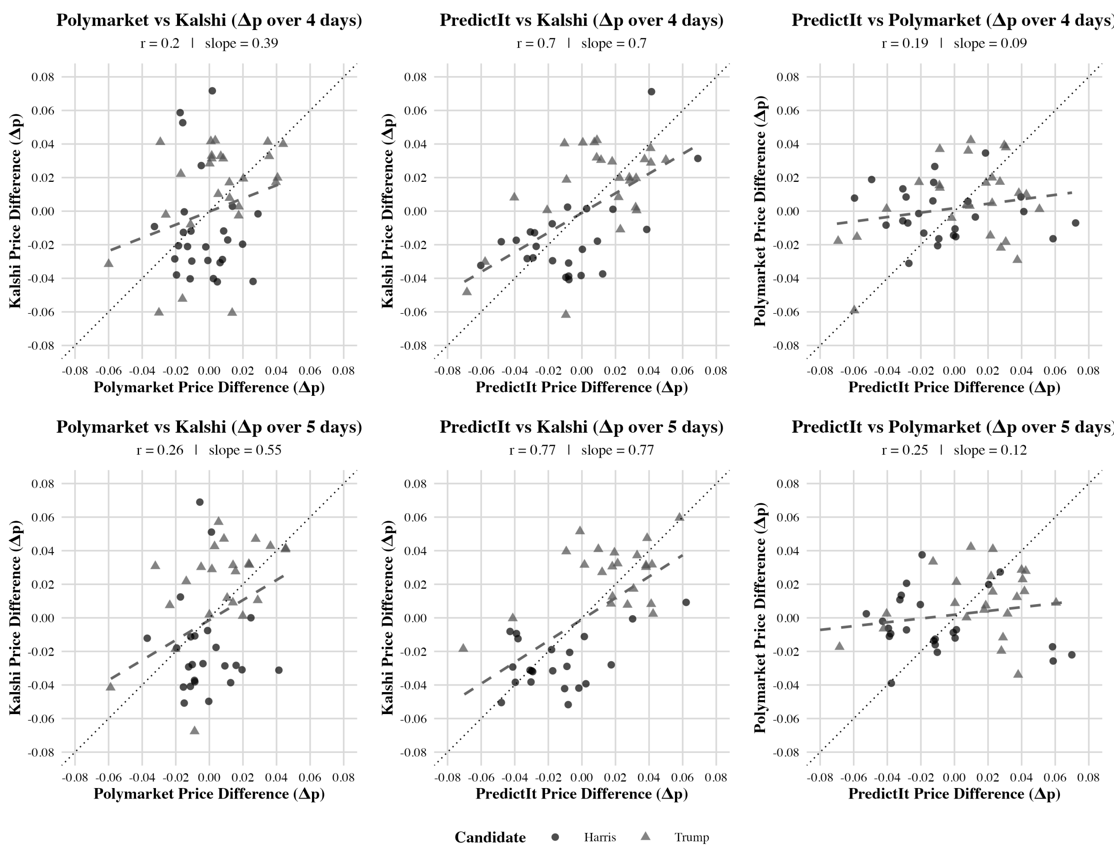


Figure A11. 4 & 5 Day Cross-Market Closing Daily Price Changes for 2024 U.S. Presidential Contracts: 10/1/24-11/4/24. Each panel compares the daily average "yes"-contract price for *Trump* and *Harris* across the *Kalshi*, *PredictIt*, and *Polymarket* exchanges. The 45-degree dotted line denotes parity between exchanges, while the dashed line is the least-squares fit for the observations.

