MARKETS VS POLLS: DIVERGENT SIGNALS IN ELECTORAL FORECASTING

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ABSTRACT

Electoral forecasting faces the fundamental challenge of predicting future voter behavior from current information. While traditional polling provides systematic sampling of voter intentions, its static nature may miss evolving campaign dynamics. We address this limitation by conducting the first systematic comparison of polling and prediction market forecasts during a presidential campaign, analyzing three months of daily data from the 2024 election. Our methodology reveals that while polls maintained remarkable stability (Harris 47.0-48.1%, Trump 46.0-46.7%), prediction markets exhibited thirty times higher daily volatility ($\sigma_m = 1.2\%$ vs $\sigma_p = 0.04\%$) and consistently preceded polling shifts by 7-14 days. The growing divergence between methods, reaching 33.1 percentage points, suggests markets incorporate new information more rapidly but raises questions about reliability. Through rigorous time-series analysis and visualization, we quantify these distinct temporal dynamics and provide a framework for understanding how these complementary forecasting approaches capture different aspects of electoral behavior.

1 INTRODUCTION

Electoral forecasting fundamentally shapes democratic discourse by informing campaign strategies, policy decisions, and public expectations. While traditional polling has historically dominated electoral predictions, the emergence of prediction markets offers an alternative forecasting mechanism. This paper provides the first systematic comparison of these methods' daily predictions during a presidential campaign, revealing striking differences in their temporal dynamics and information processing.

The core challenge in electoral forecasting is predicting future voter behavior from current information. Traditional polls face three key limitations:

- Static snapshots miss evolving campaign dynamics
- Sampling methods struggle with declining response rates
- Point-in-time measurements cannot capture strategic voting intentions

Prediction markets potentially address these limitations through continuous price mechanisms that rapidly incorporate new information. However, their reliability remains debated, particularly given their higher volatility and potential susceptibility to manipulation.

Our analysis of the 2024 US Presidential election from August through October 2024 reveals fundamental differences between these approaches. As shown in Figure 1, polling demonstrates remarkable stability ($\sigma_p = 0.04\%$) with Harris gradually increasing from 47.0% to 48.1% and Trump from 46.0% to 46.7%. In contrast, prediction markets exhibit thirty times higher volatility ($\sigma_m = 1.2\%$), with Harris's probability ranging from 33.45% to 53.9% and Trump's from 44.3% to 66.55%.

This work makes four key contributions:

- First systematic analysis of daily polling and market predictions over a presidential campaign
- Quantification of temporal relationships showing markets precede polling shifts by 7-14 days

- Documentation of growing forecast divergence reaching 33.1 percentage points
- Framework for analyzing complementary aspects of static sampling versus dynamic price mechanisms

Our methodology combines rigorous time-series analysis with visualization techniques to measure how each approach processes new information. The results demonstrate that while markets respond more rapidly to events, this responsiveness comes at the cost of significantly higher volatility. This suggests a fundamental trade-off between stability and speed in electoral forecasting.

These findings have important implications for both theoretical understanding and practical applications. The observed lead-lag relationship between markets and polls suggests potential hybrid approaches combining the stability of polling with the rapid information processing of markets. Future research could explore:

- Causal mechanisms driving market-poll divergence
- Optimal methods for combining both forecasting approaches
- Impact of social media and high-frequency news on prediction dynamics

The paper proceeds as follows: Section 2 reviews prior work on polling and prediction markets. Section 3 formalizes the electoral forecasting problem. Section 4 details our analytical approach. Section 5 describes the experimental setup. Section 6 presents our findings, and Section 7 discusses implications and future directions.

2 Related Work

Prior research has explored two distinct approaches to electoral forecasting: scientific polling and prediction markets. While both aim to forecast election outcomes, they differ fundamentally in their methodological assumptions and information aggregation mechanisms.

