Do Decentralized Markets Beat Centralized Forecasters? Evidence from the 2024 Presidential Elections

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Abstract:

This paper examines whether decentralized blockchain-based prediction markets enhance forecasting accuracy compared to traditional prediction markets and statistical models. Through a comparative analysis of three prediction markets — Polymarket (decentralized), PredictIt (centralized), and FiveThirtyEight (poll aggregator) — during the 2024 U.S. presidential election, we find a statistically significant hierarchy: decentralized markets outperform centralized counterparts, which in turn surpass poll aggregation. Decentralized platforms' censorship-resistant design, global participation, and reduced information suppression may explain their superior accuracy. Our results position decentralized prediction markets as robust tools for synthesizing crowdsourced information in real time, particularly in contexts requiring resilience to censorship and dynamic data aggregation.

Keywords:

Prediction Markets; Polymarket; US Elections; Polls.

1. Introduction:

Prediction markets, also known as information markets, are exchange-based systems designed to aggregate dispersed information into probabilistic forecasts of future events. These markets function by allowing individuals to buy and sell contracts whose payoffs depend on the outcomes of future events, such as elections. The prices of these contracts reflect the aggregated beliefs of traders regarding the likelihood of specific outcomes, generating dynamic, crowd-sourced estimates that reflect collective expectations. Over the past two decades, such platforms have gained some prominence as forecasting tools. Recent advancements have led to the emergence of novel market architectures, including decentralized platforms operating on blockchain infrastructure. Those platforms, and especially the most popular among them, Polymarket, have attracted special attention during the 2024 U.S. presidential election race, with its outcomes quoted on Bloomberg terminal and mainstream news outlets, mainly due its platform accounting for a cumulative volume of $3.7 billion. This evolution raises critical questions: Do next-generation decentralised prediction markets improve upon traditional models in terms of forecasting accuracy, and how do these systems compare to established statistical approaches, such as poll aggregation?

Our study addresses these questions through a comparative analysis of three forecasting systems during the 2024 U.S. presidential election: Polymarket, the most popular decentralized blockchainbased prediction market; PredictIt, a centralized prediction market; and FiveThirtyEight, a poll aggregation model. Following Atanasov et al. (2017), we utilize Brier Scores to quantify predictive accuracy across three forecasting systems, Polymarket (decentralized prediction market), PredictIt (centralized prediction market), and FiveThirtyEight (poll aggregator)—through pairwise comparisons of their daily probability estimates. Our results demonstrate a statistically significant hierarchy: Polymarket achieves the lowest prediction error (Brier Score: 0.211), followed by PredictIt (0.229) and FiveThirtyEight (0.289). This suggests decentralized markets' censorship-resistant design and global participation improves information aggregation relative to both traditional prediction markets and statistical polling models during the 2024 election cycle. This is despite our finding that values in the centralised prediction market, PredictIt, help predict (Granger-cause) values in Polymarket. This demonstrates that information efficiency and accuracy are not always aligned and while Polymarket may be slower to incorporate new information, relying on signals from centralised markets, it is ultimately better at filtering out noise and arriving at a more accurate outcome.

Overall, decentralized markets have the potential to achieve superior forecasting accuracy by broadening the participant pool and minimising information suppression and noise. Unlike their centralized counterparts, they operate through autonomous smart contracts on public blockchains, eliminating the need for trusted intermediaries. This structure offers three key advantages: censorship resistance, which enables global participation without geographic or identity restrictions; pseudo-anonymous trading, which may reduce self-censorship among participants; and operation within regulatory gray zones, where traditional conflicts of interest checks and balances do not apply. While they face challenges such as lower liquidity in some markets and the absence of regulatory oversight, these unique characteristics position decentralized markets as strong contenders for more accurate forecasting.

The fact that Polymarket outperforms two polling systems is possible also due to the fact that with Polymarket (or any prediction market for that matter), investors put 'their money where their mouth is'. That is, they use their own wealth in placing positions, while in polling markets, participants explain denote which party they are going to vote for. Given the former has capital at risk, arguably these investors will be more serious, have done more research and provide more information than polling data. On the other hand, financial markets are abreast with examples of investors being irrational and it may be that investors trade with their 'heart' rather than 'head'. Given that cryptocurrency markets are found to be traded mostly by right-leaning individuals (Littrell et al., 2024), we may expect Polymarket to be biased to the republican party and therefore Donald Trump.