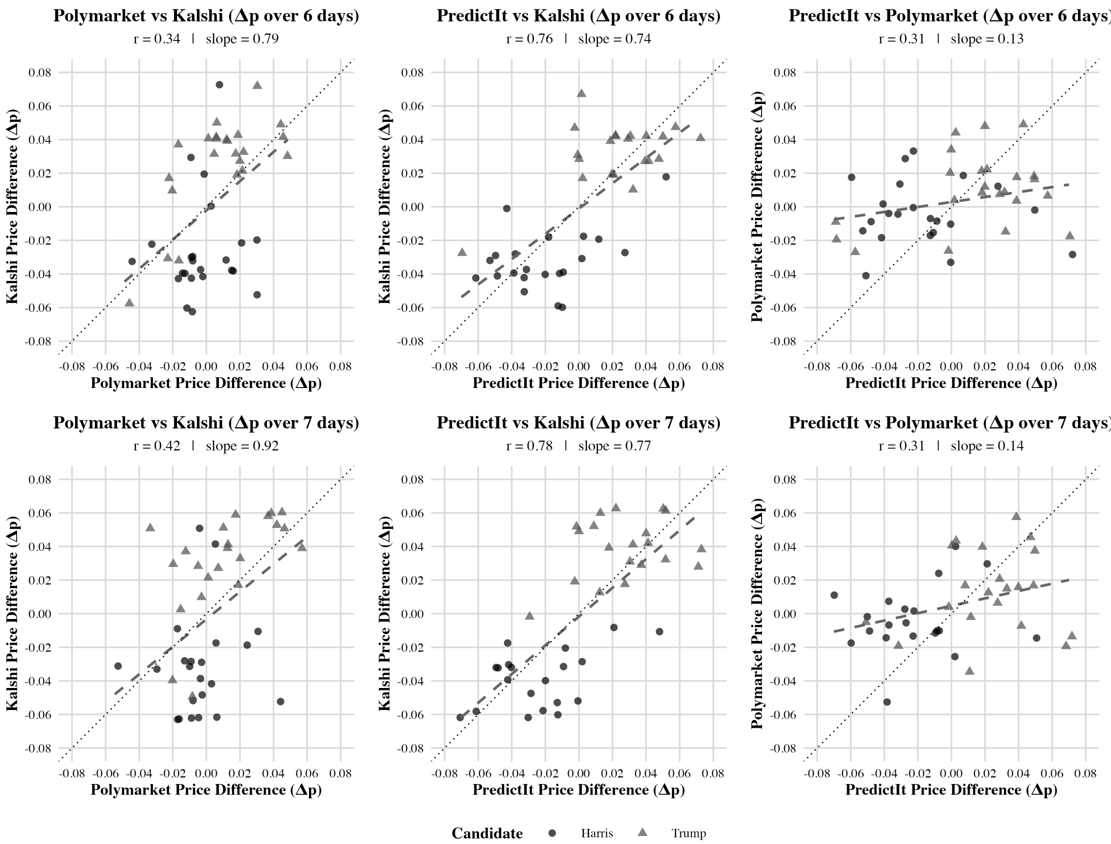


Figure A12. 6 & 7 Day Cross-Market Closing Daily Price Changes for 2024 U.S. Presidential Contracts: 10/1/24-11/4/24. Each panel compares the daily average "yes"-contract price for *Trump* and *Harris* across the *Kalshi*, *PredictIt*, and *Polymarket* exchanges. The 45-degree dotted line denotes parity between exchanges, while the dashed line is the least-squares fit for the observations.

F Margin Market Correlations: Daily Prices and Daily Price Changes

Figures A13–A19 display the full set of correlation plots for each winning-margin group (0–1% through 7%+).

