Price Discovery and Trading in Modern Prediction Markets

Financial Fraud, Misconduct and Market Manipulation Conference (FFMM 2026)

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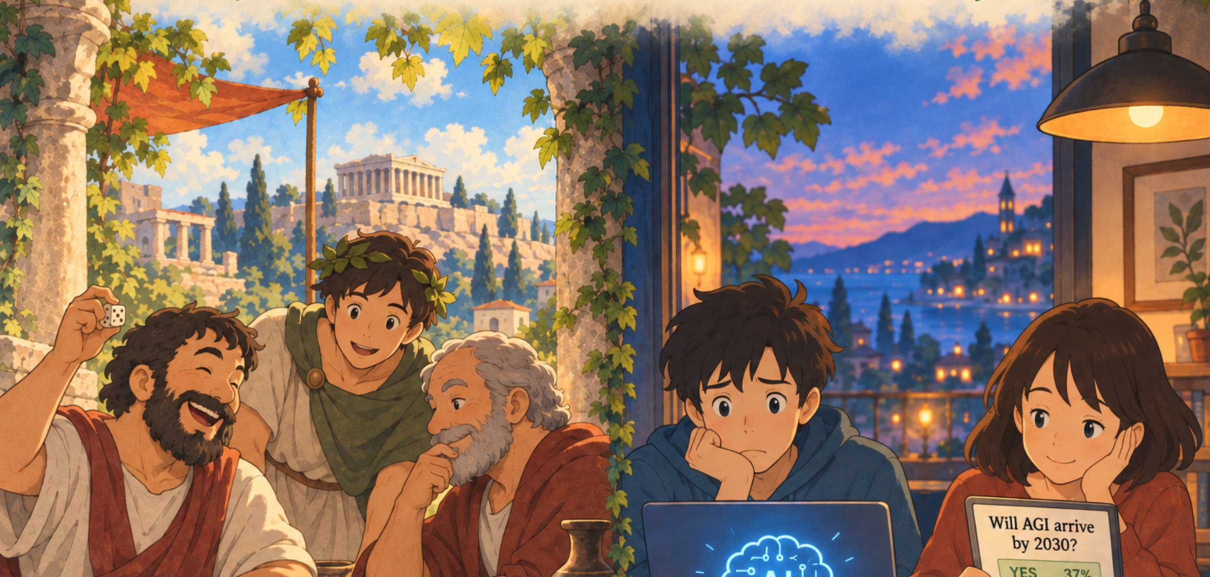
Thank you to the FFMM 2026 organizers and participants

A Question for the Room

Before I begin:

Are you worried about AI overtaking everything?

Human intelligence has had an uneven history.
Betting has had a remarkably steady one.



AI Is Big, but Uncertain

NEWSLETTERS • CIO JOURNAL

AI Spending Is Up. So Is the Guesswork.

Plus, Nvidia agrees to buy Hugging Face for $13 billion

By Tom Loftus
Sept. 3, 2026 9:18 am ET

Aa 1 Listen (1 min)

An AI sign is seen at the World Artificial Intelligence Conference in Shanghai, China July 6, 2023. REUTERS/Aly Song/File Photo

Good morning. As AI spending ricochets across the enterprise, many organization leaders still can't say with confidence what they're actually getting for it.

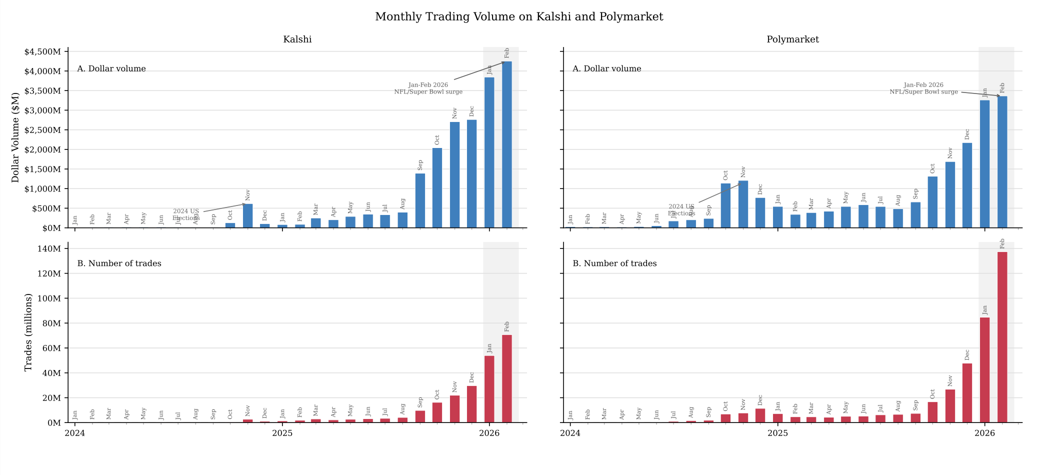
A Gartner survey of around 1,300 functional leaders from companies with at least $50 million in fiscal 2025 revenue found a sizable share—23%—have no idea of the rate of return on their AI investments. And even among those who do track it, the uses companies pursue most heavily often aren't the ones generating the highest returns.