We contribute to the literature on prediction markets. Prediction markets have been studied as mechanisms for aggregating dispersed information, often demonstrating superior forecasting accuracy compared to traditional polling methods. Most relevant to our study, Berg et al. (2008) provide evidence that prediction markets outperform polls in forecasting U.S. presidential elections, with markets being closer to the eventual outcome 74% of the time, particularly when forecasting more than 100 days in advance. Similarly, Wolfers and Zitzewitz (2004) highlight the accuracy of market-generated forecasts across various contexts, noting their ability to outperform sophisticated benchmarks. However, Manski (2006) caution against interpreting market prices as direct probabilities. Previous work by Goodell et al. (2015) shows that prediction markets outperform polls as prediction vehicles, consistent with prior work by Berg et al. (2008). Goodell et al. (2020) show that the incumbent-party election probability, derived from prediction markets, is an important measure of economic policy uncertainty in the days leading up to the US elections. Brown et al. (2019) show that prediction markets are most price efficiency hours after their release once experienced traders enter the market. We contribute to this growing literature by studying the US Presidential election of 2024 by using a new type of prediction market, Polymarket, which has not been examined in much detail up to this point.

We also contribute to the literature on Polymarket. Polymarket was only launched in 2020 but given the growth, breadth and interest in cryptocurrency markets and their usage, there has been a burgeoning literature these new prediction markets. Puri (2025) study the English Premier League (EPL) and show that Polymarket exhibits a discrepancy between the expected probabilities implied by the odds and their actual statistical outcomes, which contrasts with the famous Favourite-Longshot bias. They also note that the odd change after goal experiences a 35- minute delay, probably due to the nature of information dissemination and market illiquidity. Flynn and Tarkom (2025) show that Polymarket lead financial markets in pricing political uncertainty. We contribute to this small, but growing literature on how Polymarket is shaping election and other prediction markets.

2. Prediction Market Background:

Prediction market design and structure can significantly influence their performance, a finding particularly important for our study of a novel form of decentralised prediction market. Atanasov et al. (2017) compare prediction markets to prediction polls in a large-scale experimental setting, to find that while markets generally outperform simple poll averages, statistically aggregated polls can rival or exceed market accuracy. Brown et al. (2019) further examine the conditions under which prediction market prices are most informative, noting that information releases, such as opinion polls, can temporarily reduce price efficiency by attracting less experienced traders. Snowberg et al. (2007) also demonstrate the utility of prediction markets in isolating exogenous economic impacts, such as partisan effects on financial indicators, highlighting their value in contexts requiring realtime information synthesis. However, the emergence of decentralized blockchain-based prediction markets introduces novel dynamics, such as censorship resistance and global participation, which have yet to be systematically compared to centralized markets and statistical models. This study addresses this gap by evaluating the relative performance of decentralized (Polymarket), centralized (PredictIt), and poll-based (FiveThreeEight) forecasting systems.

Polymarket, launched in 2020, is a decentralized prediction market operating on blockchain infrastructure, utilizing smart contracts to facilitate peer-to-peer trading of binary outcome contracts for real-world events. Users trade shares corresponding to potential outcomes (e.g., "Will Donald Trump win the 2024 U.S. presidential election?"), with each share priced between $0.00 and $1.00 USDC(1), reflecting the market's collective probability estimate (0%–100%) of that outcome occurring. Prices are determined by supply and demand dynamics, with continuous order-book trading establishing real-time consensus on event likelihoods. Each outcome pair (e.g., "YES" and "NO") is fully collateralized, meaning the platform holds $1.00 USDC in reserve for every share issued, ensuring payouts are guaranteed upon resolution.