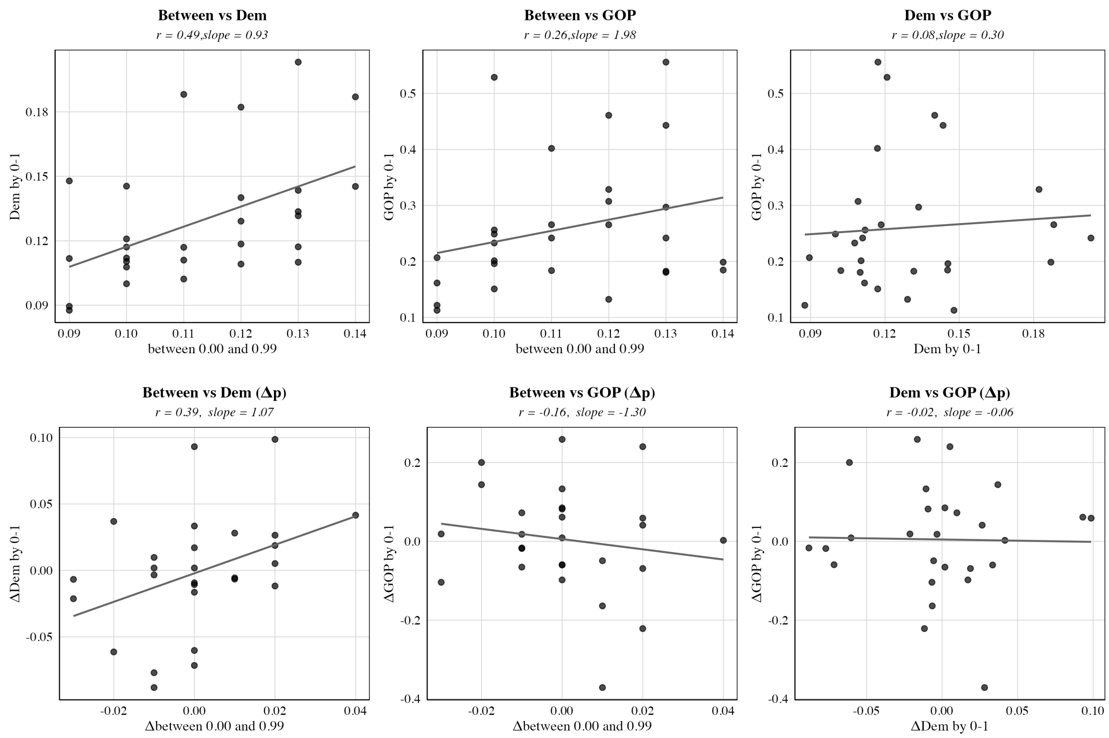


Figure A13. Price level and daily change correlations for 0–1% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

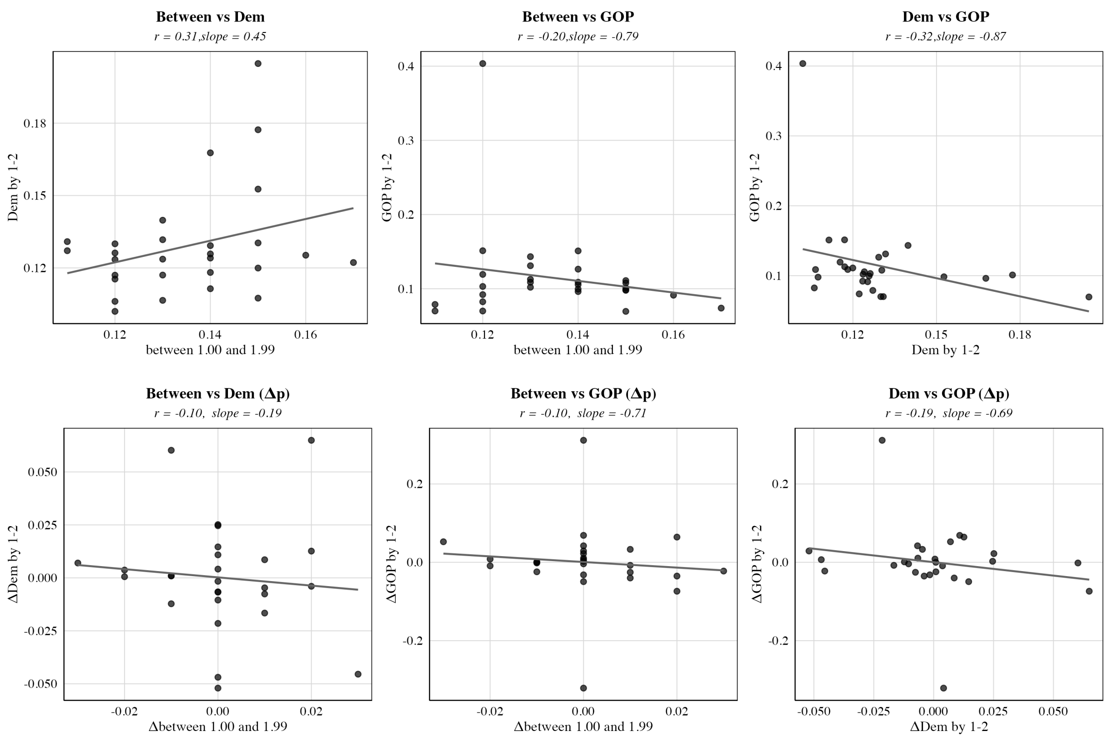


Figure A14. Price level and daily change correlations for 1–2% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