- AI investment is rising quickly, but firms still struggle to identify the payoff.
- A Gartner survey cited by the WSJ reports that 23% of large firms had no estimate of AI ROI.

But prediction markets have been rising ever since the 2024 U.S. elections.

Source: *The Wall Street Journal*, (Loftus, 2026), September 3.

Prediction Markets Became Large



The 2024 U.S. election marks the point where modern prediction markets become large enough for market-microstructure evidence.

FFMM 2026 Research Map

Misconduct and incentives. Sibille et al. (2026), Strobl and Winton (2026), and Buxton et al. (2026) study how research incentives, conflicts of interest, and AI-based signals shape misconduct detection. The political-finance papers then ask how campaign money, environmental violations, analyst share-count forecasts, CDS trading, and activism affect firm behavior and monitoring: Hess and Zährl (2026), Liu et al. (2026), Uymaz et al. (2026), Zhao and Hoque (2026), and Tiniç and Togan (2026).

Prediction markets. Rozzi and Rasooly (2025) run a field experiment and show that price shocks can remain visible for weeks. Gomez Cram et al. (2026) use Polymarket transactions and argue that forecast accuracy comes from a small group of persistently skilled accounts. Our paper moves from one platform to competing venues, asking where prices move first when the same event trades on Kalshi and Polymarket.

Detection and market design. The remaining sessions study AML features, Bitcoin ATMs, mortgage supervision, tax fraud, DeFi spillovers, cross-country manipulation rules, social-media manipulation, intraday manipulation, AI surveillance, insider trading seasonality, stock promotions, and shareholder voting: Weyders and Hambuckers (2026), Wei (2026), Pereira et al. (2026), Banulescu-Radu et al. (2026), Yu et al. (2026), Addai et al. (2026), Lin and Gurrola (2026), Tran et al. (2026), Jiang (2026), Li et al. (2025), Höfer and Offermann (2026), Parajuli and Brogaard (2026), and Erten (2026).

Our paper fits by using transaction-level prediction-market data to show how market design and trader composition shape price discovery.

Modern Prediction Markets

Prediction Markets

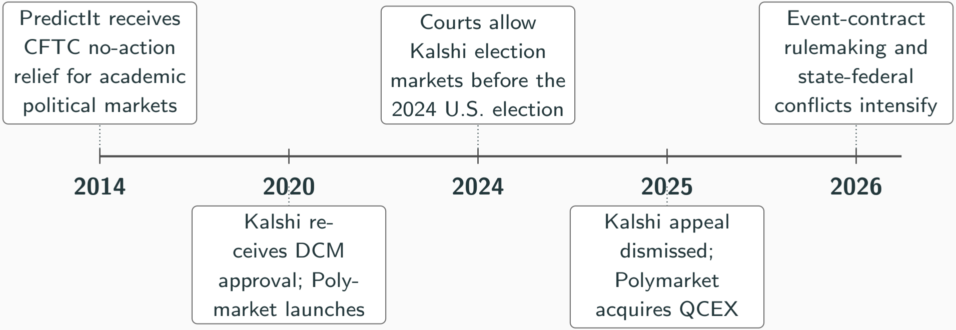
- Binary event contracts pay \$1 if an outcome occurs and \$0 otherwise.
- Prices in cents can be read as market-implied probabilities.
- Real-money trading lets beliefs update continuously before resolution.
- Question: when the same event trades on multiple platforms, where does price discovery happen first?
  - Prediction markets are often informative about future event outcomes (Wolfers and Zitzewitz, 2004; Arrow et al., 2008).

Prediction Markets Are Not New

- Political betting markets existed long before modern platforms; U.S. presidential betting markets were large and organized from 1868 to 1940 (Rhode and Strumpf, 2004).
- Wolfers and Zitzewitz (2004) emphasize that simple markets can aggregate dispersed information into useful forecasts.
- What is new today is scale, speed, and institutional overlap: the same event trades across regulated and crypto-native venues.