Markets are created and resolved through a decentralized, incentive-aligned process. To propose a market, users must stake a bond (typically $750 USDC), which is forfeited if the market violates predefined validity criteria (e.g., unambiguous phrasing, objective resolvability). Once a market concludes, any user may propose an outcome by staking additional collateral, which is subject to challenge by other participants. If unchallenged or validated via crowd-sourced verification, the proposed outcome is finalized. Correct-outcome shares are redeemable for $1.00 USDC each, while incorrect-outcome shares are rendered valueless, and trading is permanently halted.

PredictIt is a prediction market that has been operating since 2014, where users trade binary contracts on events. Prices are determined by buy/sell orders, and contract resolution is administered by platform operators based on pre-specified criteria. PredictIt and Polymarket function similarly, except that Polymarket operates on blockchain

(1) A stablecoin pegged to the U.S. dollar, represented on-chain

infrastructure. This grants Polymarket censorship resistance and global accessibility, enabling participation without geographic or identity restrictions.

FiveThirtyEight, established in 2008 by statistician Nate Silver, before becoming a licensed feature of The New York Times online in 2010 and then acquired, by ESPN in 2013, with operations transfered to ABC News in 2018. It employs a methodology centred on aggregating and statistically weighting polling data to generate probabilistic forecasts. This approach is unlike prediction markets, which derive probabilities dynamically from speculative trading activity. Instead, FiveThirtyEight's models synthesize historical polling error, demographic trends, and non-polling variables (e.g., economic indicators, incumbency status) to produce calibrated likelihoods of event outcomes. Again, unlike prediction markets which reflect real-time crowd behavior, its forecasts are retrospective.

3. Data and Methodology:

3.1. Data and Descriptive Statistics

We source Polymarket prediction odds from the popular blockchain analytics and visualization platform, Dune(2). Specifically, we query the "Yes" shares for presidential candidates and calculate the implied probability of a positive outcome as buyerPaid / sharesBought, expressed as percentage vote. Additionally, we obtain data from FiveThirtyEight, using its simulation of the 2024 presidential election titled "Who Is Favored To Win The 2024 Presidential Election?"(3). Finally, we incorporate data from PredictIt(4).

Additionally, Figure 1 presents the trading volume in USD for each share on Polymarket, while Figure 2 illustrates the average bet size. We observe that although trading volume reaches tens of millions, the average bet size remains relatively small, with most bets around $1,000. This suggests a large number of market participants. Moreover, there are no observable spikes in average bet size or discrepancies between candidates, indicating a lack of manipulation by wealthy participants (whales). However, this should be

(2) Source for actual market: https://Polymarket.com/event/presidential-election-winner-2024?tid=17

(3) Source: https://projects.fivethirtyeight.com/2024-election-forecast/

(4) Source: https://www.predictit.org/markets/detail/7456/Who-will-win-the-2024-US-presidentia l-election

interpreted with caution, as the decentralised nature of the space allows orders to be split across different addresses. Comparable PredictIt data is unavailable.

One limitation of our data is that different sources cover different time periods and adopt distinct approaches to the question at hand. Specifically, both Polymarket and PredictIt provide options for multiple candidates in the Democratic camp beyond Kamala Harris and Joe Biden, including unlikely contenders such as Kanye West. In contrast, FiveThirtyEight frames its predictions in terms of a Democratic win versus a Republican win. To mitigate these discrepancies and to account for Joe Biden's withdrawal from the race, we limit our analysis to the period from September 19, 2024, to the day before the election, October 30, 2024. This ensures that our dataset reflects a clear race between Harris and Trump. Descriptive statistics of our data are presented in Table 1, the correlation metrics for variables in Table 2, and prediction odds are plotted in Figure 3. As we can see, Polymarket has the highest mean value (of 0.55) indicating that throughout the sample, Polymarket on average had a Trump win more likely than FiveThirtyEight or PredictIt. We can also see that the correlation between the variables is very high, indicating that the markets did not disagree too much throughout the sample. This is reflected in Figure 3 which shows that FiveThirtyEight was the last prediction market to switch to a Trump win, while Polymarket was the first. Interestingly, we can see that for a short period just before the election, a Harris victory is more likely than a Trump victory for Predictit, while although the other markets show a narrowing of odds, they still have a Trump victory the most likely outcome.