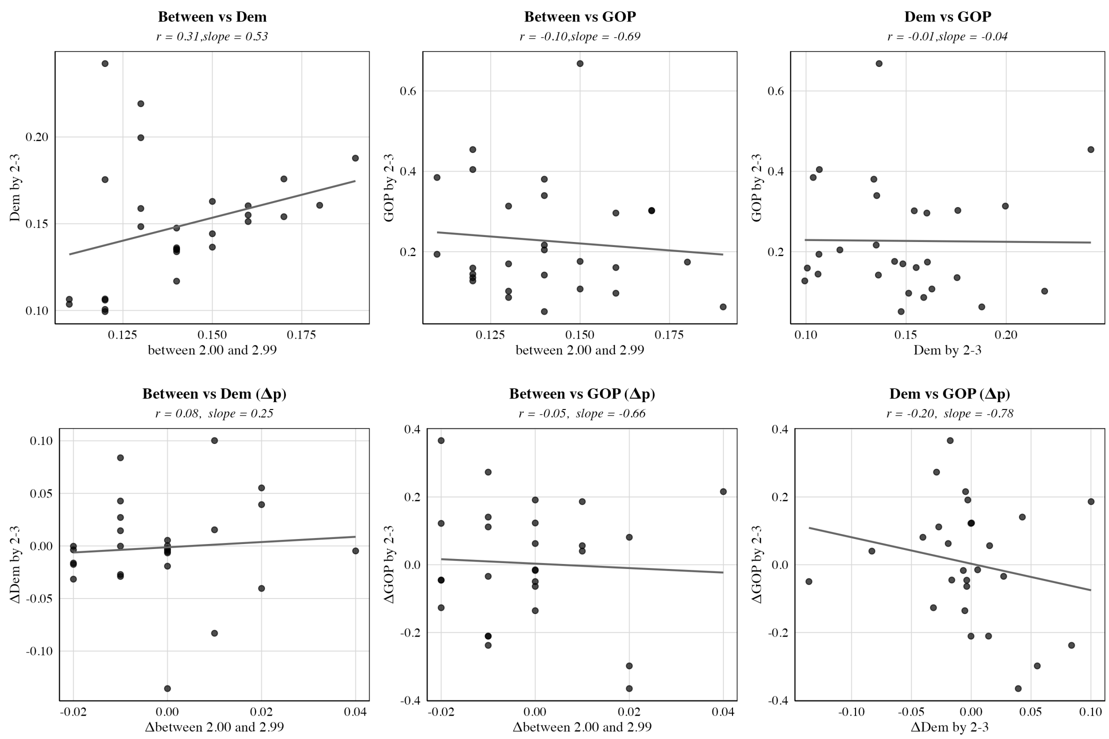


Figure A15. Price level and daily change correlations for 2–3% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