Our setting turns an old forecasting institution into high-frequency market-microstructure data.

Prediction Market Timeline ⚖️



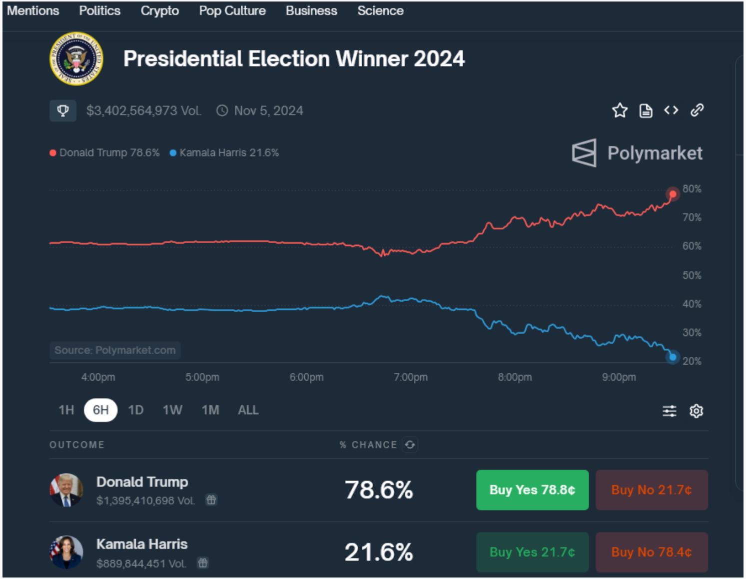
The institutional setting changes exactly when these markets become large enough to study.

Two Main Venues ⚖️

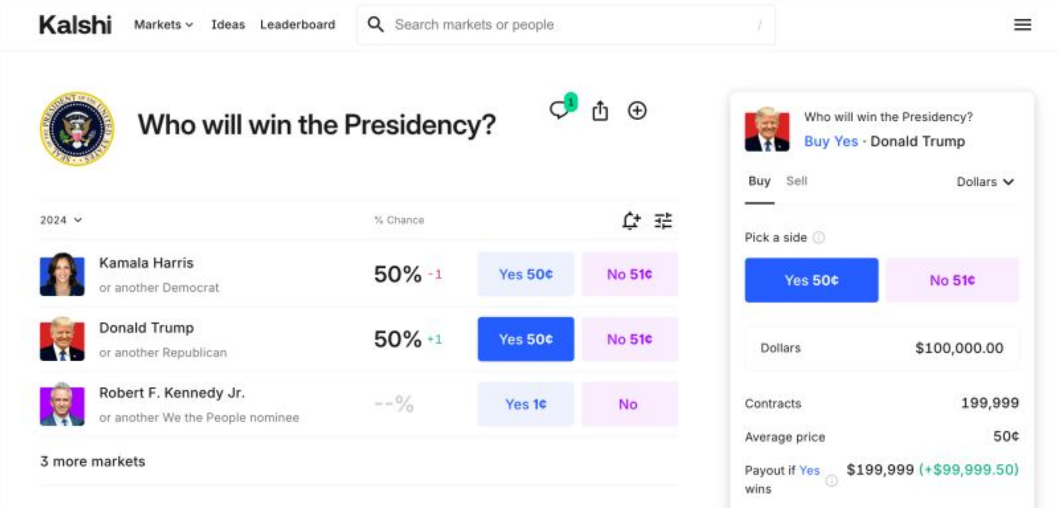
	Kalshi	Polymarket
Status	CFTC-regulated DCM	Global venue, ex-U.S. after 2022
Settlement	Fiat-collateralized	USDC on Polygon
Design	Central limit order book	Central limit order book since 2023
2026 scale	Volume exceeded \$10B in Feb 2026	Over \$10B traded in Mar 2026

- Same economic claims can trade under different access, regulation, and user bases.