3.1.1 Methodology

To evaluate the relative accuracy of decentralized prediction markets, traditional prediction markets, and poll aggregators in forecasting electoral outcomes, we employ the Brier Score as our primary metric of predictive performance. The Brier Score measures the mean squared error between predicted probabilities and actual outcomes. For each system of the prediction systems in our analysis (Polymarket, the decentralized prediction market, PredictIt, a traditional prediction market, and FiveThirtyEight a poll aggregator and statistical model), we calculate candidatespecific probabilities (Harris vs. Trump) at daily frequency. The Brier Score is computed as:

$$\text{Brier Score} = \frac{1}{N}\sum_{i=1}^{N}(p_i - y_i)^2 \quad (1)$$

Where pi represents the predicted probability of victory for the winner (Trump = 1, Harris = 0) on day i, and yi is the binary outcome indicator. Lower scores indicate better predictive performance, with perfect accuracy yielding a score of 0 and worst-case predictions scoring 1.

The Kruskal-Wallis non-parametric ANOVA tests whether Brier Scores differ significantly across systems:

$$H = \frac{12}{N(N+1)}\sum_{j=1}^{k}\frac{R_j^2}{n_j} - 3(N+1) \quad (2)$$

Where Rj represents the rank sum for system j, nj its observation count, and N the total sample size.

In addition to Brier Score comparisons, we examine the temporal dynamics between the variables in our analysis. First, we employ the Augmented Dickey-Fuller (ADF) test on each prediction series to examine stationarity, and determine the optimal lag length using the Akaike Information Criterion (AIC). Next, to assess long-term equilibrium relationships, we apply the Johansen cointegration test (Johansen, 1988, 1991), which is based on a vector autoregression (VAR) model of order p:

$$X_t = \mu + \sum_{i=1}^{p} A_i X_{t-i} + \varepsilon_t \quad (3)$$

where Xt is an n × 1 vector of integrated variables of order one, and εt is a zero-mean white noise process. This can be rewritten as by including an error correction term as:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t \quad (4)$$

where Π = ∑_{i=1}^{p} A_i - I and Γ_i = -∑_{j=i+1}^{p} A_j. If the rank of Π is r < n, then there exist n × r matrices α and β such that Π = αβ′, where β′X_t is stationary. The number of cointegrating relationships is given by r, with α representing the adjustment parameters and β containing the cointegrating vectors.

The null hypothesis for the Johansen test is tested using the trace test:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \quad (5)$$

and the maximum eigenvalue test:

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \quad (6)$$

where T is the sample size and λ^i are the estimated eigenvalues. The trace test examines whether the number of cointegrating vectors is at most r, while the maximum eigenvalue test compares r against r + 1.

Finally, we perform Granger causality tests (Engle and Granger, 1987) to assess whether past values of one forecasting system improve the predictive power of another. A time series Xt is said to Granger-cause Yt if past values of Xt provide additional explanatory power for Yt, beyond the information contained in past values of Yt. This is tested using the autoregressive models:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{p} \gamma_i X_{t-i} + \varepsilon_t \quad (7)$$

$$X_t = \delta + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{i=1}^{p} \theta_i Y_{t-i} + \eta_t \quad (8)$$

where β_i, γ_i, ϕ_i, and θi are lag coefficients, and εt, ηt are error terms. The null hypothesis that Xt does not Granger-cause Yt (Ho : $\gamma 1 = \gamma 2 = \cdots = \gamma p = 0$) is tested using an F-test. If rejected, this indicates that past values of Xt contribute to predicting Yt. We perform these tests on each pair of prediction systems to assess informational efficiency and dynamic relationships among decentralized, centralized, and poll-based forecasting models.

4. Empirical Analysis and Results:

Figure 4 summarizes the Brier Score analysis comparing the predictive accuracy of Polymarket,

PredictIt, and FiveThirtyEight. The results reveal statistically significant differences in forecasting performance across systems, with Polymarket achieving the lowest mean Brier Score (0.211, SD =

0.0568), followed by PredictIt (0.229, SD = 0.0477), and FiveThirtyEight (0.289, SD = 0.0483). The Kruskal-Wallis shows significant differences in predictive accuracy at the 1% level. This indicates that Polymarket has the better predictive accuracy than the two polling markets.