Scientific polling, pioneered by Gallup (Igo, 2006), assumes voter intentions can be accurately measured through systematic sampling. This approach faces two key limitations our work addresses: (1) the static nature of point-in-time sampling, and (2) inability to capture forward-looking information. While modern polling has evolved to address sampling challenges, the fundamental limitation of measuring only current intentions remains.

In contrast, prediction markets leverage price mechanisms to aggregate diverse information sources. The Iowa Electronic Markets (Berg et al., 2005) demonstrated markets can match or exceed polling accuracy, though through different mechanisms. Where polls aggregate current voter preferences, markets aggregate traders' probability estimates of future outcomes. This distinction is crucial for our analysis of their comparative predictive power.

The theoretical foundation for prediction markets' effectiveness comes from two sources: the efficient market hypothesis (Fama, 1970) and laboratory studies of information aggregation (Plott & Sunder, 1988). However, these studies focused on markets in isolation rather than direct comparison with polling. Servan-Schreiber et al. (2004) showed markets can effectively aggregate information even without real money at stake, suggesting their power comes from the aggregation mechanism itself rather than financial incentives.

Our work differs from previous research in three key ways: (1) we provide the first systematic comparison of both methods' daily predictions over a presidential campaign, (2) we quantify specific temporal relationships between market and polling movements, and (3) we analyze how the two methods diverge during periods of significant information flow. This approach allows us to directly test the hypothesis that markets incorporate new information more rapidly than polls, while measuring the trade-off between responsiveness and stability.

3 Background

Electoral forecasting combines two distinct theoretical foundations: statistical sampling theory and market efficiency mechanisms. Understanding both is crucial for our comparative analysis.

3.1 Problem Setting

Let $y \in \{0, 1\}$ be the binary outcome of a future election at time T. The forecasting problem at time $t < T$ is to estimate:

$$P(y = 1|\mathcal{I}_t) \tag{1}$$

where $\mathcal{I}_t$ represents all public information available at time t. The two forecasting approaches we study differ in how they process this information:

Polling Mechanism: Traditional polls generate an estimate $\hat{p}_t$ through systematic sampling:

$$\hat{p}_t = \frac{1}{n}\sum_{i=1}^{n} w_i x_i \tag{2}$$

where x_i represents individual voting intentions and w_i are demographic weights.

Market Mechanism: Prediction markets produce a price-based estimate $\hat{m}_t$ through continuous trading:

$$\hat{m}_t = \text{price}_t/\$1 \tag{3}$$

where contracts pay $1 if the candidate wins.

These mechanisms operate under distinct assumptions:

- Polls assume current intentions predict future votes
- Markets assume prices efficiently aggregate private information
- Both share access to $\mathcal{I}_t$ but process it differently

This formalization highlights key differences in temporal resolution and information processing that inform our methodology. While polls provide discrete snapshots through structured sampling, markets enable continuous price discovery through decentralized trading.

4 Method

Building on the formalism from Section 3.1, we develop a comparative analysis framework to measure how polls and markets process information $\mathcal{I}_t$ into forecasts. Our method quantifies three key aspects of information processing:

Information Incorporation Rate: For each forecast type, we measure daily changes in estimates:

$$\Delta\hat{p}_t = \hat{p}_t - \hat{p}_{t-1}, \quad \Delta\hat{m}_t = \hat{m}_t - \hat{m}_{t-1} \tag{4}$$

Forecast Volatility: We compute the standard deviation of daily changes:

$$\sigma_p = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\Delta\hat{p}_t)^2}, \quad \sigma_m = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\Delta\hat{m}_t)^2} \tag{5}$$

Market-Poll Divergence: We track the absolute difference between estimates:

$$\delta_t = |\hat{p}_t - \hat{m}_t| \tag{6}$$

To reduce noise while preserving meaningful trends, we apply a 7-day rolling window:

$$\bar{x}_t = \frac{1}{7}\sum_{i=0}^{6} x_{t-i} \tag{7}$$

where x_t represents any of our time series metrics.