Modern Prediction Markets: Polymarket



Modern Prediction Markets: Kalshi



Trading Mechanisms: Kalshi and Polymarket

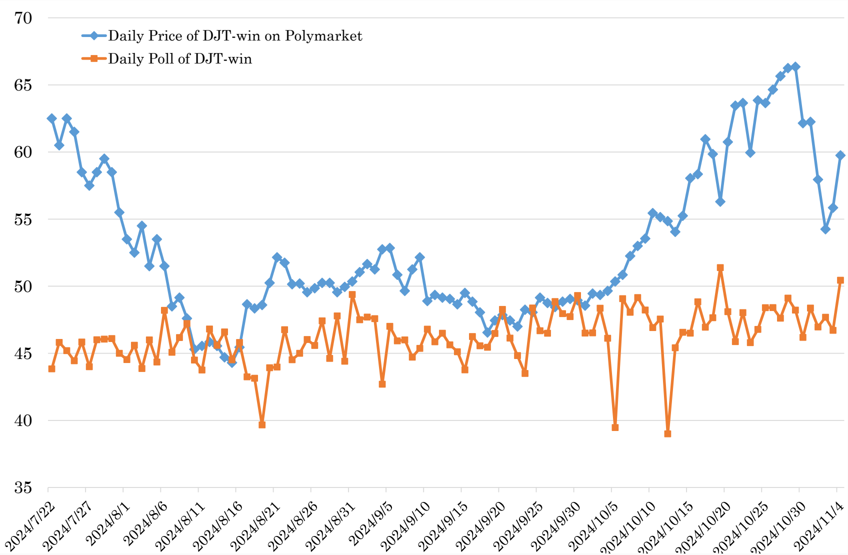
Kalshi (CFTC-regulated DCM)

- **Central Limit Order Book (CLOB)**: buy and sell orders matched directly; a position is created when Yes and No bids sum to $1.
- Fiat-collateralized; KYC required.

Polymarket (Global, crypto-native)

- **CLOB since 2023** (formerly AMM): order-book matching on Polygon blockchain, settled in USDC.
- No KYC; accessible globally (ex-US post-2022).

Why We Look at Prediction Markets



Prediction Markets vs. Polls

	Poll_t (1)	R_t^P (2)	ΔPoll_t (3)	R_t^P (4)
Poll_{t-1}	0.254**	0.001		
	[2.42]	[0.51]		
ΔPoll_{t-1}			-0.495***	0.001
			[-4.41]	[0.56]
R_{t-1}^P	13.987**	0.028	13.405**	0.03
	[2.45]	[0.24]	[2.24]	[0.25]
Intercept	34.533***	-0.036	0.073	0.000
	[7.08]	[-0.52]	[0.35]	[-0.04]
Observations	104	104	104	104
R^2	9.5%	0.3%	28.3%	0.3%
Granger Causality	6.02**	0.26	5.02**	0.31

Motivation: Why Prediction Markets?

- Prediction markets are informative and often outperform the polls.
- Polymarket prices predict poll numbers, but not the reverse.
- We reaffirm that this remains true in modern prediction markets.
- Do identical claims trade at the same price in multiple platforms?
    - If so, does there exist a hierarchy of informativeness among these markets?

Hypothesis Development

1. **Segmented venues** (regulation/access/user base) limit arbitrage ⇒ persistent **price spreads** for identical payoffs (Froot and Dabora, 1999; Makarov and Schoar, 2020).
2. **Microstructure: information enters via trading** ⇒ deeper-liquidity / lower-cost venue adjusts faster and **leads** (Kyle, 1985; Glosten and Milgrom, 1985; Hasbrouck, 1995; O'Hara, 1995).
3. **Informed trading channel:** differences in oversight/transparency ⇒ large trade order flow is more informative and can drive the lead (Chordia and Swaminathan, 2000; Chordia, Roll, and Subrahmanyam, 2002; Chordia and Subrahmanyam, 2004).

Comments We Received

- **External validity:** does the 2024 election result generalize beyond one high-profile event?
- **Market structure:** how do access, regulation, and CLOB design affect price discovery?
- **Data construction:** are matched trades and payoff directions comparable across platforms?
- **Mechanism:** is leadership about liquidity, large traders, event type, or information risk?

We now separate the election case from a broad matched-market test.

Why Expand to the Full Sample

- Election markets show a clean but unusual event.
- The full sample tests whether price leadership generalizes.
- Matching focuses on the same event, same payoff, and same direction.

Step	Remaining sample
Raw candidate market pairs	12,652
Audit payoff alignment	12,604
At least 5 overlap days	2,118
Consecutive 30-min returns	1,972 pairs
Matched events	1,533 events
Final observations	160,159

The matching keeps a conservative subset of economically equivalent markets.

Results Preview

1. **Law of one price fails across platforms**
   - Persistent cross-platform price spreads for the same payoff.
   - Example: for KH, Kalshi price $>$ Polymarket on all 33 overlapping days.
2. **Arbitrage is economically meaningful**
   - Cross-platform arbitrage profits are large (even under 2% trading cost).
   - $>$\$135K (1-second matching) and $>$\$2.58M (5-min) over the election window.
3. **Price discovery depends on market setting**
   - In the 2024 election, Polymarket leads Kalshi.
   - In the full matched sample, price discovery is bidirectional.
   - Leadership varies with relative volume, whale trading, market category, and insider-risk exposure.