Beyond the Brier analysis, we also study the Johansen test for cointegration across our markets.

First, we need to examine whether our series of odds are stationary and to do that, we conduct

Augmented Dickey-Fuller tests. Table 3 shows that forecasting systems are non-stationary at the 5% level. When the first difference is taken, the unit root tests all reject the null hypothesis of a unit root at conventional significance levels, confirming stationarity in the transformed series. Therefore, we use the first-difference of the odds where appropriate. Table 4 provides evidence of cointegration among the systems. The trace test rejects the null hypothesis of no cointegration ($r = 0$) at the 1% level (test statistic 961.97 vs. 1% critical value 111.01), with sequential testing indicating five cointegrating relationships at the 10% significance level ($r \leq 5$: test statistic 6.05 vs. 10%

critical value 7.52). This suggests complex long-run equilibrium relationships between decentralized prediction markets (Polymarket), centralized models (FiveThirtyEight), and pollbased markets (PredictIt). Given the dual evidence of difference stationarity and cointegration, we implement Granger-causality tests on first-differenced series to analyze short-term predictive dynamics. Table 5 reveals asymmetric information flows between systems where we can see three significant relationships. First, we see that predictit-harris Granger causes poly-trump, which appears to be a spurious finding as there is no logic why this would be the case. Second, we find that predictit-harris Granger causes poly-harris which suggests that, between the two polling markets, the predictit market leads the Polymarket. Third, we find that predict-trump Granger causes predictit-harris, suggesting that there may be some mean reversion in the predictit market itself. However, all other relationships appear to offer no Granger causality, indicating very little lead/lag relationships between these prediction markets.

5. Discussion and Conclusions:

Decentralised prediction markets have garnered increasing interest, and this study demonstrates why: these markets exhibited superior forecasting accuracy compared to centralised markets and statistical poll aggregation during the 2024 U.S. presidential election. The observed performance hierarchy—Polymarket, PredictIt, and FiveThirtyEight—suggests that censorship-resistant architectures broaden participation and reduce information suppression, thereby enhancing collective intelligence. We attribute the superior forecasting accuracy of decentralised markets to their structural characteristics: Their ability to broaden the participant pool, reduce information suppression, and operate within a regulatory grey area likely expanded participant diversity and minimised selfcensorship, leading to more accurate predictions. For the same reasons, Polymarket exhibits the highest standard deviation accross our forecasting systems.

The Granger causality tests show that changes in PredictIt's markets (centralised prediction market) lead to changes in Polymarket's predictions (decentralized prediction market). This means that Polymarket tends to incorporate information from PredictIt with a delay, rather than the other way around. This contrasts our expectations: we expected decentralised markets to be efficient because they aggregate information from many participants. The fact that Polymarket is not leading the other systems might suggest that its participants might rely on signals from more established systems (PredictIt), before updating their beliefs. This is a signficant finding in the context of Polymarket also being more accurate in prediction the actual election outcome, as it demonstrates that accuracy and efficiency are not always aligned. Specifically, while a centralised prediction market might be more efficient in incorporating information, a decentralised market might be better in filtering out noise and reaching an overall more accurate outcome.

Policymakers must reconcile these platforms' forecasting utility with unresolved regulatory and jurisdictional challenges. For practitioners, decentralised markets offer empirically validated tools for real-time information aggregation in contexts where traditional systems face participation constraints or censorship risks—provided that liquidity thresholds and resolution mechanisms are adequately designed.

Several limitations warrant consideration. This analysis focused on a single high-salience event, necessitating replication across diverse contexts. Differences in market liquidity, contract specifications, and resolution mechanisms between platforms may introduce unobserved confounders. Additionally, the post-Biden withdrawal timeframe precludes generalisation to earlier election phases.

Future research should examine whether the advantages of decentralised markets persist under formal regulation or vary across different event types.