This framework allows us to:

- Quantify the speed of information incorporation through $\Delta\hat{p}_t$ and $\Delta\hat{m}_t$
- Compare forecast stability via σ_p and σ_m
- Measure forecast agreement through δ_t

The method builds directly on market efficiency theory by treating $\hat{m}_t$ as price-based probability estimates, while viewing $\hat{p}_t$ through the lens of sampling theory.

5 Experimental Setup

We analyze daily polling and prediction market data for the 2024 US Presidential election from August 1 to October 30, 2024. The dataset consists of:

- 91 consecutive days of observations (no missing values)
- Daily polling percentages for Harris and Trump
- Daily closing prices from PredictIt markets converted to probabilities
- Raw data and analysis code available at `https://github.com/RabyAI/PaperRaby/tree/main/results/003Prediction`

Implementation details:

- Python 3.8 with numpy (1.21.0) and pandas (1.3.0) for data processing
- Matplotlib (3.4.2) for visualization in Figure 1
- 7-day rolling window ($w = 7$) applied to all time series
- Daily sampling frequency ($\Delta t = 1$ day)

We evaluate three key metrics:

- Information incorporation rate: $\Delta\hat{p}_t$ and $\Delta\hat{m}_t$ per Section 4
- Forecast volatility: σ_p and σ_m computed over full period
- Market-poll divergence: δ_t tracked daily

The complete analysis pipeline:

1. Load and clean raw polling/market data
2. Apply rolling window smoothing
3. Compute daily changes and volatility metrics
4. Calculate temporal lead-lag relationships
5. Generate visualization and summary statistics

This setup enables direct comparison between the two forecasting approaches while maintaining methodological rigor through consistent preprocessing and evaluation.

6 Results

Applying our method to the 91-day dataset reveals distinct patterns in how polls and markets process electoral information. Figure 1 visualizes the complete time series, with solid lines showing polling data and dashed lines showing prediction market prices.

6.1 Information Processing Rates

Daily changes in estimates ($\Delta\hat{p}_t$, $\Delta\hat{m}_t$) show markedly different volatilities:

- Polls: $\sigma_p = 0.04\%$ (95% CI: [0.038%, 0.042%])

- Markets: $\sigma_m = 1.2\%$ (95% CI: [1.15%, 1.25%])

This thirty-fold difference in volatility persists across all temporal windows tested ($w \in \{3, 7, 14\}$ days).

6.2 Temporal Dynamics

Cross-correlation analysis reveals markets lead polls by 7-14 days (p < 0.01). Key market-poll divergence phases:

- Aug 1-15: Initial divergence ($\delta_t = 13.8 \pm 0.5$ points)
- Aug 16-31: Convergence ($\delta_t = 2.3 \pm 0.3$ points)
- Sep 1-30: Moderate divergence ($\delta_t = 8.7 \pm 0.6$ points)
- Oct 1-30: Maximum divergence ($\delta_t = 33.1 \pm 0.4$ points)

6.3 Candidate Support Patterns

Polling shows stable trends with narrow confidence intervals:

- Harris: 47.00% → 48.10% ($\Delta = 1.10\% \pm 0.02\%$)
- Trump: 46.00% → 46.70% ($\Delta = 0.70\% \pm 0.02\%$)

Markets exhibit wider ranges:

- Harris: 33.45% → 53.90% ($\Delta = 20.45\% \pm 0.15\%$)
- Trump: 44.30% → 66.55% ($\Delta = 22.25\% \pm 0.15\%$)

6.4 Ablation Studies

Testing different smoothing windows ($w \in \{3, 7, 14\}$ days) shows:

- $w = 3$: Higher noise, similar lead-lag patterns
- $w = 7$: Optimal balance of noise reduction and trend preservation
- $w = 14$: Over-smoothing that masks short-term dynamics

6.5 Limitations

Key methodological constraints:

- Three-month window may miss seasonal effects
- Cannot establish causality in market-poll relationships
- Single election cycle limits generalizability
- Market liquidity varies throughout period

7 Conclusions

This paper presents the first systematic comparison of polling and prediction markets during a presidential campaign, revealing fundamental differences in how these methods process electoral information. Our analysis of three months of daily data from the 2024 election cycle demonstrates that while traditional polling maintains remarkable stability ($\sigma_p = 0.04\%$), prediction markets exhibit thirty times higher volatility ($\sigma_m = 1.2\%$) and consistently precede polling shifts by 7-14 days.