Contribution

1. **Prediction markets and forecasting**
   - Prediction markets often outperform polls in forecasting (Wolfers and Zitzewitz, 2004; Arrow et al., 2008; Atanasov et al., 2017).
   - *Ours: First large-scale study of modern, liquid, multi-platform election prediction markets.*
2. **Limits to arbitrage**
   - Noise trading and frictions prevent price convergence (De Long et al., 1990; Shleifer and Vishny, 1997; Gromb and Vayanos, 2010).
   - Crypto exchanges show large cross-exchange dispersions (Makarov and Schoar, 2020)
   - *Ours: Persistent cross-platform arbitrage in prediction markets despite low trading costs.*
3. **Price discovery across markets**
   - Price discovery occurs where liquidity concentrates (Eun and Sabherwal, 2003; Karolyi, 2006; Tetlock, 2008; Chordia, Roll, and Subrahmanyam, 2008; Chordia et al., 2009).
   - *Ours: Price leadership changes with relative trading activity, market category, and insider-risk exposure.*

Contribution

- An increasing number of studies leverage prediction markets to extract useful financial market information
  - Eichengreen et al. (2025); Taillard and Zeng (2025); Li and Xie (2025); Gómez-Cram et al. (2025)
- Our study shows that when multiple platforms trade the same event, price discovery depends on where trading activity and informed order flow concentrate.

Data

Four Betting Platforms Analyzed

- **Kalshi** – Founded in 2018, Kalshi became the first federally approved exchange for real-money event contracts.
- **Polymarket** – Launched in 2020, Polymarket is a crypto-native platform built on the Polygon blockchain. Though closed to U.S. users after a 2022 CFTC settlement, it offered early access to 2024 election markets globally and reached over $3.6 billion in election volume.
- **Robinhood** – Popular mobile trading app. Entered the election market late on October 28. Limited to mobile-only trading during study period.
- **PredictIt** – U.S. political betting platform operated for academic purposes. In September 2025, PredictIt received full regulatory approval from the CFTC to operate as a DCM and derivatives clearing organization (DCO).

Our Data

- ✓ **Election sample**: 2024 U.S. presidential election markets on Kalshi and Polymarket, from **10/4/2024** to **11/5/2024**. **Transaction-level data** collected.
- ✓ **Daily price sample**: Kalshi, Polymarket, PredictIt, and Robinhood prices for DJT-Win and KH-Win markets.
- ✓ **Matched-market panel**: Polymarket and Kalshi markets that settle on the same outcome, spanning **9/13/2023** to **3/29/2026**.
- ✓ Final panel: 1,533 matched events, 1,972 market pairs, and 160,159 30-minute observations.

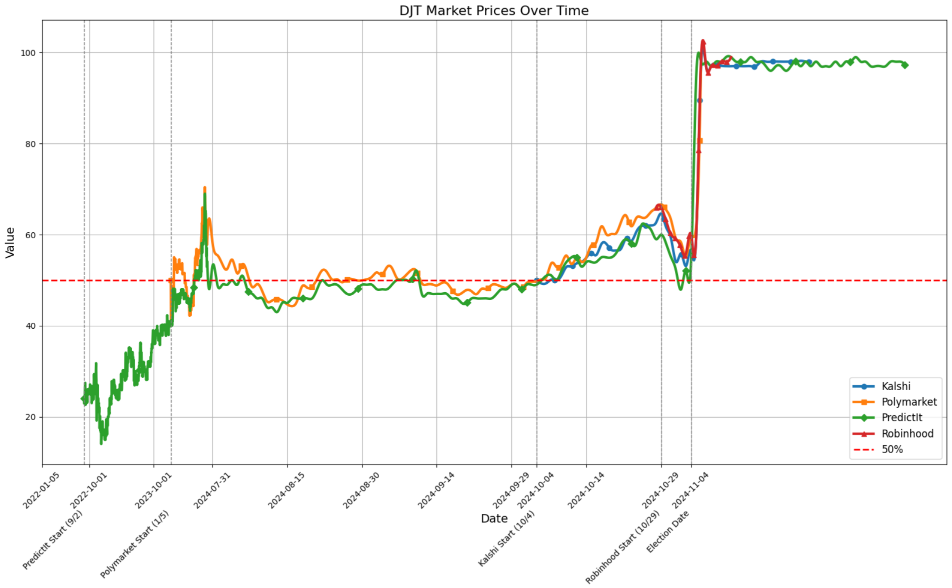
Matched Market Sample

- Start from platform event inventories, then match markets with the same underlying event and payoff direction.
- Exclude parlays, multivariate products, and low-confidence matches.
- Require at least five overlapping active days and aligned 30-minute returns on both platforms.