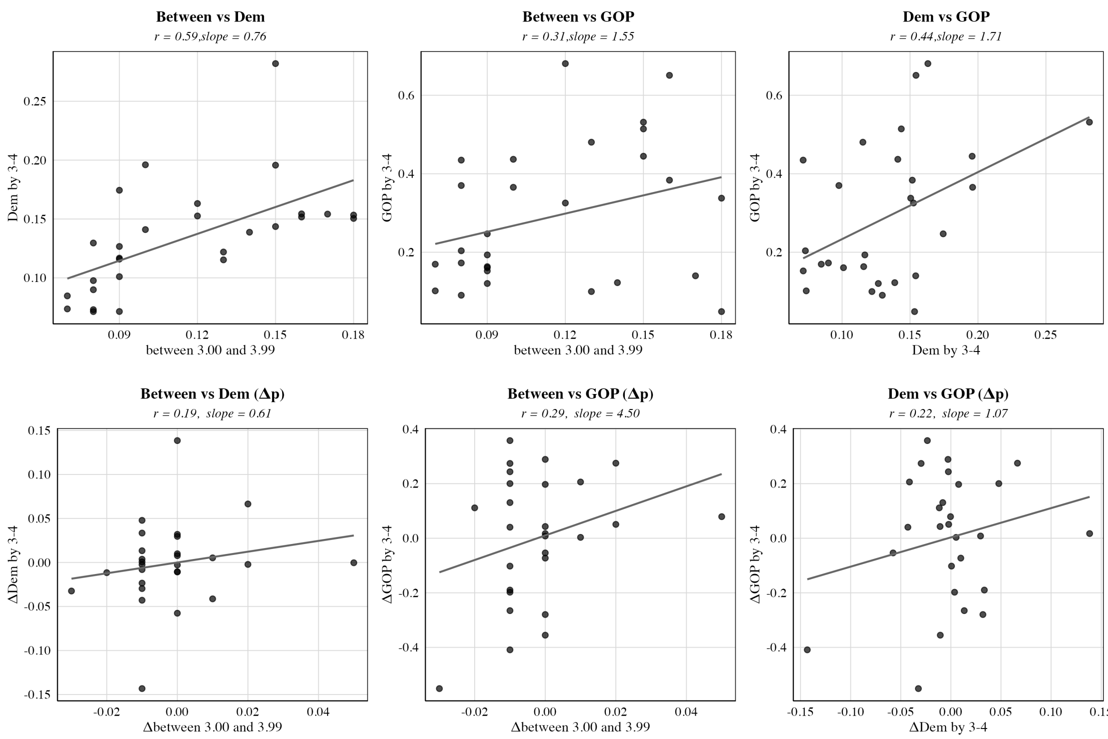


Figure A16. Price level and daily change correlations for 3–4% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

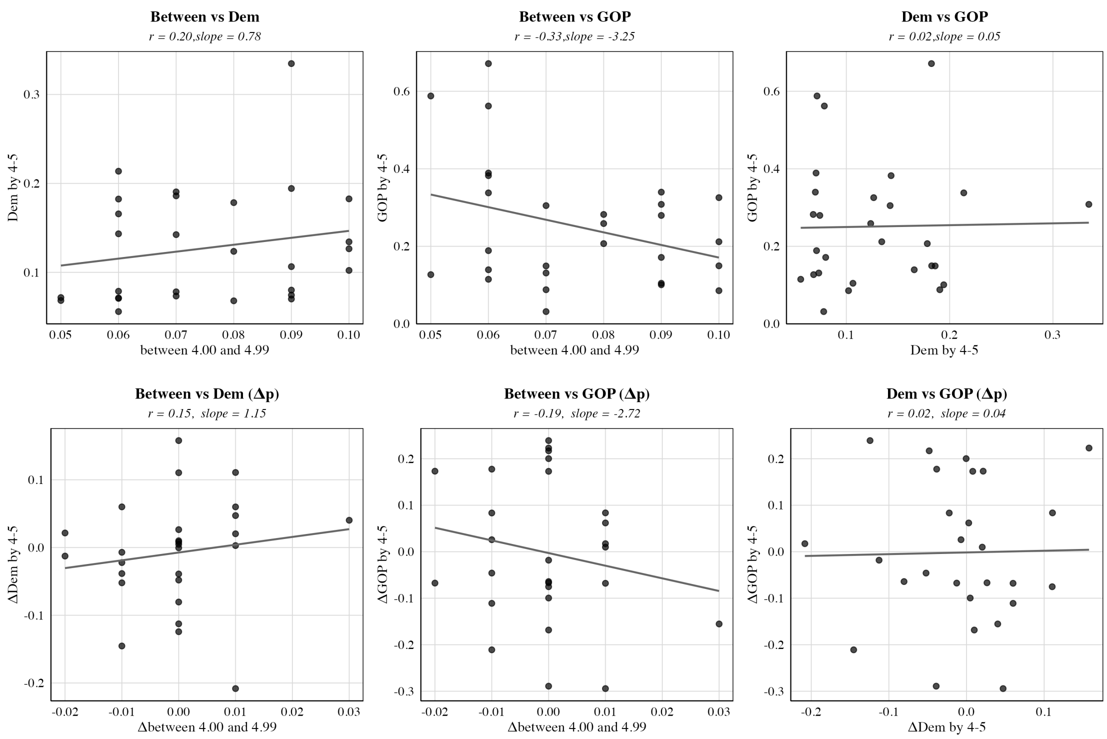


Figure A17. Price level and daily change correlations for 4–5% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