6. Figures and Tables:

Table 1: This table presents summary statistics for betting odds from Polymarket, FiveThirtyEight, and PredictIt for Trump and Harris. The variables are: poly_trump, betting odds for Trump from Polymarket; poly_harris, betting odds for Harris from Polymarket; 538_harris, betting odds for Harris from FiveThirtyEight; 538_trump, betting odds for Trump from FiveThirtyEight; predictit_trump, betting odds for Trump from PredictIt; and predictit_harris, betting odds for Harris from PredictIt. Column 'n' represents the number of observations. Sd is the standard deviation. Min and max are the minimum and maximum values, respectively. Skew is the measure of asymmetry in the distribution. Se is the standard error of the mean.

andard error of the mean:

	vars	n	mean	sd	median	min	max	range	skew	kurtosis	se
poly_trump	1	41	0.55	0.06	0.53	0.47	0.66	0.19	0.45	-1.37	0.01
poly_harris	2	41	0.45	0.06	0.46	0.34	0.52	0.18	-0.48	-1.29	0.01
fivethreeeight_harris	3	41	0.53	0.05	0.54	0.45	0.62	0.17	-0.15	-0.95	0.01
fivethreeeight_trump	4	41	0.46	0.05	0.46	0.38	0.55	0.17	0.24	-0.99	0.01
predictit_trump	5	41	0.52	0.05	0.52	0.45	0.62	0.17	0.27	-1.15	0.01
predictit_harris	6	41	0.51	0.05	0.52	0.42	0.58	0.16	-0.20	-1.25	0.01

	poly_trump	poly_harris	harris_538	trump_538	pred_trump	pred_harris
poly_trump	1.00	-1.00		0.93	0.96	-0.95
poly_harris	-1.00	1.00	0.93	-0.94	-0.96	0.94
fivethreeeight_harris	-0.92	0.93	1.00	-1.00	-0.92	0.92
fivethreeeight_trump	0.93	-0.94		1.00	0.93	-0.92
predictit_trump	0.96	-0.96		0.93	1.00	-0.98
predictit_harris	-0.95	0.94	0.92	-0.92	-0.98	1.00

Table 2: This table presents the correlation matrix for betting odds from Polymarket, FiveThirtyEight, and PredictIt for Trump and

Harris. The variables are: poly_trump, betting odds for Trump from Polymarket; poly_harris, betting odds for Harris from Polymarket; 538_harris, betting odds for Harris from FiveThirtyEight; 538_trump, betting odds for Trump from FiveThirtyEight; predictit_trump, betting odds for Trump from PredictIt; and predictit_harris, betting odds .for Harris from PredictIt

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fivethreeeight_ harris	-0.92	0.93	1.00	-1.00	-0.92	0.92
fivethreeeight_ trump	0.93	-0.94	-1.00	1.00	0.93	-0.92
predictit_trump	0.96	-0.96	-0.92	0.93	1.00	-0.98
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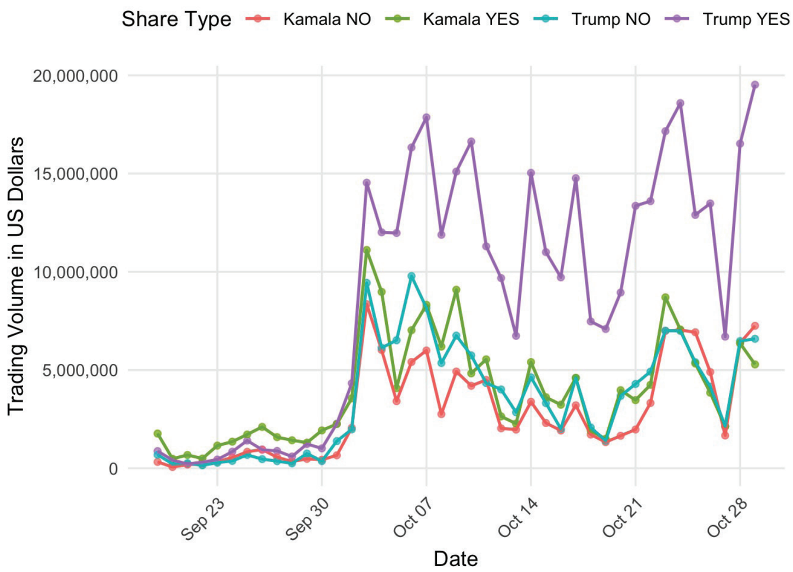

Figure 1: Trading Volume on Polymarket

Trading volume on Polymarket in USD for each share option for Harris and Trump.