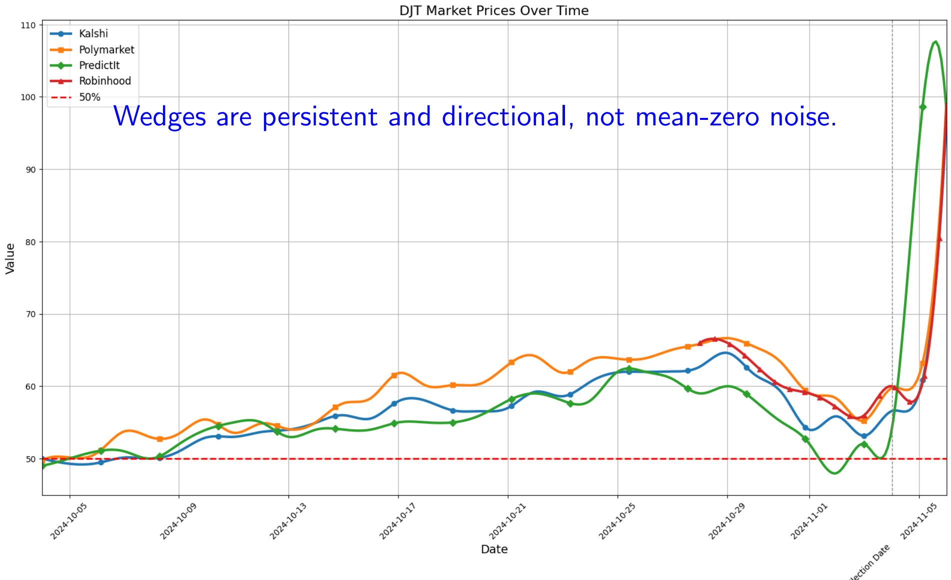
Category	Market pairs	Volume leader
Sports	1,385	Kalshi
Entertainment	265	Kalshi
Politics/Elections	237	Polymarket
Other categories	85	Mixed
Total	1,972	

Results

Price Discrepancies



Price Discrepancies: Zoom-In to 1-month ahead of Election



Price Spreads in Numbers

Table 1: Number of Days (Price of Column > Price of Row) across Platforms

	Kalshi	Polymarket	PredictIt	Robinhood
Kalshi	—	0 (33)	32 (33)	9 (9)
Polymarket	1 (33)	—	32 (33)	9 (9)
PredictIt	21 (33)	29 (33)	—	1 (9)
Robinhood	1 (9)	5 (9)	1 (9)	—

Note: Values in parentheses are the total number of overlapping days (DJT contract, KH contract).

Price Spreads in Numbers

Table 2: Average Signed Price Spread across Platforms

	Kalshi	Polymarket	PredictIt	Robinhood
Kalshi	—	-3.2676***	3.5597***	2.3878***
	—	[-14.73]	[2.86]	[6.01]
Polymarket	-2.5885***	—	6.8273***	6.0889***
	[-8.29]	—	[5.32]	[12.90]
PredictIt	0.1161	2.7045**	—	-1.0000
	[0.10]	[2.22]	—	[-0.22]
Robinhood	-2.1644***	0.9889**	-1.5556	—
	[-5.67]	[2.18]	[-0.36]	—

Note: Values are averages of column price − row price (DJT contract, KH contract).

Cross-Platform Arbitrage Algorithm (Kalshi vs. Polymarket)

Step 1. Form candidate pairs within each time bin (1s/1m/5m)

- For each bin, sort trades on each platform by lowest price first.

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Step 3. Compute realizable (volume-weighted) profit

- Match size is constrained by observed liquidity: $q = \min(\mathrm{size}_j, \mathrm{size}_k)$;
- Profit: $\pi := q \times (1 - \delta - S(j,k))$.

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Step 4. Iterate until no more profitable matches in the bin

- After each match, reduce the larger trade by the matched amount ("leftover size") and continue;
- Stop until $S(j,k) \geq 1 - \delta$.