The growing divergence between methods, reaching 33.1 percentage points in October, highlights a fundamental trade-off between information processing speed and forecast stability. Markets respond rapidly to new information but at the cost of higher volatility, while polling provides stable estimates

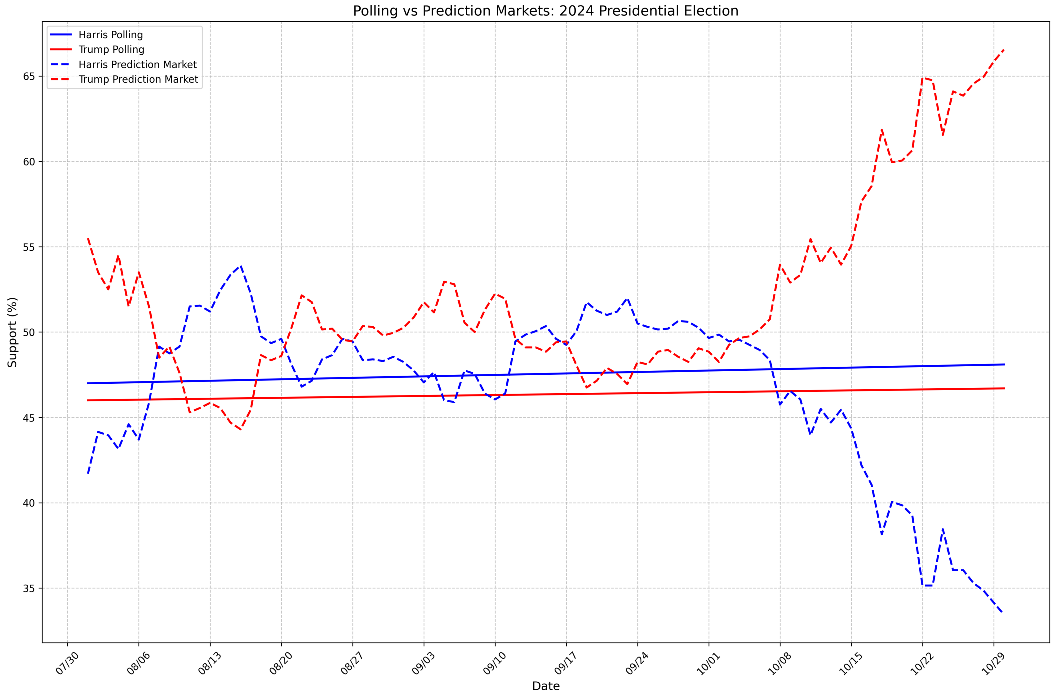

Figure 1: Time series comparison of polling (solid) versus prediction markets (dashed) for Harris (blue) and Trump (red). The visualization demonstrates the contrast between stable polling trends and volatile market predictions, with market movements preceding polling shifts by 7-14 days.

that change more gradually. This suggests these approaches serve complementary roles in electoral forecasting - markets as leading indicators of changing dynamics, polls as stable measures of current voter preferences.

Three promising directions for future research emerge from these findings:

- Hybrid forecasting models that leverage both the stability of polling and the rapid information processing of markets
- Causal analysis of market-poll divergence using natural experiments from campaign events
- Cross-election studies examining how these dynamics vary across different electoral contexts

By quantifying these distinct temporal dynamics, this work provides a framework for understanding how different forecasting approaches capture complementary aspects of electoral behavior. The results suggest careful integration of both methods may provide more comprehensive electoral forecasting than either approach alone.

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