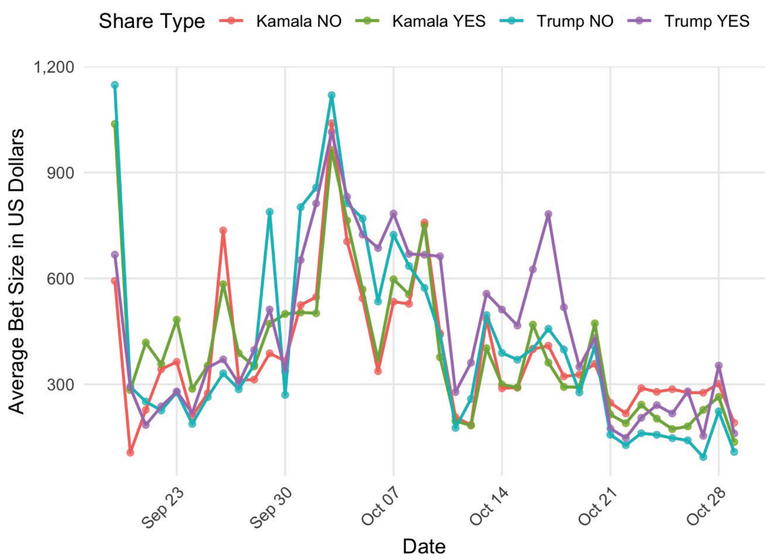

Figure 2: Average Bet Size on Polymarket

Average bet size in Polymarket in USD for each share option fro Harris and Trump.

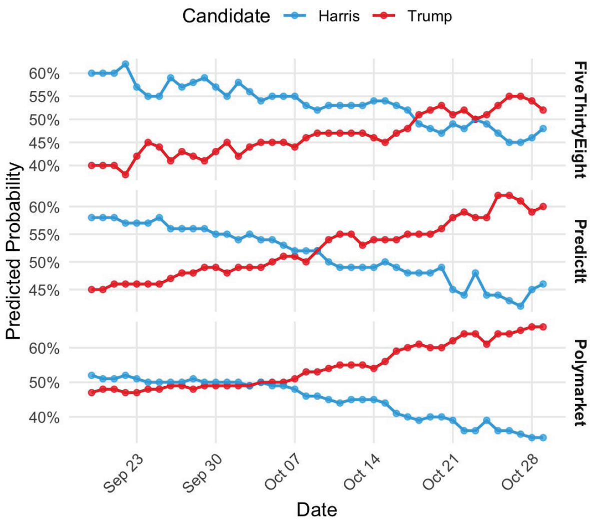

Figure 3: Election Odds from Different Prediction Sources

Predicted probabilities of victory for Harris and Trump over time from FiveThirtyEight, PredictIt, and Polymarket.