Cross-Platform Arbitrage Profit

Table 3: Aggregated Profits across All Bins

Interval	Platform with Long DJT Position	Total Violation Value (Without Fee)	Total Violation Value (2% Fee)
1-Second	Kalshi	135,480.41	42,741.94
1-Second	Polymarket	238.80	4.00
1-Minute	Kalshi	1,630,571.29	591,150.29
1-Minute	Polymarket	1,798.35	183.67
5-Minute	Kalshi	2,581,975.65	1,008,229.99
5-Minute	Polymarket	10,562.77	420.92

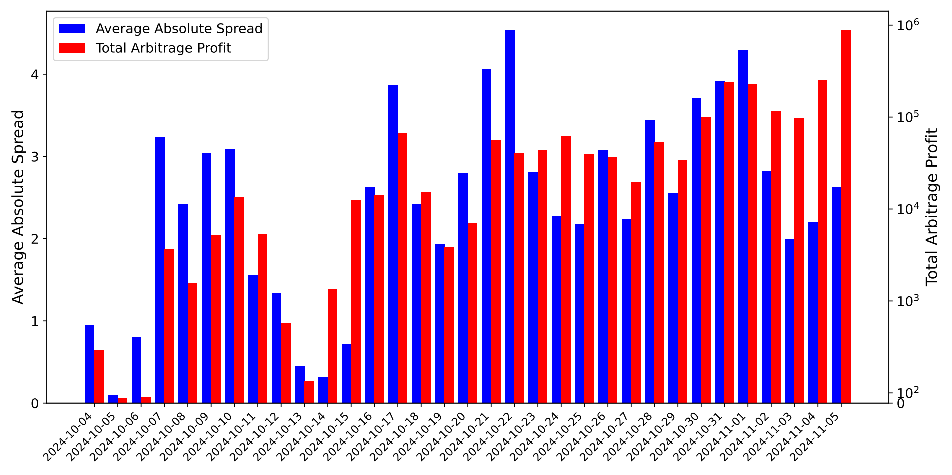
Volume

Within-Platform Arbitrage Profit

Table 4: Aggregated Profits across All Bins

Interval	Platform	Total Violation Value (Without Fee)	Total Violation Value (2% Fee)
1-Second	Kalshi	2,955.34	256.06
1-Second	Polymarket	77,868.54	1,831.01
1-Minute	Kalshi	14,448.40	1,902.62
1-Minute	Polymarket	331,503.18	7,215.02
5-Minute	Kalshi	45,043.82	6,627.88
5-Minute	Polymarket	640,006.61	27,525.05

Trading Profits Over Time



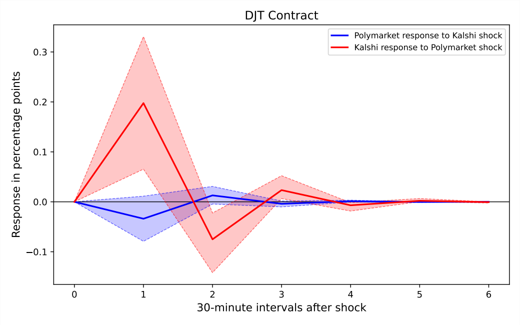
Price Discovery

- Prediction market prices are highly informative
- Large price gaps exist across multiple markets
- Next: where does price discovery happen?
  - 💡 Explore using return lead-lag between markets
- Empirical Model (VAR):

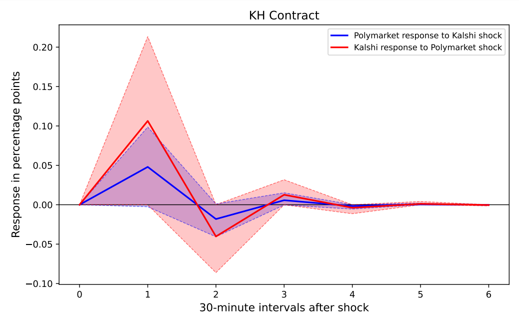
$$\mathbf{R}_t = \mathbf{c} + \mathbf{\Phi}_1 \mathbf{R}_{t-1} + \mathbf{u}_t,$$

where the dependent variable $\mathbf{R}_t$ is a 2×1 vector of returns (in %) for a given contract on Kalshi (R_t^K) and Polymarket (R_t^P) at the t-th 30-minute interval.

Lead-Lag Analysis: Main Results



(a) DJT Contract



(b) KH Contract

- A 1 p.p. Polymarket return predicts a 0.20 p.p. Kalshi response for DJT.
- The KH response is smaller but still significant at 0.11 p.p.
- Kalshi does not significantly lead Polymarket for DJT.