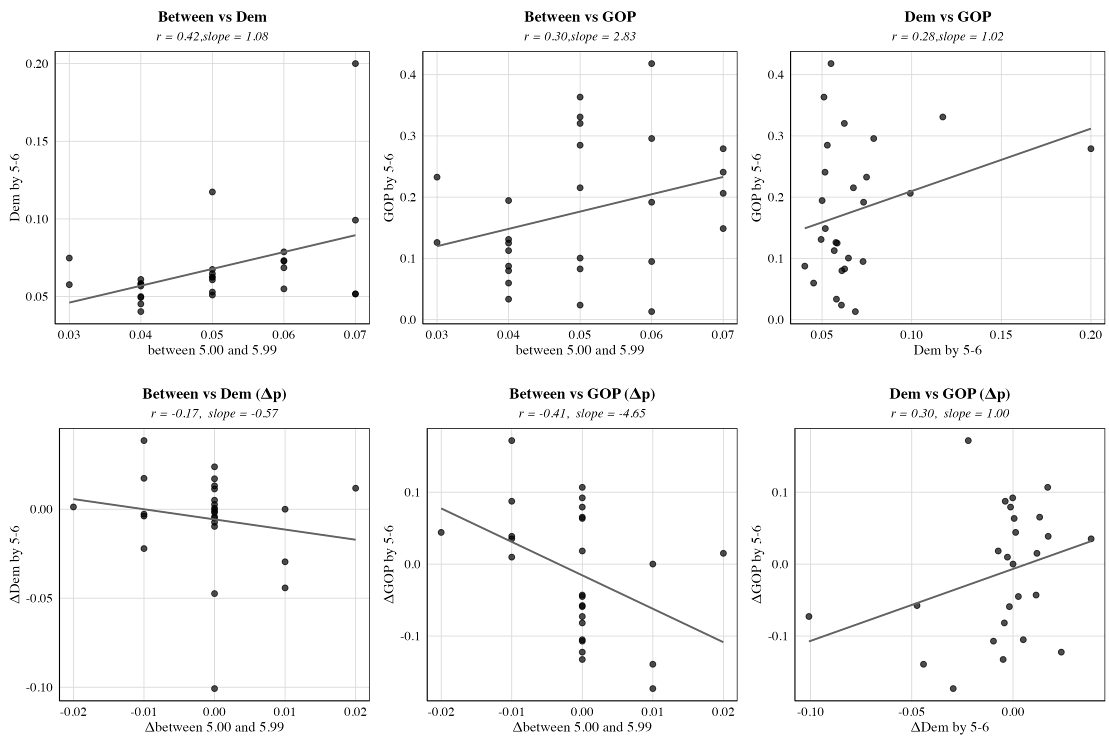


Figure A18. Price level and daily change correlations for 5–6% winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