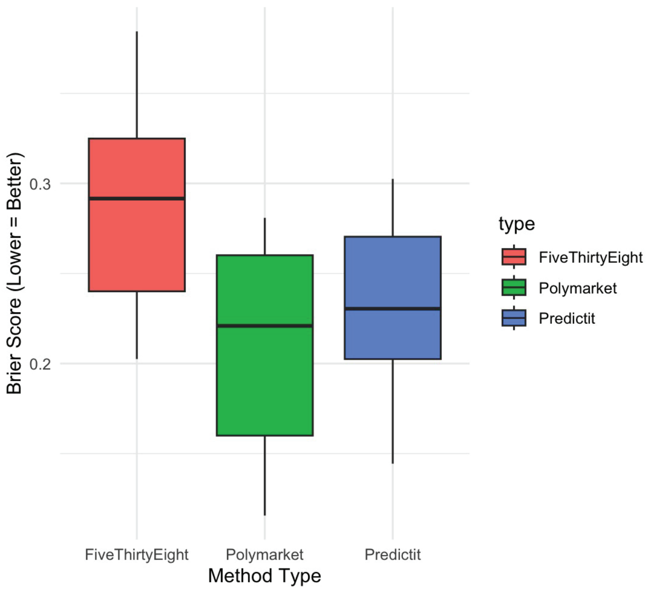

Figure 3: Election Odds from Different Prediction Sources

Predicted probabilities of victory for Harris and Trump over time from FiveThirtyEight, PredictIt, and Polymarket.

Figure 4: Brier Score Comparison by Prediction Type:

Comparison of Brier scores for FiveThirtyEight, Polymarket, and PredictIt. Lower scores indicate better predictive accuracy.

Table 3: This table reports the trace statistics from the Augmented Dickey-Fueller test for variables in levels, as well as in first differences, denoted by the prefix "diff". ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Variable	Test_Statistic	P_Value
poly_trump	-1.92	0.60
poly_harris	-1.65	0.71
fivethreeeight_harris	-3.43	0.07
fivethreeeight_trump	-3.33	0.08
predictit_trump	-2.50	0.38
predictit_harris	-3.15	0.12
diff_poly_trump	-4.92	0.01
diff_poly_harris	-5.06	0.01
diff_fivethreeeight_harris	-3.72	0.04
diff_fivethreeeight_trump	-3.81	0.03
diff_predictit_trump	-3.90	0.02
diff_predictit_harris	-4.48	0.01

Table 4: This table reports the trace statistics from the Johansen cointegration test, including critical values at the 10%, 5%, and 1% significance levels.

Rank Condition	Test Statistic	10%	5%	1%
r ≤ 5	6.05	7.52	9.24	12.97
r ≤ 4	22.95	17.85	19.96	24.60
r ≤ 3	51.79	32.00	34.91	41.07
r ≤ 2	114.34	49.65	53.12	60.16
r ≤ 1	263.39	71.86	76.07	84.45
r = 0	961.97	97.18	102.14	111.01

Table 5: This table presents p-values from Granger causality tests between first-differenced betting odds from Polymarket, FiveThirtyEight, and PredictIt. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

cause	effect	p_value
poly_harris	poly_trump	0.71
fivethreeeight_harris	poly_trump	80 .0
fivethreeeight_trump	poly_trump	0.72
predictit_trump	poly_trump	0.56
predictit_harris	poly_trump	** 0.03
poly_trump	poly_harris	0.60
fivethreeeight_harris	poly_harris	0.99
fivethreeeight_trump	poly_harris	0.95
predictit_trump	poly_harris	0.64
predictit_harris	poly_harris	*** 0.00
poly_trump	fivethreeeight_harris	0.38
poly_harris	fivethreeeight_harris	0.55
fivethreeeight_trump	fivethreeeight_harris	0.12
predictit_trump	fivethreeeight_harris	0.21
predictit_harris	fivethreeeight_harris	0.61
poly_trump	fivethreeeight_trump	0.26
poly_harris	fivethreeeight_trump	0.37
fivethreeeight_harris	fivethreeeight_trump	0.34
predictit_trump	fivethreeeight_trump	0.17
predictit_harris	fivethreeeight_trump	0.60
poly_trump	predictit_trump	0.40
poly_harris	predictit_trump	0.13

Follow: Table 5: This table presents p-values from Granger causality tests between first-differenced betting odds from Polymarket, FiveThirtyEight, and PredictIt. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

cause	effect	p_value
fivethreeeight_harris	predictit_trump	0.43
fivethreeeight_trump	predictit_trump	0.50
predictit_harris	predictit_trump	0.14
poly_trump	predictit_harris	0.51
poly_harris	predictit_harris	0.20
fivethreeeight_harris	predictit_harris	0.99
fivethreeeight_trump	predictit_harris	1.00
predictit_trump	predictit_harris	*** 0.00