Full Sample Lead-Lag

- Full matched panel:
  - 1,533 events
  - 1,972 market pairs
  - 160,159 30-minute observations
- Price discovery is bidirectional on average.
- Transmission is stronger in active markets.

	Equal weighted	Volume weighted
$P \rightarrow K$	0.100***	0.265***
	[7.80]	[3.16]
$K \rightarrow P$	0.095***	0.636***
	[5.52]	[2.67]
Observations	160,159	151,032
Market pairs	1,972	1,944

Relative Trading Volume

- We compare cumulative trading activity on Polymarket relative to Kalshi.
- Low regime: Polymarket volume is low relative to Kalshi.
- High regime: Polymarket volume is high relative to Kalshi.

	Low relative volume	High relative volume
$P \to K$	0.073***	0.031
$K \to P$	0.220***	0.009

- Kalshi leads only when Kalshi dominates trading volume.
- When Polymarket volume is high, the Kalshi lead disappears.

Whale Trading Activity

- Whale trades proxy for informed order flow.
- In the matched panel, whale volume uses the same relative-regime design as total volume.

	Low relative whale volume	High relative whale volume
$P \to K$	0.077***	0.051
$K \to P$	0.196***	0.010

- Kalshi-to-Polymarket price discovery weakens when whale activity shifts toward Polymarket.
- Polymarket's lead is more stable across regimes.

Market Category

	Politics/Elections	Entertainment	Sports
$P \rightarrow K$	0.178***	0.059***	-0.074
	[5.87]	[3.39]	[-0.40]
$K \rightarrow P$	-0.028	0.040	1.414***
	[-1.17]	[0.55]	[4.72]
Observations	50,382	12,160	82,311
Market pairs	237	265	1,385

- Polymarket leads in politics and entertainment.
- Kalshi leads in sports, where Kalshi trading volume is much larger.

Insider and Manipulation Risk

- We score each matched market's exposure to insider information and manipulation risk.
- The strongest shift appears in politics/elections and entertainment.

	Politics/Elections	Entertainment
High insider-risk shift		
$\Delta(P \rightarrow K)$	0.111***	0.197***
$\Delta(K \rightarrow P)$	-0.106***	-0.340**
High manipulation-risk shift		
$\Delta(P \rightarrow K)$	-0.065	0.070
$\Delta(K \rightarrow P)$	-0.097*	-0.072

- Polymarket's leadership strengthens when private information is more likely to matter.

Conclusion

Conclusion

- Prediction market prices are highly informative and outperform polls in the 2024 election.
- Persistent cross-platform price gaps generate economically meaningful arbitrage.
- In the 2024 election, Polymarket leads Kalshi in price discovery.
- In the full matched sample, leadership is bidirectional and depends on market conditions.
- Relative volume, whale trading, market category, and insider-risk exposure help explain where prices move first.
- **Policy implication:** liquidity provision and monitoring of large trader activity are central for market efficiency.

Thank you

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Central Limit Order Book (CLOB)

- Uses a **central limit order book** — each buy order must match a sell order.
- Market positions are created when "Yes" and "No" bids sum to \$1 (e.g., \$0.40 Yes, \$0.60 No).
- No transaction or platform fees — users only pay Polygon network gas (usually $< \$0.01$) ✅
- **CLOB Bid-Ask Spread Function**:

$$P_t = \frac{A_t + B_t}{2}$$

Where A_t = best ask, B_t = best bid

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Automated Market Maker Mechanics (AMM)

AMM uses some Market Scoring Rule (MSR):

$$P_t = \frac{e^{q_t/b}}{e^{q_t/b} + e^{r_t/b}}$$

- q_t: demand for "Yes"; r_t: demand for "No"
- b: liquidity sensitivity parameter — higher b = smoother prices

Liquidity and Execution:

- Institutional liquidity by Susquehanna (SIG).
- AMM absorbs imbalance — traders can always buy/sell.

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Cross-Platform Arbitrage Matched Volumes

Table A: Aggregated Matched Volumes across All Bins

Interval	Platform with Long DJT Position	Total Matched Volumes (Without Fee)	Total Matched Volumes (2% Fee)
1-Second	Kalshi	4,805,344.67	3,284,969.63
1-Second	Polymarket	45,991.51	379.18
1-Minute	Kalshi	49,345,555.10	37,005,520.32
1-Minute	Polymarket	287,234.14	684.64
5-Minute	Kalshi	70,943,135.48	55,730,280.92
5-Minute	Polymarket	1,128,087.33	47,618.70

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