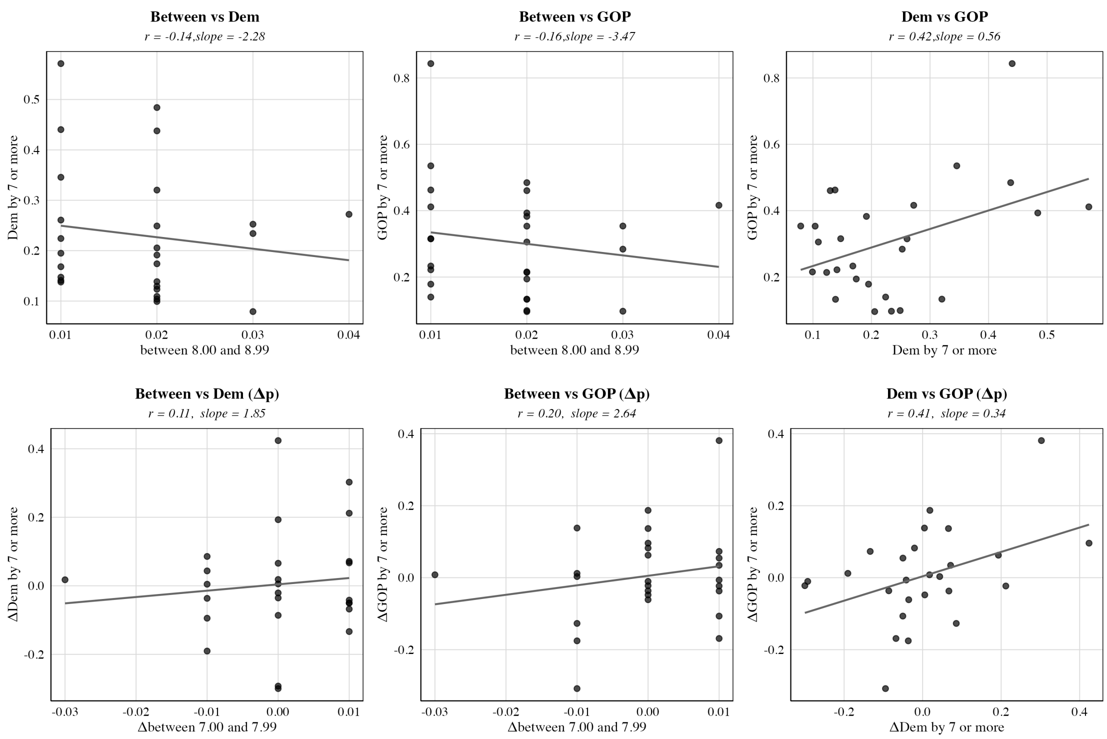


Figure A19. Price level and daily change correlations for 7%+ winning margin group. Each point represents a single trading day (October 1–November 5, 2024).

G Price Shifts in the Event Analysis

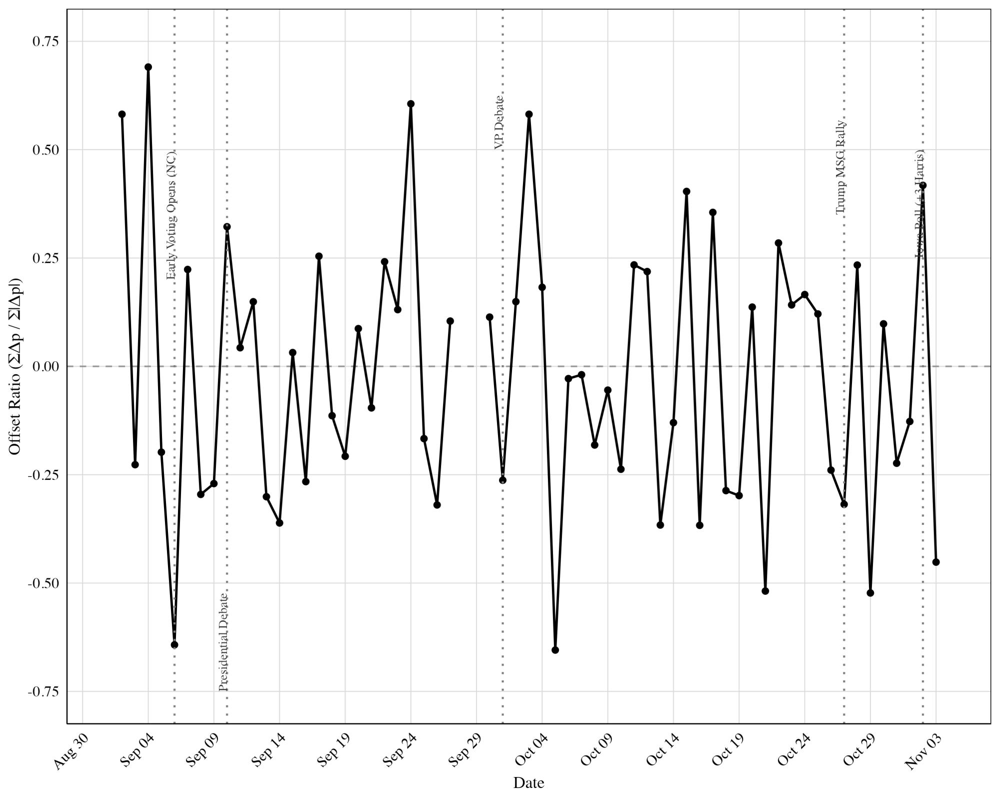
To analyze the reason why $\iota =$ in Figure 7 we consider the type of price changes occurring on similar contracts related to a Harris or Trump victory. To assess whether price changes across related contracts move coherently in the same direction, we compute for each candidate c on day t the ratio of the net price change to the total absolute price change:

$$R_{ct} = \frac{\sum\limits_{i \in \mathcal{C}} \Delta P_{i,t}}{\sum\limits_{i \in \mathcal{C}} |\Delta P_{i,t}|},$$

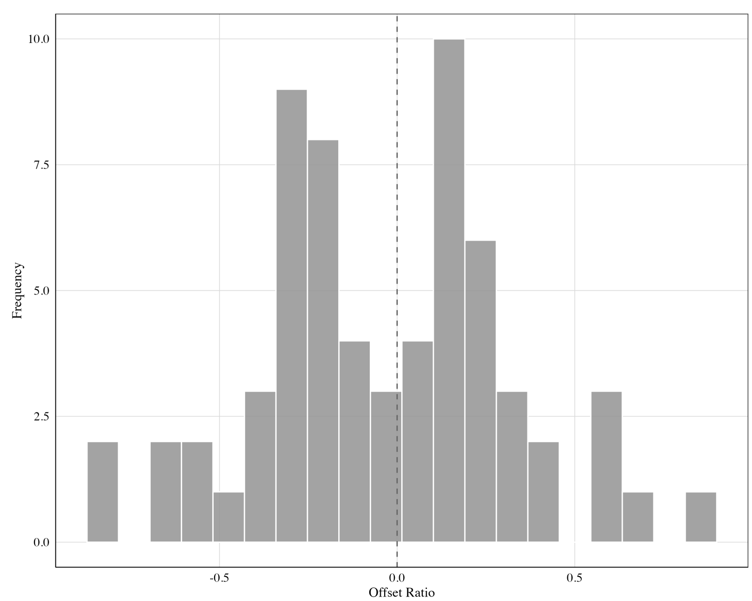
where $\Delta P_{i,t} = P_{i,t} - P_{i,t-1}$ is the daily change in the price of contract i, and $\mathcal{C}$ denotes the set of all contracts associated with candidate c. The ratio $R_{ct} \in [-1, 1]$ equals 1 when all contract prices move up together, -1 when they all move down together, and approaches 0 when positive and negative changes offset one another.

Of primary interest is whether the ratio is close to zero on day t when $\iota_t = 0$. If so, this would mean that offsetting price changes occur on that day and that there is, as a result, no average change in prices. But the fact prices on similar contracts related to the same political event are both increasing and decreasing seems hard to rationalize in terms of information updating by traders seeking to predict whether the event occurs. Finding R_{ct} close to 1 or -1 would suggest that, consistent with rational updating, even though all of the prices are moving in the same direction the overall magnitude of that common change is not statistically distinguishable from zero given the variation in price changes we observe.

Figures A20 plot the computed ratios for each candidate and day as well as the overall distribution of ratios and shows that most of the ratios are near zero – suggesting the presence of off-setting price changes occurring on contracts involving the same political event. As a result, finding $\iota = 0$ is more likely to indicate the presence of irrational and offsetting price changes than it is the absence of any meaningful price change due to no new information being revealed on that day.



(a) Daily Offset Ratio of Market Price Changes.



(b) Distribution of Daily Offset Ratios.

Figure A20. ***Offset Ratio of Market Price Changes.*** The offset ratio quantifies how unified market responses were to new information. When the ratio approaches ± 1, most contracts moved in the same direction, suggesting strong consensus. Ratios near 0 reflect offsetting adjustments—markets moving in opposite directions as traders reassess probabilities. Panel (a) shows daily variation in the offset ratio with major 2024 campaign events (vertical dotted lines). Panel (b) shows the overall distribution of daily offset ratios.